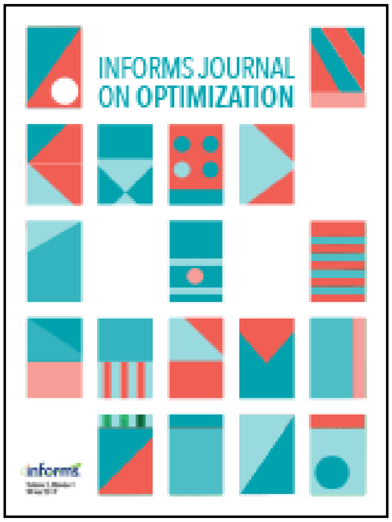

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The Nutritious Supply Chain: Optimizing Humanitarian Food Assistance

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Abstract. The World Food Programme (WFP) is the largest humanitarian agency fighting hunger worldwide, reaching approximately 90 million people with food assistance across 80 countries each year. To deal with the operational complexities inherent in its mandate, WFP has been developing tools to assist its decision makers with integrating supply chain decisions across departments and functional areas. This paper describes a mixed integer linear programming model that simultaneously optimizes the food basket to be delivered, the sourcing plan, the delivery plan, and the transfer modality of a long-term recovery operation for each month in a predefined time horizon. By connecting traditional supply chain elements to nutritional objectives, we are able to make significant breakthroughs in the operational excellence of WFP's most complex operations. We show three examples of how the optimization model is used to support operations: (1) to reduce the operational costs in Iraq by 12% without compromising the nutritional value supplied, (2) to manage the scaling-up of the Yemen operation from three to six million beneficiaries, and (3) to identify sourcing strategies during the El Niño drought of 2016.

Keywords: supply chain • nutrition • MILP • humanitarian logistics • WFP

1. Introduction

Humanitarian organizations are currently facing an incredible amount of complex crises. Conflicts in countries such as Syria, South Sudan, and Yemen have been unprecedentedly long and large in scale, and many African countries are suffering from droughts and poor harvests. These crises result in rapidly deteriorating living conditions for everyone in the vicinity, threatening millions of innocent people with hunger, malnutrition, and worse. For decades, humanitarian organizations, such as the United Nations (UN), Médecins sans Frontières, and the International Committee of the Red Cross, have been doing everything in their power to provide assistance to those in need.

There are nearly 690 million undernourished people in the world today (Food and Agriculture Organization of the United Nations et al. 2020). This means that 1 in 11 people in the world do not have access to enough food to be healthy and lead an active life. Currently a global pandemic (COVID-19) is threatening the health and livelihoods of these people even further, so these numbers are expected to increase. However, the UN considers hunger one of the greatest solvable problems (Food and Agriculture Organization of the United Nations et al. 2015). The second sustainable development goal is zero hunger, and it calls on all people to do their part to eliminate hunger in our lifetimes.

One of the key players in responding to emergencies and eliminating hunger is the United Nations World Food Programme (WFP). WFP is the world's largest humanitarian organization fighting hunger worldwide with more than 18,000 employees across the globe. In emergencies, it distributes food where it is needed, saving the lives of victims of war, civil conflict, and natural disasters. After the cause of an emergency has passed, WFP uses food assistance to help communities rebuild their lives and return to a semblance of normality. In 2019, a total of 97 million people spread across 88 countries were reached directly by WFP assistance, covering 70% of those facing critical hunger levels (World Food Programme 2020).

Delivering food to this number of people in these complex environments requires a supply chain that is agile, adaptable, and aligned (Lee 2004). Every year, WFP procures, transports, and distributes around four million metric tons (four billion kilograms) of food to people in need. The poor infrastructure conditions and high levels of insecurity in conflict areas necessitate creativity and flexibility in delivering this food, and WFP has been known to employ every variety of transportation method—from elephants and camels to airplanes and barges. In 2017, on any given day WFP had 5,000 chartered trucks on the road, 92 chartered planes in the air, and 20 chartered ships at sea (World Food Programme 2018). By virtue of its excellent logistical performance, WFP is even mandated to lead logistics operations whenever a humanitarian agency requires a joint response from UN agencies and the humanitarian community.

1.1. Literature

There are several phases in responding to a disaster. In the literature, we generally see that disaster timelines are split into four stages: mitigation, preparedness, response, and recovery (Altay and Green 2006, Van Wassenhove 2006, Ergun et al. 2011). Mitigation focuses on the prevention of a disaster and the reduction of its intensity, for instance, by setting up alert systems that warn against floods or by defining building guidelines for areas that are vulnerable to earthquakes or hurricanes. Preparedness is more concerned with setting up the appropriate resources (both physical and human), such as the building and stocking of strategic warehouses or the training of personnel. Response starts once the disaster has occurred; it includes activities such as the delivery of food and services to those in need, evacuation of the affected region, and the collection of debris. Finally, the recovery phase aims to return a semblance of normality to the area affected.

Holguín-Veras et al. (2012) split up the recovery phase into short- and long-term recovery, in which short-term recovery is a transitional stage covering damage assessments, repairs, housing, etc. Long-term recovery may span multiple years and includes the rebuilding of infrastructure and distribution of medical and food supplies to prevent disease and malnutrition. This long-term recovery is one of the focus areas of WFP. Most literature on humanitarian logistics focuses on the preparedness and response side of a disaster, whereas long-term recovery is a topic that does not receive much attention.

Many researchers have characterized and discussed the challenges and opportunities of humanitarian logistics. Van Wassenhove (2006) discusses how the private sector can learn from the agility and adaptability inherent in humanitarian supply chains and how the humanitarian sector can learn from the established supply chain management (SCM) best practices in the private sector. In a follow-up paper, Van Wassenhove and Pedraza Martinez (2012) illustrate the potential of operations research in particular for adapting such SCM best practices to humanitarian logistics. Apte (2010) discusses research issues and potential actions surrounding the field of humanitarian logistics and reviews analytical models from the literature to understand the state of the art in humanitarian logistics. Apte (2010) mentions the sustaining of long-term developmental aid when discussing research gaps. Çelik et al. (2012) also mention that there is a research gap in relation to long-term recovery, using the term "long-term humanitarian development" instead. Additionally, they highlight that there is a lack of good implementation of decision support tools in humanitarian operations. Holguín-Veras et al. (2012) pinpoint research gaps that need to be filled to enhance both the efficiency of humanitarian logistics and the realism of the mathematical models designed to support it. They argue that humanitarian logistics is too broad a field to fit neatly into a single definition of operational conditions and urge researchers to treat these different operational conditions separately.

Despite the qualitative attention to long-term recovery, there are few mathematical formulations available that cover the entire scope of a humanitarian supply chain. Most existing research is focused on (a combination of) three subproblems, namely that of facility location (Balcik and Beamon 2008), distribution (Haghani and Oh 1996, Özdamar and Demir 2012, Rottkemper et al. 2012, Rancourt et al. 2015), and inventory control (Beamon and Kotleba 2006, Pérez-Rodríguez and Holguín-Veras 2016). Humanitarian researchers have extended the traditional models for these three subproblems with constraints, objectives, and solution methods to facilitate the special requirements of a humanitarian supply chain. These extensions include (but are not limited to) research on the appropriate objective function (Holguín-Veras et al. 2013, Gralla et al. 2014, Gutjahr and Nolz 2016) and modeling uncertain demand, prices, and capacities (Ben-Tal et al. 2011, Rawls and Turnquist 2012, Bozorgi-Amiri et al. 2013). For an in-depth discussion of what is necessary to make a traditional (i.e., commercial) supply chain model work in a humanitarian context, we refer to Holguín-Veras et al. (2012).

For food assistance in particular, the design of food baskets is an important topic. Many papers illustrate how mathematical models can be used to generate food baskets or nutritious products that satisfy all nutritional requirements (Briend et al. 2003, Fleige et al. 2010, Ryan et al. 2014, Deptford et al. 2017, Bose et al. 2019). For example, Carlson et al. (2003) develop a quadratic optimization model that, for each age–gender group, selects the optimal food plan that meets the dietary standards, adheres to the budget constraints, and resembles the reported food consumption for that specific age–gender group (therefore, making it more likely that the food plan "sticks"). Similarly, Chastre et al. (2007) develop linear programming routines to generate hypothetical diets using a combination of foods that enable a family to meet their energy and nutrient requirements as recommended by the World Health Organization and the Food and Agriculture Organization of the UN at the lowest possible cost. As the software (Cost of the Diet) can account for the frequency at which foods are eaten, for example, by specifying that a particular food is eaten three times a day, the food baskets can be adjusted to reflect typical dietary patterns.

One aspect of humanitarian aid that is not yet covered in the operations research literature is that humanitarian organizations have several methods at their disposal for delivering assistance. Whereas, in the past, transfers were done exclusively in-kind (i.e., the organization buys, transports, and distributes commodities), these days, it has become common to provide beneficiaries with cash or vouchers instead, allowing them to purchase their own commodities at local markets or selected retailers. Lentz et al. (2013) discuss the rise of these new food-assistance instruments. There are multiple interacting effects to be considered, and it is important to weigh the benefits (reduced transportation costs, increase in the beneficiary's dignity) against the dangers (the influx of cash or vouchers may disrupt the local economy). They state that no single tool is always and everywhere preferable and seek to educate the reader on their appropriate use. In particular, the economic repercussions of choosing one transfer modality over another are notoriously hard to measure, making it difficult to select the appropriate instrument. Ryckembusch et al. (2013) discuss an analytical tool that is able to compare the cost-effectiveness of transfer modalities. Their tool, the "omega value," considers the trade-off between total costs (procurement, transportation, services, etc.) and the nutrient value score (NVS). The NVS is a weighted score function that shows to what extent all nutritional requirements are met (for nutrients such as energy, protein, vitamins, etc.). The omega value shows the nutritional value per dollar spent and can assist policy makers in making the right choice of food basket and transfer modality.

For the successful application of the types of mathematical models described, availability of good data are crucial. Paradoxically, humanitarians face the double burden of insufficient data and information overload. On the one hand, it is often difficult to find the data that is required to support analyses; Altay and Labonte (2014) describe eight data challenges in particular, such as the inconsistency between data sources (e.g., different definitions, master data, geographical scopes, etc.) and the inaccessibility of vital information (e.g., because of physical access constraints or sudden disruptions). On the other hand, and in particular for sudden-onset emergencies, information is being collected by dozens of agencies and thousands of volunteers, all of whom are trying to support the relief activities. It is becoming increasingly complex to analyze all this data to distill the critical information needed for decision making (United Nations Office for the Coordination of Humanitarian Affairs 2002, Harvard Humanitarian Initiative 2010).

1.2. Research Questions

The literature survey highlights several challenges and research gaps. In particular, we find

a. Long-term humanitarian assistance has received little attention.
b. Most papers focus on subproblems (e.g., facility location).
c. Alternative transfer modalities (e.g., cash, vouchers) have not been addressed yet.
d. There is a lack of models that are actually being implemented (e.g., because of data challenges).

In this paper, we try to close these four gaps by addressing our main research question: how can optimization help WFP to improve the cost-effectiveness of its operations? In answering this question, we pay particular attention to the integration of WFP's key supply chain decisions (i.e., food basket design, transfer modality selection, and sourcing and delivery plan) into a single tractable mathematical model and how such a model can be implemented in practice. Although the focus of the paper is on WFP, many of the models and lessons learned can be applied to other humanitarian supply chains.

The rest of the paper is structured as follows: in Section 2, we provide a brief description of the key components of WFP's supply chain. In Section 3, we develop a mixed integer linear programming (MILP) model that optimizes the food basket design, transfer modality selection, sourcing plan, and delivery plan of a long-term recovery operation for each month in a predefined time horizon. In Section 4, we discuss various insights that can be gained from this integrated model and how it influences decision making. In Section 5, we apply this model to three WFP use cases: Iraq, Yemen, and El Niño, demonstrating how we can use the optimization model to reduce the operational costs and improve the effectiveness of complex operations. In Section 6, we extend the core model with additional features and reflect on future research. In Section 7, we provide our concluding remarks. The appendix contains the detailed model specifications (constraints, variables, etc.) and a short history of the project (Appendix C).

2. WFP's Supply Chain

Before defining the mathematics, it would be prudent to offer a brief discussion of WFP's supply chain and the components of our model. We consider the food basket, transfer modalities, sourcing, and logistics network.

2.1. Food Basket

WFP's food assistance depends on the context of the crisis and the beneficiaries' health, demographics, and access to non-WFP food. The bulk of food assistance is provided through General Food Distribution (GFD), a monthly parcel that provides enough food for a standard-sized family. Additional food assistance is supplied to more vulnerable beneficiaries, such as those suffering from malnutrition, young children, and pregnant or nursing women. Nutritionists track the nutrients that WFP's food baskets provide and make sure that they align with the needs of the different beneficiary types (e.g., a young child may receive a fortified cereal on top of the generic ration). Traditionally, demand was defined in terms of predetermined food baskets per beneficiary type, but in this paper, we take one step back and define demand as nutritional requirements, allowing us to optimize the food baskets rather than using the predefined ones. For the applications in this paper, we consider 11 nutrients (three macronutrients and eight micronutrients), but the developed methodology works for any number of nutrients.

2.2. Transfer Modalities

There are multiple ways of satisfying the demand—be it a predefined food basket or a nutritional requirement. Whereas WFP used to supply the necessary commodities itself, in the last decade, there has been a transition toward cash-based transfers (also known as cash and vouchers). Traditional food transfers require WFP to source, store, transport, and distribute the commodities, whereas a cash-based transfer allows beneficiaries to obtain the commodities themselves from local markets and shops. Food transfers allow for more control over the food assistance and benefit from economies of scale (e.g., making use of bulk purchases, price seasonality, tax waivers, etc.). Cash-based transfers (CBT), on the other hand, are more direct (so more of the donation is spent on procurement), but they are dependent on local market availability, and their impact is harder to measure up front. We consider three types of CBT assistance:

1. Commodity vouchers: These vouchers entitle a beneficiary to a specific ration of one or more commodities (e.g., 15 kg of maize) to be redeemed at WFP-contracted stores.

2. Value vouchers: These vouchers entitle a beneficiary to purchase a range of commodities from WFP-contracted stores up to a certain value (e.g., US$20). Each beneficiary can choose what combination of commodities best fits their needs.

3. Cash: This is an unrestricted form of assistance, and beneficiaries have full control over where they spend their money and what they spend it on.

Note that each of these transfer modalities can be delivered to the beneficiary in different ways (e.g., distribution of physical vouchers, e-money, SMS vouchers, etc.), and the most appropriate transfer mechanism is heavily dependent on the location and what (financial) tools are already being used by the assisted population. In this paper, we develop and apply a model that considers commodity vouchers as an alternative transfer modality to in-kind assistance, allowing us to replace or expand traditional rations with locally available commodities that would be difficult to supply in-kind (e.g., fresh vegetables, dairy, meat, etc.). In Section 6, we develop a model that also incorporates the value vouchers and cash and include some preliminary results.

2.3. Sourcing

Depending on the transfer modality, multiple sources are available. Cash-based transfers (such as e-vouchers and direct cash transfers to debit cards) allow beneficiaries to purchase commodities at local markets. For food transfers, WFP has more purchasing options. We distinguish three supplier types: international suppliers, regional suppliers, and local suppliers. Local suppliers (wholesale) can be found in the recipient country; regional suppliers can be found in neighboring countries, and transport from the supplier to the recipient country is usually done by land. Procuring from international suppliers involves shipping the commodities to a discharge port (DP).

2.4. Logistics Network

The handover between suppliers and WFP is flexible and dependent on the Incoterms (Ramberg 2011). Usually, WFP takes charge of the commodities at a loading port (for international purchases) or at one of its hubs (for local and regional purchases). From discharge ports, WFP moves commodities into the country to so-called extended delivery points (EDPs), transshipment points at which commodities can be stored, packaged, consolidated, etc. From the EDPs, the commodities are transported (usually by truck) to the final delivery points (FDPs), at which they are handed over to WFP's cooperating partners: local NGOs that take care of what is called the last mile distribution (Balcik et al. 2008) in order to reach the final distribution points (e.g., schools, villages, hospitals, etc.). Note that the logistics network setup may vary between countries and is very context dependent; WFP may take charge of the entire delivery network (from pickup at the supplier to last mile distribution), or it may outsource the network partially or entirely to local logistics providers or sometimes even the government. For example, WFP has about 5,000 trucks on the road every day, but its own fleet consists of "only" 1,000 trucks, illustrating that much of the transportation is outsourced.

3. Model and Implementation

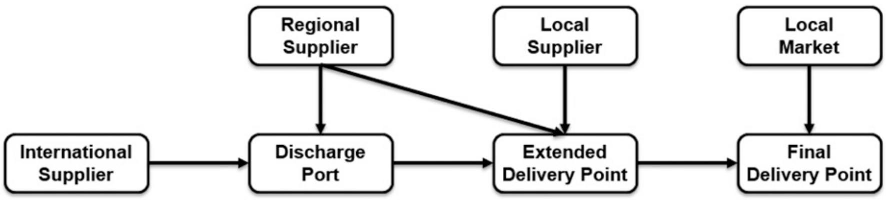
In this paper, we extend a capacitated, multicommodity, multiperiod network flow model with nutritional components. For an introduction to network flow models, we refer to Ball et al. (1995); an example tailored to a humanitarian supply chain can be found in Haghani and Oh (1996). This type of model is commonly used to optimize sourcing and delivery strategies, two of the four components that we aim to integrate. The supply chain network is sketched as per Figure 1. The suppliers are modeled as source nodes with the discharge ports and WFP warehouses acting as transshipment nodes. The demand (or sink) nodes are the FDPs, at which demand is dependent on the (variable) food basket and the number of beneficiaries.

To integrate the food basket design into the network flow model, we define a ration variable that governs the commodities flowing into an FDP, ensuring that the food WFP sends addresses the nutrient gap, is distributable, and is palatable. This link between nutrients, commodities, and rations resembles the flexible bill of materials sometimes found in the manufacturing industry (Ram et al. 2006), for which the end product is a (monthly) food basket and the number of beneficiaries in the FDP is the demand for this end product. An interesting distinction is that, in the manufacturing industry, the end product is fixed and the fulfilled demand is variable, whereas here we usually consider the fulfilled demand fixed (100% of beneficiaries should receive a food basket) and make the quality of the end product variable instead. So, when there is a funding shortfall, WFP typically prefers to supply a less nutritious food basket to all beneficiaries rather than supplying the full food basket to fewer beneficiaries. Product design and sourcing are traditionally done separately, and there is much potential to improve end-to-end performance through joint decision making (Novak and Eppinger 2001).

Integrating the transfer modality selection is possible but not straightforward. The most pragmatic approach is to model local markets as source nodes that are linked directly to FDPs. Beneficiaries can then receive some or all of their commodities from these local markets through commodity vouchers (one of the transfer modalities). We discuss a more advanced approach that also covers value vouchers and cash in Section 6.

Note that the model we are using at WFP is vast and needs to be able to handle a plethora of (mathematically trivial) constraints, such as sourcing restrictions, capacity utilization, beneficiary preferences, funding allocation, etc. Although this comes with an increased risk of conflicting constraints, in practice, it is rarely an issue. Additionally, the core of the model is based on two traditional mathematical problems: a network flow model (Ball et al. 1995) combined with a diet problem (Dantzig 1990). Because these two formulations are well known, in the main body of the paper, we discuss only our unique contribution: how to connect the two. A more comprehensive description of the model that was used for the case studies can be found in Appendix A.

Figure 1. High-Level Overview of the Modeled Supply Chain Network



3.1. Defining Demand

Typically in multicommodity network flows, the demand is defined as a parameter dem_{ikt} that specifies the quantity that should be delivered for every location i, commodity k, and period t. In order to connect such a network flow to a diet problem, here we break up the demand using several parameters:

dem_{it} = number of beneficiaries at location i in period t
$days_t$ = feeding days in period t
$nutreq_l$ = daily requirements for nutrient l
$nutval_{kl}$ = contribution to nutrient l per gram of commodity k.

We define variables R_k (continuous, nonnegative) to optimize the food basket composition, where R_k represents the gram per person per day of commodity k that WFP supplies. These ration variables ensure that beneficiaries receive the same food basket and allow us to impose restrictions on the composition of the ration. For example, this formulation makes it easy to specify that beneficiaries should receive at least 300 grams of rice per day ($R_{rice} \geq 300$) or that split peas are not accepted ($R_{split\ peas} == 0$). Generally speaking, R_k should be such that the nutrient gap is closed:

$$\sum_k nutval_{kl} \times R_k \geq nutreq_l \quad \forall l. \tag{1}$$

Rather than a fixed demand parameter dem_{ikt}, we end up with a variable demand:

$$D_{ikt} = dem_{it} \times days_t \times R_k \forall i, k, t. \tag{2}$$

Note that the ration variable R_k can easily be extended to allow more flexibility; for example, defining rations as R_{kt} allows for a food basket that is dynamic over time. This helps WFP to make the most of seasonal price windows (e.g., the harvest season basket could be different from the lean season basket) or temporarily reduce rations (e.g., in case of a pipeline break). Similarly, we can define the rations as R_{bk} to cover the needs of different beneficiary types (e.g., different nutritional requirements). Differentiation by location (R_{ik}) is less common for in-kind food baskets as humanitarian organizations strive to harmonize distribution across operations (based on principles of fairness and equality). When consumption patterns differ within assisted populations (e.g., refugee camps versus local population), alternative rations are typically modeled using the R_{bk} approach; that is, they are considered a different beneficiary type. Within each beneficiary type, the aim is typically to harmonize distribution across locations, but differentiation could open up opportunities to diversify the basket using commodities that are only available in a handful of locations (e.g., procurement from local markets). An example of location differentiation for CBT (with which such an approach is more commonly accepted) is discussed in Section 6.

3.2. Objective and Goals

Conventional network flow models usually revolve around profit maximization or cost minimization, but for humanitarian operations, there are often additional considerations. We refer to Holguín-Veras et al. (2013) for a comprehensive treatise on this subject.

In this paper, we consider four main classes of objectives:

1. *Efficiency* relates to resource utilization and covers objectives such as the cost of the operation and the utilization of port capacity.
2. *Effectiveness* relates to the nutritional impact of WFP's assistance and covers objectives such as the remaining nutrient gap and the dietary diversity score.
3. *Development* relates to the impact on the local economy and covers objectives such as the dollars spent on local procurement and CBT assistance.
4. *Agility* relates to the responsiveness of the solution and covers objectives such as the maximum and average lead time of the supply chain.

Typically, users of the model specify a range of programmatic goals (e.g., they request a solution that covers 100% of the nutrient gap, covers 30% of the needs through local procurement with a lead time of at most three months). The model then identifies the solution that meets these targets at the lowest possible cost (i.e., Pareto optimal). Some examples of common goals and their mathematical formulation are provided in Appendix A.4.

Depending on the goals and objective chosen, additional variables and constraints are added to the base model. Many goals can be formulated as linear constraints even if the measure itself is nonlinear (e.g., percentage local procurement). Note that not all combinations of objectives and goals are possible in a linear model. For example, maximizing the number of beneficiaries would conflict with a variable food basket because, in the demand constraint of the network flow model, we multiply the number of beneficiaries with their demand; if both are variable, the resulting model is nonlinear.

3.3. Data

One of the biggest challenges of applying prescriptive analytics to humanitarian operations is finding and processing the necessary data, which is typically of poor quality or even nonexistent. Often, we see that humanitarian applications fail postpilot because their data requirements are too difficult to collect or sustain over a longer period of time. To avoid this common pitfall, from the start, the optimization model was rooted in data that was already being collected across the organization for other purposes (e.g., reporting, budgeting, payments, etc.). Although every country was using a different combination of systems and tools to manage their operations, there were enough commonalities to ensure that core parameters, such as procurement costs, beneficiary figures, and transportation options, were always available. The underlying model was designed in such a way that many parameters are optional, so even if a country does not have part of the data (e.g., price forecasts) and there is no time to collect it, they can still apply the model.

Although data availability can be very limiting, the existence of data does not mean it is easily usable. In practice, data are spread over many different sources, systems, and technologies. In the worst case, data has to be extracted from scanned copies of reports (pdf files), but more likely it comes from Excel files or databases. To ensure the sustainability of an analytics-heavy tool, a lot of emphasis should be on the integration of data from disparate sources. For any parameter, there are multiple possible data sources, each following a different taxonomy (i.e., master data). Properly consolidating data from multiple sources, therefore, requires significant investments in data integration.

For the first three years, the data pipeline required for this optimization model was managed in Excel, involving labor-intensive manual collection and integration of data sets prior to any analysis. During 2018 and 2019, the entire data logic was automated with hundreds of data sets across more than a dozen systems automatically being refreshed and integrated every night. By minimizing the dreaded “data request” that typically precedes optimization exercises, users can now quickly start interacting with the model to identify improvements to their operation.

3.4. Solution Approach

The mathematical model is implemented in Python and solved using the COIN-OR solver (Saltzman 2002) with the PuLP module (Mitchell et al. 2011) acting as the interface between the two. PuLP does not support multithreading, so all calculations are performed using a single processor. Parallel processing is supported, however, so it is possible to run multiple scenarios simultaneously (asynchronous). The coding language, solver, and module are all freeware, making the tool easy to implement in a humanitarian context.

WFP staff can interact with the mathematical model through a web application (Optimus) coded in Python and hosted using Django. The web app allows them to add operational constraints and specify goals for the key outputs and gives them access to a range of automated analyses. Results from their analyses are displayed in interactive graphics (e.g., maps, pivot tables, etc.) that provide quick insights into all of the important decision variables (e.g., food basket composition, sourcing plan, delivery plan, etc.) and the resulting performance (e.g., cost, nutritional contents, etc.).

Optimized plans are typically generated in an iterative way. Starting from a baseline scenario that mirrors the current plans for the operation (i.e., the food basket, sourcing strategy, and delivery plan), alternative scenarios are generated (e.g., by relaxing some of the constraints) to identify potential areas of improvement. Local experts validate the resulting plans and key performance indicators to assess their feasibility and relevance, which often leads to additional constraints being included in subsequent runs of the model. Some practical examples and outputs of this approach are described in the “Applications” section.

3.5. Verification and Validation

When using analytics to (re)design or manage an operation, it is of paramount importance that the model and data are thoroughly verified and validated. In the humanitarian field in particular, many people are analytically averse—there used to be a general consensus that humanitarian operations are too difficult to model and optimize. This made extensive and continual verification and validation crucial. The optimization model and tool were developed over the course of many years (starting in 2013) in close collaboration with the end users and consumers of the outputs: WFP decision makers in the field. Iterative development helped identify the required capabilities, model them, and ensure that they were implemented correctly.

For example, when collaborating with WFP's country offices, a recurring validation step is to ensure that the model outputs mirror the budgeted costs when imposing the current plan on the optimization model. This allows users to quickly compare the model's calculations with theirs, which immediately highlights any components that are estimated differently or for which some unmodeled costs are incurred. The latter triggers a series of in-depth discussions during which we identify the unmodeled costs and find a way to introduce them into the mathematical model.

Another form of validation employed regularly is comparing the current operational plan to unrestricted solutions from the optimization tool, allowing analysts running the optimization tool to rapidly identify operational constraints and preferences. This approach also generates strong buy-in from the local experts because they start appreciating the scope, flexibility, and speed of the optimization tool.

The frequent rounds of verification and validation contribute significantly to the adoption rate of the tool and ensure that the model is built on data that is actually available and that its results are intuitive and usable for WFP decision makers.

3.6. Assumptions and Limitations

Every optimization tool of this size comes with a long list of assumptions and limitations; we highlight the most important ones.

We assume that every beneficiary (of a certain type) receives the same food basket and that no beneficiary goes unfed. This assumption is based on the humanitarian principles of humanity and impartiality; it would be unethical to feed only those beneficiaries that are conveniently located, for instance.

We do not model the transportation network between suppliers and loading ports. WFP floats tenders in specific countries to ensure competitive prices, and this means that price forecasts are done at the country level. As a result of the tendering process, the suppliers may differ every time WFP orders, making the cost from a supplier to the loading port difficult to estimate. Generally, WFP requests free-on-board offers, which means that the supplier takes care of the transportation up to the loading of the ship at a major port in their country.

Costs are captured using dollars per metric ton rates. Given WFP's economies of scale and the type of contracts that it usually has with suppliers and contractors, these linear rates are representative of the actual costs.

The modeled nutrition measure, the nutrient value score, is a simple average across all nutrients. We are working with WFP's nutrition department to come to better measures, reflecting the importance of some nutrients over others, and covering a larger range of nutrients overall. For general food distribution, for example, a shortfall in macronutrients (energy, protein, fat) is often considered more severe than a shortfall in minerals or vitamins. In programs that prevent or treat malnutrition, on the other hand, we want to favor these micronutrients more heavily.

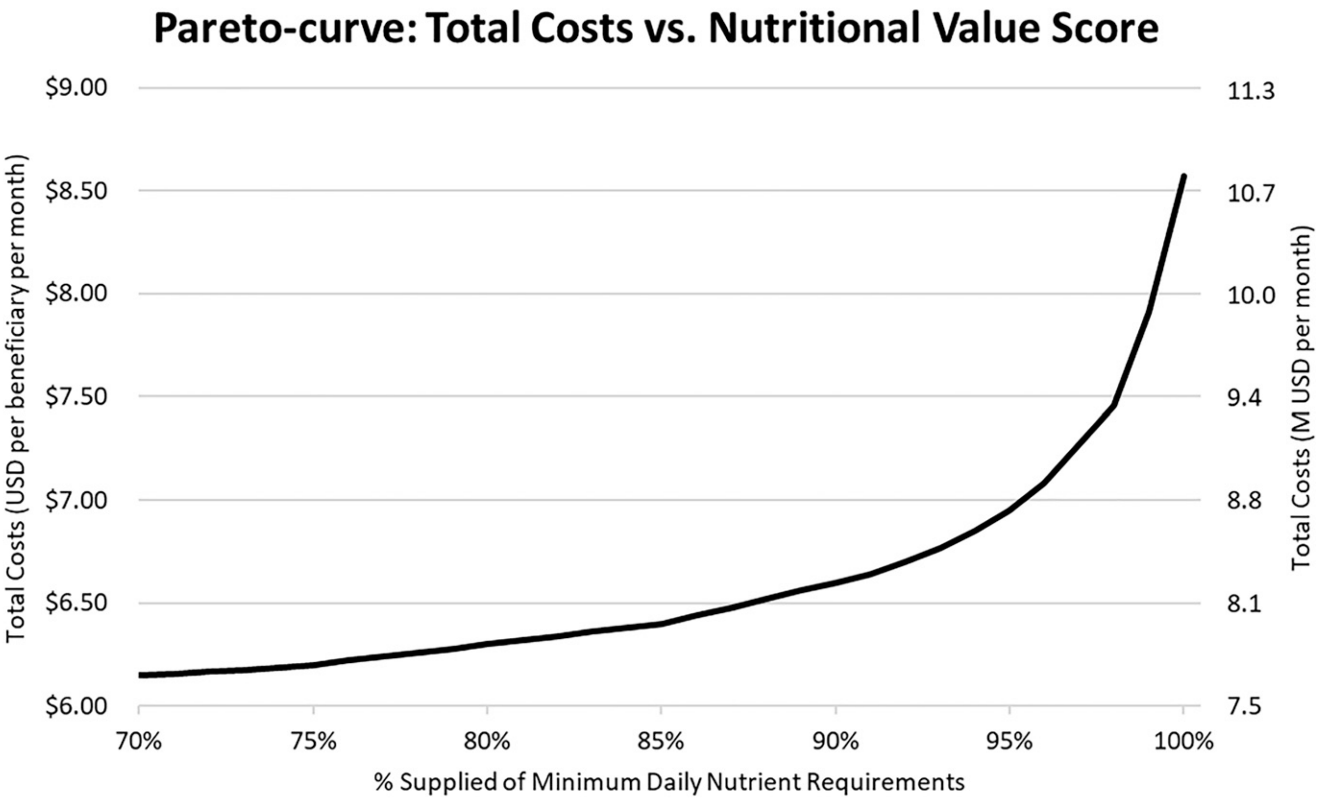
We consider the supply chain network to be fixed. WFP has a large and well-established presence in most countries, and although questions surrounding the setup of these networks arise occasionally (e.g., opening or closing of corridors and hubs), they are typically not addressed using this particular model (which is more focused on the design of the food basket and other programmatic decisions).

The current model is not robust against uncertain parameters (such as costs, lead times, and capacities). Although we recognize the potential of robustness in optimizing humanitarian supply chains (see, for example, the El Niño application in the next section), the introduction of robust optimization has been put on hold for the moment. Explorations of robustness extensions by masters students indicate that many types of uncertainty can be introduced without significantly affecting the tractability of the model (which becomes conical but remains convex). However, these extensions come with significant interpretation challenges and make it difficult for decision makers to understand (and, therefore, validate and implement) the resulting plans. In the meantime, users of the model verify with WFP's experts that the parameter values used are the current "best guess" and base the analyses on that.

4. Analyses and Insights

The model described in Section 3 is very flexible and supports a wide range of analyses that can help evaluate and improve the efficiency and/or effectiveness of WFP operations. In this section, we explore some of the insights that can be obtained from this integrated optimization approach and how this is supporting decision making at WFP.

Figure 2. The Pareto-Efficient Curve for the NVS



Notes. For different levels of NVS, the optimization tool finds the cheapest food basket, sourcing plan, and delivery plan. On the y-axes, we have the cost per beneficiary per month (left) and the cost of the entire operation per month (right).

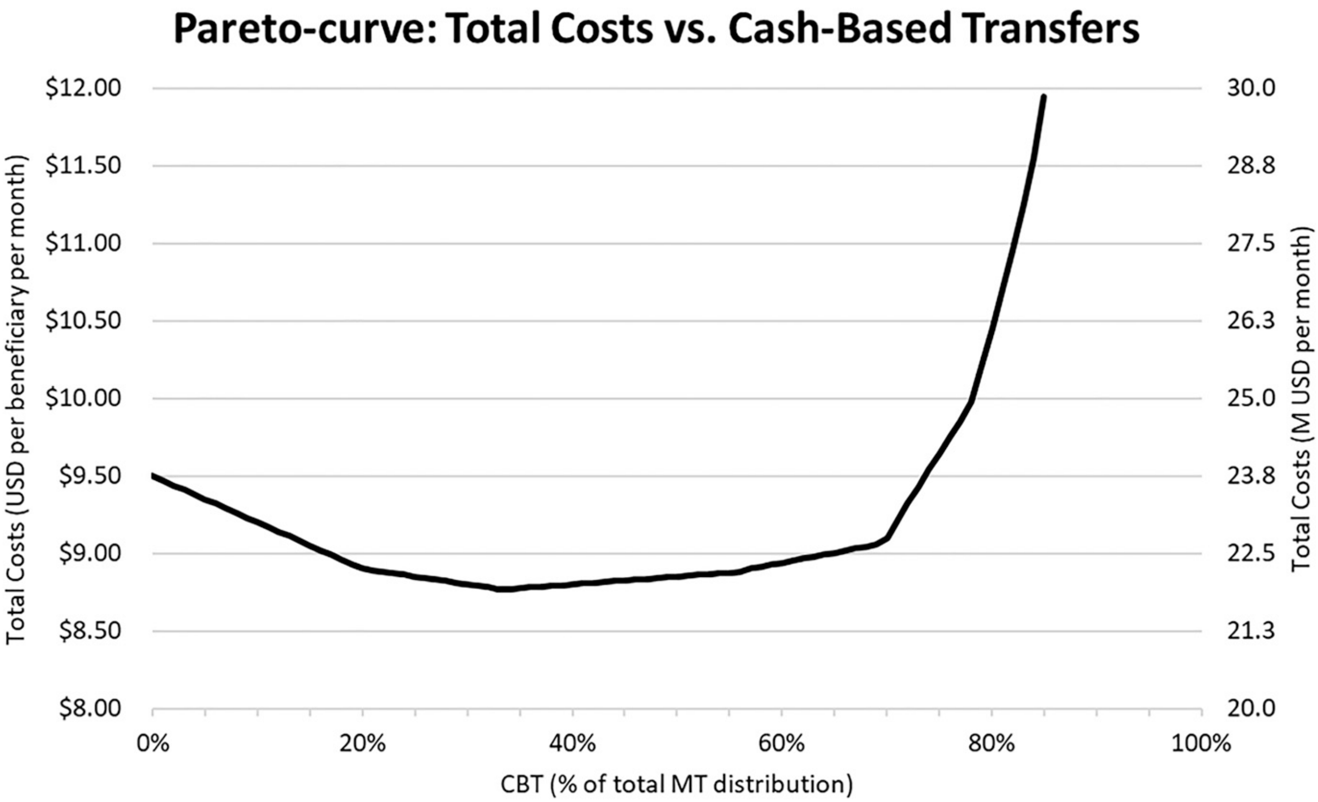
4.1. Trade-offs

To optimize humanitarian operations, it is important to evaluate and balance a wide range of (often conflicting) objectives. Although the mathematical model has a single objective (usually costs), solutions are evaluated using multiple metrics (efficiency, effectiveness, agility, and development). A goal programming approach can be used to find Pareto-efficient curves for the various metrics, providing insight into what kind of outcomes are achievable and how this would affect the cost of the operation. We highlight two of these trade-off analyses in particular: one for the nutritional value score (effectiveness) and one for the cash-based transfer ratio (development).

The nutritional value score trade-off curve (Figure 2) shows the lowest cost at which WFP can attain different levels of nutrition (effectiveness). Each plot represents a solution to the mathematical model; that is, it corresponds to an optimized food basket, sourcing plan, and delivery plan that takes into account all user-added constraints. Ideally, beneficiaries receive 100% of the recommended daily intake (RDI), but depending on the context (available funding, number of beneficiaries in need, access to nutritious commodities), this may not be realistic. With this trade-off graph, decision makers can see the price tag of supplying different levels of nutrition. In Figure 2, for instance, we can see that supplying 95% of the required nutrients reduces the cost of the operation from US$10.8M to US$8.8M (18.7% reduction). This means that WFP could still supply all beneficiaries with 95% of their requirements if its funding is 18.7% short or, alternatively, that it could reach 15%–20% more beneficiaries with 95% of their requirements if there is no funding shortfall. Because of this significant difference in cost and potential outreach, it is important to understand what level of nutritional requirements is most appropriate. If supplying 95% is still OK for the majority of beneficiaries, it may have a big impact on how humanitarian organizations design their programs.

The cash-based transfer ratio trade-off (Figure 3) shows the lowest cost at which WFP can attain different levels of cash and voucher transfers. CBT are very popular among many donors at the moment, but depending on the operation, CBT may be more expensive than supplying the food in-kind, so it is important to assess whether the premium price weighs up against its benefits. This graph displays the most cost-efficient level of CBT and how the cost increases as one deviates further from the optimal ratio. We can observe (Figure 3) that,

Figure 3. The Pareto-Efficient Curve for the Cash-Based Transfers Metric



Notes. For different levels of CBT (as a percentage of the total metric tons distributed), the optimization tool finds the cheapest food basket, sourcing plan, and delivery plan. On the *y*-axes, we have the cost per beneficiary per month (left) and the cost of the entire operation per month (right).

initially, the cost decreases when increasing CBT as the model starts supplying the most cost-effective local commodities through commodity vouchers. Increasing CBT further means that the model has to start using less cost-effective local commodities in order to supply the required nutrients. The example shows that the optimal ratio for this operation is 33% but that it is possible to scale up to 70% CBT with only a small increase in cost (US$0.9M; 4.4%). Decision makers have to weigh the added value of increasing CBT for local markets and beneficiaries against this increase in cost. Insight into the relative cost of CBT compared with in-kind and to what extent the local markets can absorb this increased demand is very important when deciding on the optimal transfer modality.

4.2. Cost-Effectiveness of Commodities

Optimal food baskets are highly dependent on the available commodities, their nutritional profile, and the nutrient gap that we aim to close. For example, let us consider four cereals that are viable for the Nigeria operation: rice, sorghum, wheat, and (white) maize.

Table 1 displays the nutritional contents of these four cereals for 11 nutrients. By optimizing the sourcing strategy for these four cereals, we can obtain their minimum cost (end to end). Combining the optimal costs with the nutritional contents allows us to calculate the relative cost-effectiveness of each of these commodities. Table 2 shows how much (in U.S. dollars) WFP would have to spend on each cereal to supply 100% of the RDI. For example, we can observe that it requires $0.66 worth of rice to supply a days' worth of kilocalories (2,100) to a beneficiary as opposed to $0.54 in the case of sorghum. Similarly, we can learn that wheat is the most cost-effective when it comes to supplying proteins, white maize for riboflavin, et cetera. Across all nutrients, sorghum is the most cost-effective cereal for Nigeria, and rice is the least cost-effective. Of course, a food basket is composed of more than just cereals, so the availability of commodities, such as oils and pulses, and their respective cost-effectiveness decides what the optimal cereal is. All commodities have a unique nutritional profile, and the optimization model described in this paper can help balance these nutritional values when designing food baskets while taking into account the resulting costs.

Table 1. The Nutritional Value of Four Cereals (per 100 g) with the RDI for Reference

Cereal	Energy, kcal	Protein, g	Fat, g	Calcium, mg	Iron, mg	Iodine, μg	Vitamin A, μg	Thiamine, mg	Riboflavin, mg	Niacin, mg	Vitamin C, mg
Rice	360.00	7.00	0.50	9.00	1.70	0.00	0.00	0.10	0.03	5.58	0.00
Sorghum	335.00	11.00	3.00	26.00	4.50	0.00	0.00	0.34	0.15	5.00	0.00
Wheat	330.00	12.30	1.50	36.00	4.00	0.00	0.00	0.30	0.07	8.92	0.00
White maize	350.00	10.00	4.00	7.00	2.71	0.00	0.00	0.39	0.20	2.20	0.00
RDI	2100.00	52.50	40.00	450.00	22.00	150.00	500.00	0.90	1.40	13.86	28.00

Note. The units differ by nutrient (e.g., energy is measured in kilocalories, whereas iron is measured in milligrams).

One of the benefits of the integrated model is that these cost-effectiveness calculations can be done at the location level; for any location hosting beneficiaries, the end-to-end costs are calculated and incorporated into the final recommended ration. Traditionally, the design of the ration was decoupled from the supply chain execution, which means "optimal" rations were designed based on the nutritional values of commodities and a simpler estimation of the costs for each commodity—typically, just the procurement cost. In this Nigeria example, sorghum and wheat cost approximately the same ($0.01 per kilogram difference) to provide to beneficiaries (considering end-to-end costs). However, the average procurement cost for sorghum during the last four years has been $0.36 per kilogram, whereas wheat was purchased on average for $0.24—a third cheaper. If the design were based on such simpler cost estimations, the optimized rations would be heavily skewed toward wheat instead of the sorghum that comes out on top if we consider the operational costs more holistically.

Rather than redesigning food baskets from scratch using these insights, in practice, it is often more pragmatic to stay close to the current design of an operation (making any recommendations much easier to implement). We highlight one particular analysis that allows WFP to identify slight changes to the current food basket that can significantly improve the performance of an operation: a commodity swap analysis.

The commodity swap analysis (Figure 4) shows the impact of swapping one commodity in the current food basket on the performance of the operation—in this case, on the supplied nutrients (effectiveness) and operation costs (efficiency). The graph shows an analysis of cereals and grains for one of WFP's activities. In each iteration of the model, one of the cereals/grains in the current food basket is replaced with a cereal/grain that is not currently included (using the same ration size). We can observe, for example, that replacing the wheat in the current basket with white maize would increase the NVS by 0.3%, and reduces the cost of the operation by US$4.5M (26.5%). Decision makers can combine these quantitative insights with context-specific constraints (such as donor and beneficiary preferences) to find the best food basket design. For instance, changing to sorghum/millet makes no sense if the beneficiaries have no idea how to prepare this grain no matter how cost-effective the commodity is. In this analysis, we stay close to what the beneficiaries are already receiving. One of the major benefits of this approach is that we can arrive at solutions that, although not mathematically optimal, are easy to validate and have a significantly higher likelihood of actually being implemented.

5. Applications

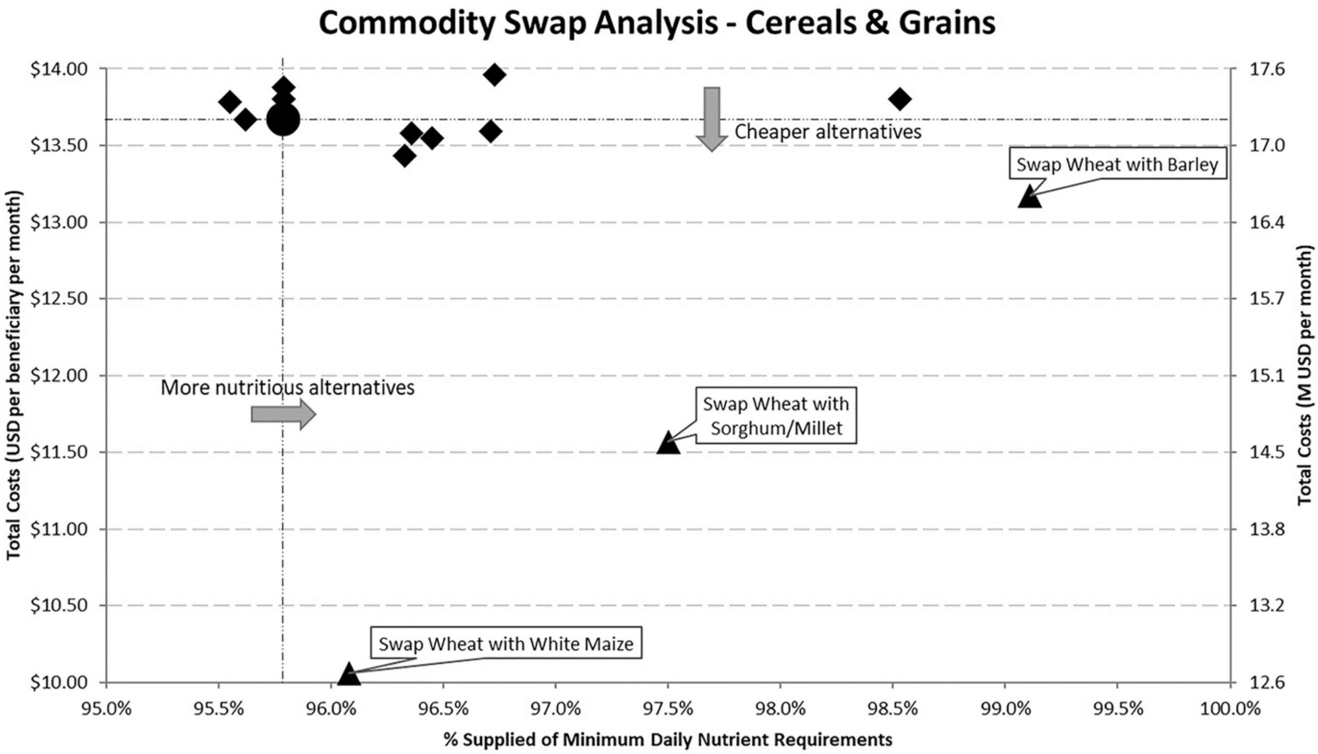
The mathematical model presented in this paper is the result of iterative development over many years (since 2013). Through regular pilots we were able to identify what data are reliably available, what kind of analyses are the most impactful, and how the optimization tool fits into WFP's business processes. Additionally, these pilots were used to continually verify and validate the mathematical model underlying the tool by scheduling

Table 2. The Relative Cost-Effectiveness of Four Cereals with Respect to Supplying Different Nutrients

Cereal	Cost, $/kg	Energy, $	Protein, $	Fat, $	Calcium, $	Iron, $	Iodine	Vitamin A	Thiamine, $	Riboflavin, $	Niacin, $	Vitamin C
Rice	1.13	0.66	0.84	9.01	5.63	1.46			1.01	5.25	0.28	
Sorghum	0.86	0.54	0.41	1.14	1.48	0.42			0.23	0.80	0.24	
Wheat	0.87	0.55	0.37	2.32	1.09	0.48			0.26	1.74	0.14	
White maize	0.93	0.56	0.49	0.93	5.96	0.75			0.22	0.65	0.58	

Notes. Each value indicates how much U.S. dollars we have to spend on the cereal every day to supply 100% of the nutritional requirement, so the lower the value, the more cost-effective the commodity is for that particular nutrient. The cereals do not provide iodine, vitamin A, or vitamin C so no cost-effectiveness measure can be calculated for these nutrients..

Figure 4. This Commodity Swap Analysis Shows the Impact on Nutrition and Cost of Swapping One Commodity (from the Cereals and Grains Food Group)



Notes. The y-axes show the efficiency with the cost per beneficiary per month on the left and the monthly operation costs on the right. On the x-axis, we show the effectiveness as a percentage of the minimum daily nutrient requirements. Each plot corresponds to a unique food basket (including its optimal sourcing and delivery plan) with the circle representing the current food basket. All plots that are below and to the right of the circle are, therefore, strict improvements (from a cost and nutrition perspective, respectively).

in-depth sessions with experts throughout the organization and by comparing the tool's outputs to historical performance.

Since we started applying the tool, optimization gained significant traction within WFP. At present, the software is used on a regular basis to provide WFP's biggest and most complex operations with optimization support, such as Syria, Ethiopia, South Sudan, and Yemen. In this section, we highlight some of the results we achieved in Iraq, Yemen, and the South African region and show how different types of analyses are being used to support strategic decision making for WFP's most complex operations. For each of the analyses, we provide some context, such as the cause of the crisis and the number of people affected, but please note that ongoing crises evolve rapidly and, therefore, the provided statistics may no longer be up to date at the time of reading.

5.1. Iraq

Years of conflict have hindered Iraq's economic development. Since 2014, the occupation of the Islamic State of Iraq and the Levant in Iraq has resulted in the displacement of more than three million people. When, two years later, the Iraqi Security Forces launched a military offensive to regain control, fighting deepened insecurity, rolled back development, and exacerbated vulnerabilities. Many Iraqis sought refuge in neighboring countries and in Europe. Beset by violence, social disruption, and economic hardship, thousands of Iraqi families were left in desperate need of food assistance.

Although many are now returning home every month, around 700,000 Iraqis are still living in camps with few possibilities to earn an income that enables them to put food on the table. In addition, an estimated quarter of a million Syrian refugees have sought refuge in northern Iraq, placing additional pressure on limited resources. At the end of 2017, around 800,000 people still require some sort of food assistance in Iraq every month; some 10 million need humanitarian assistance in general. The security landscape remains volatile, sometimes posing access challenges for humanitarian actors (World Food Programme 2015a).

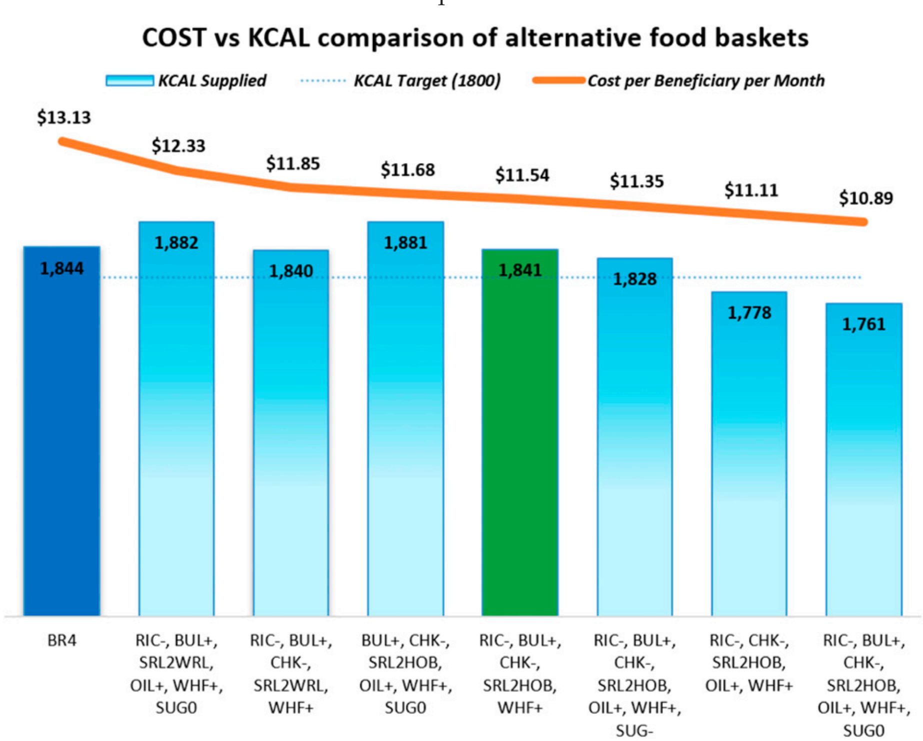
WFP has been operating in Iraq since 1991 and has provided food assistance in the country since April 2014 through emergency operations to assist those hundreds of thousands of Iraqis forced from their homes by recent violence. In the face of further mass displacement from major Iraqi cities, such as Mosul and Ramadi, WFP scaled up activities to reach an average of 1.5 million people per month in all 18 governorates, including hard-to-reach areas. WFP is assisting people through monthly family food parcels for those with access to cooking facilities, food vouchers that can be redeemed at local shops, and ready-to-eat food known as immediate response rations that provide a family of five with food for three days.

WFP's operations in Iraq often face funding shortfalls, so it is vital that the operation's design is as cost-effective as possible. In October 2015, Iraq's country office requested optimization support to redesign the food basket for different levels of funding, allowing it to supply as many kilocalories as possible from the donations that it receives.

We worked intensively with the field staff to gather all the necessary data and to identify operational constraints (with respect to procurement, logistics, transfer modalities, beneficiary preferences, etc.). Once we had a good grasp of the situation, we ran hundreds of analyses using the optimization tool to identify alternative designs that could improve the performance of the operation. Many of the solutions were pushing the envelope, so there was much going back and forth to verify the feasibility of these solutions. This intense collaboration and the iterative process resulted in the field staff feeling a strong sense of ownership of the final outcomes, resulting in a rapid implementation of the final recommendation.

One of the main deliverables to Iraq's management was Figure 5, containing our recommendations for Iraq's family food parcel (FFP)—supplied to half a million Iraqis every month. The first column represents the latest official food basket (BR4), supplying 1,844 kilocalories (daily) at a cost of US$13.13 per beneficiary per month. Each subsequent column is an optimized basket that uses different interventions (commodity swaps, ration adjustments, etc.) to improve the cost-effectiveness of the operation. Iraq officially adopted the food basket represented by the green column, supplying 1,841 kilocalories (only three kilocalories fewer) and 69% of the

Figure 5. An Overview of Alternative Food Baskets for Iraq's FFP



Notes. We compare the kilocalories and cost per beneficiary per month of each option (as given by the acronyms on the *x*-axis). The acronyms show how the food basket changed compared with the original food basket (BR4). RIC = rice, BUL = bulgur wheat, WHF = wheat flour, SRL = split red lentils, WRL = whole red lentils, WIB = white beans, CHK = chickpeas, HOB = horse beans, OIL = sunflower oil, SUG = white sugar. A "+" or "−" denotes an increase or decrease in the current ration size. A "0" denotes a removal of the commodity, whereas the "2" denotes that we change commodity a to commodity b using the same ration size. Ration size increments are predefined and based on commercial packaging types for that specific commodity. The green option has been implemented in practice, representing a cost reduction of 12% while supplying only three kilocalories fewer.

nutrient gap (same as BR4) at a cost of US$11.54 per beneficiary per month (12% reduction). At the time of implementation, the FFP was being supplied to 800,000 beneficiaries every month, so this adoption corresponded to US$1.3M monthly savings. This meant that WFP could supply the same amount of beneficiaries with a nutritious food basket in the case of up to a US$1.3M funding shortfall per month, or these 12% savings could be used to supply an additional 109,000 (14%) beneficiaries with an FFP every month if funding remained at the same level. Note that, in this analysis, all savings result from changing the food basket; we did not identify any significant savings on the existing supply chain network. The optimized food basket was distributed throughout 2016 and 2017, representing total savings of more than US$25M, with positive feedback from the beneficiaries regarding the changes in commodities and ration sizes compared with the original food basket.

5.2. Yemen

Even before fighting broke out in early 2015, Yemen was one of the poorest countries in the Arab world. With an average life expectancy below 64, the nation is ranked 178th out of 188 on the human development index, a composite statistic of life expectancy, education, and per capita income indicators that is used to rank countries into four tiers of human development.

Nearly four years of conflict have left thousands of civilians dead and three million internally displaced. Its impact on the country's infrastructure has been devastating with major overland routes and airports severely damaged. Despite ongoing humanitarian assistance, 15.9 million people wake up hungry every day, which is more than half of Yemen's population of 28 million. It is estimated that, in the absence of food assistance, this number would go up to 20 million (World Food Programme 2015b).

WFP has been active in Yemen since 1967. In 2019, WFP is scaling up to provide 12 million people with monthly food assistance through direct food distributions or vouchers that people can use at retailers in areas where the markets are functioning. Each family of six gets a monthly ration of wheat flour, pulses, vegetable oil, sugar, and salt. Beneficiaries include internally displaced persons and returnees, vulnerable populations in the most food-insecure areas, people affected by transient crises, infants, pregnant and nursing women affected by acute and chronic malnutrition, and school-age children.

Since the start of the main operation, WFP has gradually been scaling up toward the 12 million beneficiaries and this is proving to be a Herculean task in light of the limited resources available and the escalation of conflict within Yemen. In December 2015, WFP was still reaching three million beneficiaries with in-kind food assistance every month with the aim of increasing this to five million in 2016. Cash-based transfers were being scaled up to one million beneficiaries in parallel, allowing WFP to reach six million people with life-saving assistance. In November 2015, Yemen's management team requested optimization support for their pending scale-up from three to six million beneficiaries.

Similar to our approach in Iraq (and all other applications), we worked intensively with local experts and management to gather the necessary data and identify all operational constraints from a supply chain and donor/beneficiary preference perspective. We were requested to keep the commodities in the food basket the same and focus mainly on the optimization of ration sizes. Given that distribution is carried out in active

Figure 6. This Beneficiary Matrix (Yemen) Shows the Interdependence of Funding Levels, Nutritional Targets, and Beneficiary Numbers

Basket Name	USD per Beneficiary	KCAL	NVS	20M USD	30M USD	40M USD	45M USD	50M USD	55M USD	60M USD	70M USD	80M USD	90M USD	100M USD
Current basket	$ 13.89	100%	95%	1.4	2.2	2.9	3.2	3.6	4.0	4.3	**5.0**	5.8	6.5	7.2
WHE75 SYP10 OIL5 WSB10	$ 13.69	98%	94%	1.5	2.2	2.9	3.3	3.7	4.0	4.4	5.1	5.8	6.6	7.3
WHE75 SYP10 OIL7 WSB05	$ 13.28	97%	91%	1.5	2.3	3.0	3.4	3.8	4.1	4.5	5.3	6.0	6.8	7.5
WHE75 SYP10 OIL5 WSB05	$ 12.87	93%	89%	1.6	2.3	3.1	3.5	3.9	4.3	4.7	5.4	6.2	7.0	7.8
WHE50 SYP10 OIL7 WSB15	$ 11.92	85%	94%	1.7	2.5	3.4	3.8	4.2	4.6	**5.0**	5.9	6.7	7.6	8.4
WHE50 SYP10 OIL6 WSB15	$ 11.72	83%	94%	1.7	2.6	3.4	3.8	4.3	4.7	5.1	6.0	6.8	7.7	8.5
WHE50 SYP10 OIL7 WSB10	$ 11.10	80%	90%	1.8	2.7	3.6	4.1	4.5	**5.0**	5.4	6.3	7.2	8.1	9.0
WHE50 SYP10 OIL5 WSB10	$ 10.70	76%	88%	1.9	2.8	3.7	4.2	4.7	5.1	5.6	6.5	7.5	8.4	9.3
WHE50 SYP10 OIL6 WSB05	$ 10.08	73%	84%	2.0	3.0	4.0	4.5	**5.0**	5.5	6.0	6.9	7.9	8.9	9.9

Notes. Columns (2)–(4) show the performance of a food basket (column (1)). We display the cost per beneficiary per month and two effectiveness measures: the kilocalories and the percentage of all nutrients supplied (as percentages of the minimum daily requirements). The remaining columns show how many beneficiaries we can supply (in million beneficiaries per month) with these food baskets under different funding scenarios (ranging from US$20 to 100M per month). For example, the current food basket can supply 4M beneficiaries if WFP receives US$55M per month and 5M beneficiaries in the case WFP receives US$70M per month.

conflict zones, we designed the food baskets in such a way that the monthly ration for each family (of six) corresponds to an industry-standard packaging size, making distribution as quick and seamless as possible. We presented a breakdown of our recommendations in the form of a column chart similar to the one used in Iraq, but the most powerful deliverable is a "beneficiary matrix."

The beneficiary matrix (Figure 6) shows the interdependence of funding levels, nutritional targets, and beneficiary numbers. It shows decision makers how much it costs to supply different numbers of beneficiaries with the current food basket and how alternative food baskets allow WFP to either cope with funding shortfalls (without cutting down on beneficiary numbers) or to increase the number of beneficiaries reached with the available funding (by cutting down on nutrition). For example, suppose WFP is supplying four million beneficiaries with the current food basket and would like to scale up to five million. The matrix shows us that supplying five million beneficiaries with the current basket would cost US$70M per month (US$15M or 27% more than the current cost). Alternatively, WFP could reach the five million beneficiaries by slightly reducing the nutrition levels of the food basket. In this case, we can observe that there is a food basket (WHE50 SYP10 OIL7 WSB10) that supplies five million beneficiaries with 80% kilocalories and 90% NVS for the same level of funding (US$55M). Insight into this trichotomy allows WFP to manage its scale-up properly and enables it to communicate clearly to donors what is required from them if WFP is to reach all people at risk within Yemen with nutritious food. Every few months, the matrix is updated to reflect the latest data changes to the point at which WFP was able to reach 13 million beneficiaries in 2019.

5.3. El Niño

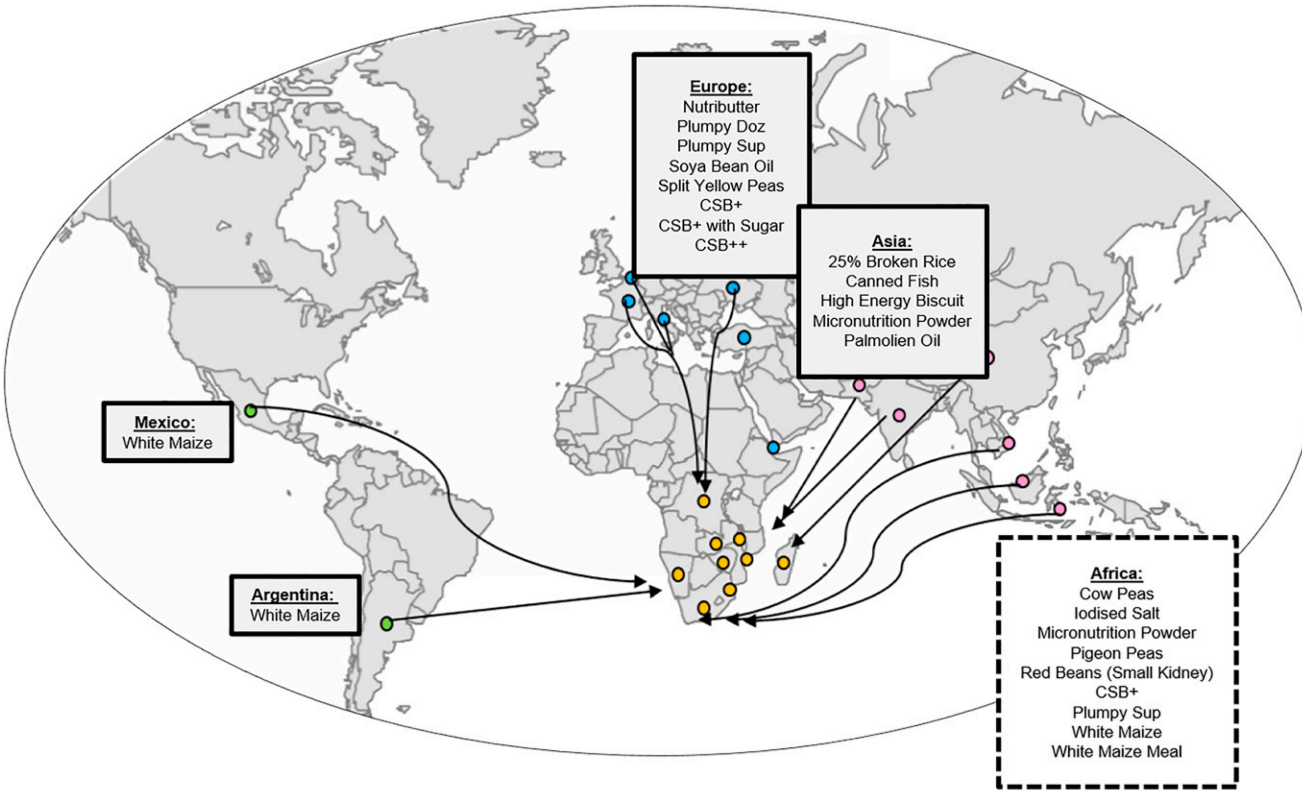
In 2016–2017, the El Niño climate pattern, which is strongly linked to weather fluctuations around the globe, was fueling an international food-security crisis for millions of people. By disturbing rainfall and temperature patterns, El Niño affected agriculture, water supplies, and the spread of disease and was threatening the food security and livelihoods for some 60 million people worldwide. Particular areas of concern included nearly all of Southern Africa, which was the hardest hit region; Ethiopia and its neighbors Somalia and Sudan in East Africa; central America's "dry corridor", nearby Haiti, and the northern region of South America; and many of Asia's island nations, including Indonesia, Papua New Guinea, and Philippines.

Between October 2015 and January 2016, El Niño conditions caused the lowest recorded rainfall in at least 35 years across many regions of Southern Africa. The same period also recorded the hottest temperatures in the past 10 years. El Niño's impact on rain-fed agriculture is severe. Poor rainfall combined with excessive temperatures created conditions that were unfavorable for crop growth in many areas. In Lesotho, South Africa, Swaziland, Zambia, and Zimbabwe, planting was delayed by up to two months or more, which severely impacted maize yields. It became evident that the 2015–2016 maize harvest would be insufficient to cover full cereal needs for the region without significant importation.

As more information about the impact became available, we were asked to provide support by drafting various contingency analyses. Given that the local cereal availability would be too limited to meet all needs, we used the model to explore global sourcing strategies under different capacity and export assumptions. For example, if some of the countries barely have enough to meet their own needs, they may impose export bans to ensure availability for their own population. We found that many countries appeared to be self-sufficient, but WFP would need to source about 20,000 metric tons of white maize from international markets—more than a quarter of the total needs. Given the market prices and the strong GMO restrictions in the South African region, Argentina and Mexico were identified as the optimal sourcing locations by our model. In Figure 7, we show the global sourcing plan.

With slow-onset disasters, such as the El Niño crisis, the assumptions and forecasts are very prone to change as the crisis develops. Because of this, it is important to perform sensitivity and robustness analyses so that WFP can ensure its plans are still valid if the forecasts change. At the time of the analysis, South Africa was procuring significant quantities locally, in particular for cereals and pulses. If the availability of commodities reduces because of poor harvests, we often see significant price spikes in local markets, so it was important to evaluate whether a local procurement strategy still made sense if the local prices increased drastically. In Figure 8, we show an optimized sourcing strategy under different price scenarios with Figure 9 showing the detailed plan (aggregated by origin country) for white maize. We find that, for the current prices, the optimal breakdown is to purchase 29.7% international, 31.9% local, and 38.4% regional (across all commodities). Price increases as little as 10% already increase the optimal international procurement ratio to 40% and up to 78% when local/regional prices double. If we consider the cost of the baseline plan (i.e., optimal plan under the assumption that the prices remain stable) under different price scenarios, we see that it is up to US$700,000 more expensive per month (7.8%) than the optimized plan for scenarios in which prices increase. We see that,

Figure 7. (Color online) An Optimized Global Sourcing Plan in Case Local Cereal Production Is Not Sufficient to Meet All Needs in the Most Affected South African Countries



depending on El Niño's effect on the local markets, which is likely to increase local prices, we may have to consider transitioning to a more international-heavy sourcing plan. The large differences between the scenarios mean that the current sourcing strategy for white maize is not robust against price uncertainty. Considering that a shift toward international (and more price-stable) procurement would increase lead times by up to two months for many commodities, it is important to start shifting straight away.

6. Extensions and Future Research

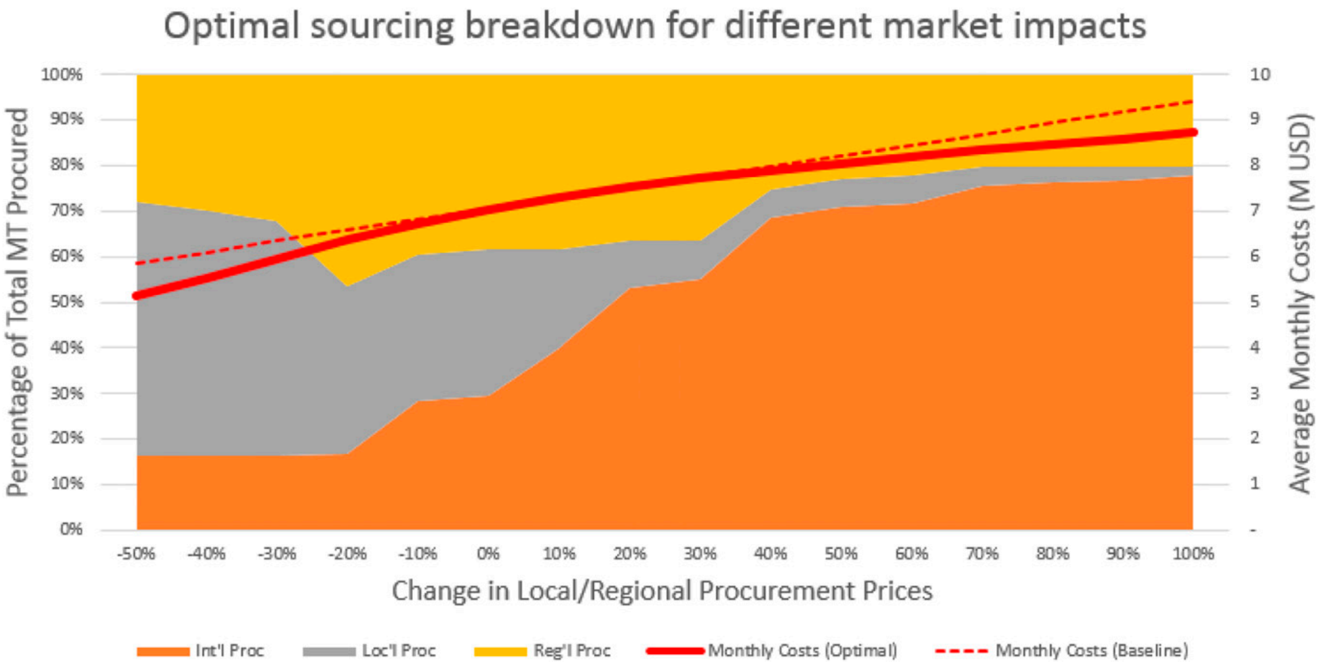
The underlying model described in this paper is very adaptable, so there are many opportunities to extend it to cover additional levels of complexity or to apply it to non-WFP supply chains. For example, the model was initially developed to manage two transfer modalities: in-kind transfers and commodity vouchers. Since then, the humanitarian community and WFP, in particular, have seen a steady shift toward less restricted forms of assistance, such as value vouchers and cash. In this section, we describe how the model can be extended to deal with these transfer modalities as well. Additionally, we describe some other use cases that we are exploring as future research.

6.1. Cash-Based Transfers

Even though cash-based transfers were introduced more than a decade ago (2007), it is still difficult to properly evaluate and compare the various transfer modalities from a cost-effectiveness perspective. The main reason for this is that, for two of the three CBT approaches (value vouchers and cash), the effectiveness of the transfer is dependent on the beneficiary's purchasing behavior and local market conditions (cost, availability). For commodity vouchers, we know exactly what the beneficiary will receive and base our effectiveness on that. In practice, we consider two main approaches for evaluating the effectiveness of CBT assistance: ex ante and ex post.

In an ex ante analysis, we make a best guess about the purchasing behavior of the beneficiary (e.g., 15 kg maize, 5 kg pulses, 2 L oil, etc.) and calculate the effectiveness based on the assumption that all beneficiaries purchase and consume this basket. This "best guess" basket is usually based on local expert knowledge and

Figure 8. Optimized Sourcing Strategies Under Different Price Scenarios



Notes. On the left axis, we show the percentage of the total need supplied through the three sourcing types (local, regional, and international). On the *x*-axis, we show the different price scenarios (from very favorable at −50% to very unfavorable at +100%). The red line is plotted against the right axis and shows how the optimal monthly costs differ for these scenarios (US\$7M currently and US\$8.7M if local/regional prices increase by 100%). The dotted line shows the costs under these scenarios if we implement the optimized plan as per the current price estimates (i.e., the 0% plan).

household surveys. This projection of the effectiveness requires little data and can provide some initial insights into the potential cost-effectiveness of CBT assistance.

In practice, however, the expected purchasing behavior can be very different from the actual purchasing behavior. In an ex post analysis, we analyze the effectiveness of CBT assistance based on actual expenditure data that is increasingly being collected by several branches within WFP (e.g., through point-of-sale–level stock-keeping unit (SKU) data). We can link each purchase to a nutritional contribution and cost, and this allows us to define the actual expenditure pattern of beneficiaries and the effectiveness of WFP assistance for any location and period in which actual expenditure data are available (again assuming that what beneficiaries buy is also what they consume). This is a very data-heavy approach (SKUs have to be converted to weights and commodities, and all entries have to be translated to English) and can only be applied after CBT assistance has been implemented.

Figure 9. Optimized Sourcing Strategies for White Maize Under Different Price Scenarios

Sum of Metric Tonnes	-50%	-40%	-30%	-20%	-10%	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
⊟WHITE MAIZE	72,756	72,756	72,756	72,756	72,756	72,756	72,756	72,756	72,756	72,756	72,756	72,756	72,756	72,756	72,756	72,756
TANZANIA	21,949	21,949	21,949	21,949	21,949	21,949	21,949	6,367	3,591							
ZIMBABWE	21,875	18,874	15,404													
ZAMBIA	11,944	14,944	18,414	33,818	33,818	33,818	27,127	24,501	24,501	7,609	4,138	3,000				
SOUTH AFRICA	8,028	8,028	8,028	8,028												
MALAWI	7,466	7,466	7,466	7,466	7,466	7,466	7,466	7,466	7,466	7,466	7,466	7,466	4,351	3,336	2,756	1,202
SWAZILAND	1,494	1,494	1,494	1,494	1,494	1,494	1,494									
ARGENTINA					8,028	8,028	14,720	34,422	37,198	57,681	61,151	62,289	68,405	69,420	69,999	71,554
Grand Total	72,756	72,756	72,756	72,756	72,756	72,756	72,756	72,756	72,756	72,756	72,756	72,756	72,756	72,756	72,756	72,756

Notes. The table shows how the 73,000 metric tons of maize are purchased predominantly locally/regionally for scenarios in which prices are stable or become cheaper. Then, as the local/regional prices increase, we can observe a steady shift toward an international source: Argentina. The large differences between the scenarios mean that the sourcing strategy for white maize is not robust against price uncertainty.

Outputs from these ex ante and ex post analyses are generally compared against the cost-effectiveness of in-kind food assistance to decide on the most appropriate transfer modality. In practice, the transfer modality decision is made for each FDP (i.e., either the FDP receives an in-kind basket or CBT assistance), and ideally, decision makers would like to switch flexibly between the modalities during the planning horizon (e.g., CBT during harvest season, in-kind during the lean season). Note that commodity vouchers are sometimes considered as a form of in-kind assistance because beneficiaries do not have the freedom to choose what to spend their vouchers on. To illustrate the flexibility of the underlying model, we show how to incorporate the transfer modality selection more explicitly in the model, seeing as the initial model covered only the commodity voucher assistance.

6.2. Location Differentiation Approach

The idea behind this extension (location differentiation) is to decide for each FDP individually whether it should use an in-kind food basket (may include commodity vouchers) or a CBT contribution (value voucher or cash); the in-kind basket is optimized as before, and the CBT contribution would result in performance (cost, effectiveness) as per our best guess (i.e., data input). The CBT basket (which may differ by location and by month) would ideally be based on an ex post evaluation of prior CBT distributions so that we can compare the actual performance of CBT in each location against the actual performance of an optimized in-kind basket. The mathematical formulation for this extension can be found in Appendix B.

The main outputs of the location differentiation approach are an optimized food basket for the selected activity and an indication for each FDP for each month whether it should opt for CBT assistance (for which the effectiveness may differ by location and by month) or the in-kind assistance (for which the effectiveness may differ by month but not by location). The model chooses CBT in those FDPs in which it makes the most sense (e.g., well-established markets) and/or during the periods that make the most sense (e.g., postharvest season). This allows a very flexible approach and a very elegant way to trade off between CBT and in-kind while utilizing all of the functionality of the core model (e.g., specifying programmatic goals, funding restrictions, etc.).

We implemented the location differentiation approach in our web app and tested it using data from WFP's Mali operation. We found that the optimal cost was US$20.22 per beneficiary per month if we allow for in-kind only. When we allowed for unrestricted CBT (location differentiation approach) as per an ex post evaluation, we found that the cost decreased to US$17.65 (13% reduction). In the optimized scenario, about 53% of the beneficiaries received unrestricted CBT with an average NVS of 73% for FDPs that receive CBT and 100% for those that receive in-kind. We found that the optimal transfer modality is heavily dependent on the location as prices (and expenditure patterns) may vary significantly in different settlements.

Note that this extension is very focused on evaluating the nutritional cost-effectiveness of different modalities, but recently, we see that many humanitarian agencies are shifting away from using such analyses as drivers for the transfer modality selection. Cash-based transfers bring unique benefits to beneficiaries—from financial inclusion to increased dignity and autonomy over the assistance they receive—often difficult to capture in a quantitative framework. As the humanitarian community continues exploring and researching the benefits that each transfer modality brings to beneficiaries, it is important to integrate the latest findings and approaches into mathematical models such as this one to support decision makers in identifying the best modality choices.

6.3. Other Possible Applications

WFP supplies life-saving assistance to some 100 million beneficiaries every year, but it is not the only actor when it comes to providing food assistance. For example, national governments often have their own school feeding programs in place, supplying children in primary and secondary education with nutritious meals. Sometimes they also provide takeaway rations to further incentivize parents to continue sending their children to school. Consider that India alone is already providing some 120 million children with school lunches through its mid-day meal scheme. Applying the methods developed in this paper to such school meal programs has a huge potential, and we have been engaging with several countries to help them improve the cost-effectiveness of their school feeding initiatives (e.g., Benin, Colombia, Egypt, India, etc.).

Another humanitarian area in which the methodology developed has merit is in the supply chain for nonfoods (e.g., UN Humanitarian Response Depot; water, sanitation, and hygiene; health kits; etc.). Currently, beneficiary needs are defined in terms of nutrients, but needs for nonfood items, such as mosquito nets and vaccines, could be modeled in very similar ways. This becomes particularly interesting when some nonfood items supply multiple needs; for example, you could provide a kit instead of individual items if it makes sense from a cost perspective. Additionally, it would allow for coordination across multiple humanitarian actors and avoids duplication of efforts (e.g., there is need for one mosquito net regardless of how many agencies aim to provide one).

7. Conclusion

In this paper, we explore the possibilities of integrating key supply chain decisions, such as the food basket design, the transfer modality selection, and the sourcing and delivery plan, into a single model to support decision making at WFP. We define a MILP model based on a multicommodity, multiperiod network flow that covers the full spectrum of operational decisions at WFP and is rooted in data that is reliably available.

Applications in some of WFP's most complex emergencies (Iraq, Yemen, and El Niño) demonstrate the added value of optimization in managing humanitarian operations. In Yemen, optimization enabled the supply chain management team to scale up its operation from three to six million beneficiaries through rapid evaluation of the trichotomy between beneficiary numbers, food basket quality, and available funding. This insight allowed the supply chain management team to scale up the operation responsibly while providing donors with evidence-based information about the resources necessary to reach all people in need and the impact of lack and/or untimeliness of resources on beneficiaries and operational costs. In Iraq, optimization enabled the supply chain management team to reduce the cost of general food distribution (supplying 800,000 beneficiaries with their daily nutritional needs) by 12% (representing more than US$25M savings over the course of two years) while only providing three kilocalories fewer than the original food basket. In South Africa, we used optimization to generate sourcing and delivery plans for different contingency scenarios, such as limited local availability and significant price spikes because of El Niño.

Through the development of the model presented in this paper, optimization has become an enabler for cross-functional collaboration at WFP. By integrating key decisions, performance measures, and operational constraints for all major components of WFP's supply chain into one model, WFP is now able to rapidly assess the impact of operational decisions on its overall performance. By connecting the composition of the food basket to the supply chain that is necessary to deliver it, we are able to increase the efficiency and effectiveness of WFP operations, ensuring that, with the funds available, WFP can continue to supply life-saving assistance to as many people in need as possible.

Acknowledgments

The work described in this paper is the result of more than seven years of iterative development in collaboration with universities, private sector partners, and WFP colleagues around the world. Without their enthusiasm, pragmatism, and constructive criticism, this initiative would have fallen flat a long time ago. Instead, the authors are able to see it grow every month with more and more operations looking to optimization when faced with complex operational challenges, and many staff having started using the web application autonomously. The authors thank everyone who helped them better understand WFP operations, those who invited them to support their operations, those who have championed their work, and those who have contributed funding so they could continue this work.

Appendix A. Full Model Specification

In Section 3, we focus on describing the differences with standard network flow models. For the sake of completeness, here we provide a full breakdown of parameters and constraints that are used for the applications in Iraq, Yemen, and South Africa. This means that the formulation is based on commodity vouchers but not yet on value vouchers and cash transfer modalities.

A.1. Sets

We define multiple subsets for the nodes in particular to ease the definition of constraints and statistics.

$\mathcal{N}$ = set of nodes ($i, j \in \mathcal{N}$)
$\mathcal{N}_S$ = set of source nodes
$\mathcal{N}_{IS}$ = set of international suppliers
$\mathcal{N}_{RS}$ = set of regional suppliers
$\mathcal{N}_{LS}$ = set of local suppliers
$\mathcal{N}_{LM}$ = set of local markets
$\mathcal{N}_P$ = set of procurement nodes ($\mathcal{N}_{IS} \cup \mathcal{N}_{RS} \cup \mathcal{N}_{LS} \cup \mathcal{N}_{LM}$)
$\mathcal{N}_{DP}$ = set of discharge ports

(Continued)

$\mathcal{N}_{EDP}$ = set of extended delivery points
$\mathcal{N}_T$ = set of transshipment nodes ($\mathcal{N}_P \cup \mathcal{N}_{DP} \cup \mathcal{N}_{EDP}$)
$\mathcal{N}_{FDP}$ = set of final delivery points
$\mathcal{K}$ = set of commodities ($k \in \mathcal{K}$)
$\mathcal{G}$ = set of food groups ($g \in \mathcal{G}$)
$\mathcal{L}$ = set of nutrients ($l \in \mathcal{L}$)
$\mathcal{B}$ = set of beneficiary types ($b \in \mathcal{B}$)
$\mathcal{T}$ = set of months ($t \in \mathcal{T}$)

Note that the suppliers ($\mathcal{N}_{IS}, \mathcal{N}_{RS}, \mathcal{N}_{LS}$) provide access to commodities that WFP ships to final delivery points ($\mathcal{N}_{FDP}$) using its network of discharge ports ($\mathcal{N}_{DP}$) and extended delivery points ($\mathcal{N}_{EDP}$). Local markets ($\mathcal{N}_{LM}$) provide beneficiaries with direct access to commodities when they receive a cash-based transfer. Each procurement node ($\mathcal{N}_P$) may be linked to multiple source nodes ($\mathcal{N}_S$), which we use to model procurement restrictions. Procurement nodes represent physical handover points between WFP and a supplier, whereas in our implementation, the source node represents the country of origin for the commodity (which may differ from the country where WFP takes ownership).

A.2. Parameters

Because of the unique nature of long-term food distribution, we require some nonconventional parameters, such as nutritional values and feeding days.

α = conversion rate from metric tons (mt) to grams (g) (10^6)
ben = the beneficiary type to be optimized ($ben \in \mathcal{B}$)
cap^H_{it} = handling capacity (in mt) of node $i \in \mathcal{N}_{EDP} \cup \mathcal{N}_{DP}$ in month t
cap^T_{ijt} = transportation capacity (in mt) from node i to node j in month t
cap^P_{ikt} = procurement capacity (in mt) of commodity k from source $i \in \mathcal{N}_S$ in month t
$cost_{ijkt}$ = cost (in \$/mt) of moving commodity k from node i to node j in month t
$days_b$ = current number of feeding days per month for beneficiaries of type b
dem_{bit} = number of beneficiaries of type b at node $i \in \mathcal{N}_{FDP}$ in month t
dur_{ij} = duration (in days) of moving from node i to node j
$group_k$ = the food group to which commodity k belongs ($group_k \in \mathcal{G}$)
hc_i = handling costs (in \$/mt) at node $i \in \mathcal{N}_{DP} \cup \mathcal{N}_{EDP} \cup \mathcal{N}_{FDP}$
inv_{ikt} = incoming arrivals (in mt) of commodity k at node $i \in \mathcal{N}_{EDP} \cup \mathcal{N}_{DP}$ in month t
ltp_{ij} = maximum duration (in days) to supply all FDPs if we procure from source $i \in \mathcal{N}_S$ at node $j \in \mathcal{N}_P$
$nutreq_{bl}$ = nutritional requirement of beneficiaries of type b for nutrient l
$nutval_{kl}$ = nutritional value per gram of commodity k for nutrient l
$odoc^{CV}$ = other direct operational costs rate (in %) for C&V transfers
$odoc^F$ = other direct operational costs rate (in \$/mt) for food transfers
rat_{bk} = current ration size (gram/person/day) of commodity k for beneficiaries of type b
sc_i = storage costs (in \$/mt/month) at node $i \in \mathcal{N}_{DP} \cup \mathcal{N}_{EDP}$

Handling/storage capacities (cap^H_{it}) are only tracked for DPs and EDPs although we can easily extend it to other nodes. Basically, the suppliers take care of any handling/storage taking place at procurement nodes, and WFP's cooperating partners do the same at the FDP level. Costs ($cost_{ijkt}$) are captured for all movements through the supply chain network; movements between source and procurement nodes incur procurement costs, and other movements are transportation costs. Costs may change over time because of seasonality and stock market movements for procurement and because of rainy seasons for transportation. We split demand (dem_{bit}) per location and beneficiary type, and allow it to change over time so we can phase out or scale up operations. It is important to distinguish between beneficiary types because their nutritional requirements are vastly different. The needs of a child are very different from those of a newly arrived refugee or a nursing woman for example. The food baskets currently used (rat_{bk}) and their (monthly) feeding days ($days_b$) are predefined for each beneficiary type. The model optimizes one of these baskets at a time (ben) and supplies the other beneficiary types with their predefined basket. Optimizing all food baskets simultaneously is mathematically possible (and tractable) but rarely done in practice because prioritization across beneficiary types is difficult to quantify. We use inv_{ikt} to model initial inventories and incoming shipments, allowing us to easily integrate the model's decisions with the current status of an operation. Other direct operational costs (ODOC) ($odoc^F$ and $odoc^{CV}$) are surcharges per transfer modality that take care of additional costs that are incurred beyond the procurement, transport, storage, and handling of the commodities (such as milling, packaging, monitoring, reporting, etc.), and $odoc^F$ is usually defined in dollars per metric ton and $odoc^{CV}$ as a percentage surcharge for every dollar transferred to beneficiaries.

A.3. Variables

The two major variables are the ones governing commodity flows (F_{ijkt}) and ration sizes (R_{kt}); the others are mainly used to calculate statistics.

F_{ijkt} = flow of commodity k from node i to node j in month t (metric ton)
R_{kt} = ration of commodity k in the food basket of month t (gram/person/day)
S_{lt} = shortfall (slack variable) of nutrient l in month t (fraction)
O_{lt} = overshoot (slack variable) of nutrient l in month t (fraction)
SFI_{lt} = binary indicator: one if there is a shortfall for nutrient l in month t
P_{ijt} = binary indicator: one if food is procured from source i at procurement node j in month t
LT_t = maximum lead time of commodities purchased in month t (days)

A.4. Objectives

In order to adequately track and constrain the model's outputs, we define dozens of statistics (most of them linear combinations of the variables). Here, we focus on the two most important statistics for each of the four goal classes (efficiency, effectiveness, development, and agility).

TOC = total operation cost (efficiency 1)
FCR = full cost recovery rate (efficiency 2)
CAL = kilocalories (effectiveness 1)
NVS = nutritional value score (effectiveness 2)
LOC = local procurement (development 1)
CBT = cash-based transfers (development 2)
ALT = average lead time (agility 1)
MLT = maximum lead time (agility 2)

A multiobjective approach that allowed users to optimize any of the statistics was included in earlier versions of the model, but we discarded it for the sake of solvability. We found that the solution times are significantly higher (3–20×) when incorporating performance measures other than costs into the objective function. For cost objectives, little branch and bound is necessary to find the optimal solution; this is not the case for other objectives. Because of this big difference in solution speed, it is more practical to use the other statistics as constraints (akin to a goal programming approach).

We define the eight main measures as follows:

$$TOC = \sum_{i\in\mathcal{N}_S}\sum_{j,k,t} cost_{ijkt}\times F_{ijkt}, \tag{A.1}$$

$$+\sum_{i\notin\mathcal{N}_S}\sum_{j\neq i}\sum_{k,t} cost_{ijkt}\times F_{ijkt}, \tag{A.2}$$

$$+\sum_{i\in\mathcal{N}_{DP}\cup\mathcal{N}_{EDP}}\sum_{k,t} sc_i\times F_{iikt}, \tag{A.3}$$

$$+\sum_{i\in\mathcal{N}_{DP}\cup\mathcal{N}_{EDP}}\sum_{j\neq i,k,t} hc_i\times F_{ijkt}+\sum_{j\in\mathcal{N}_{FDP}}\sum_{i,k,t} hc_i\times F_{ijkt}, \tag{A.4}$$

$$+\sum_{i\in\mathcal{N}_S}\sum_{j\notin\mathcal{N}_{LM}}\sum_{k,t} odoc^F\times F_{ijkt}, \tag{A.5}$$

$$+\sum_{j\in\mathcal{N}_{LM}}\sum_{i,k,t} cost_{ijkt}\times odoc^{CV}\times F_{ijkt}, \tag{A.6}$$

$$FCR = \frac{\sum_{i,j,k,t} cost_{ijkt}\times F_{ijkt}}{\sum_{i,j,k,t} F_{ijkt}}, \tag{A.7}$$

$$CAL = \frac{\sum_k nutval_{k,energy}\times R_{kt}}{|\mathcal{T}|}, \tag{A.8}$$

$$NVS = \frac{\sum_{l,t}(1-S_{lt})}{|\mathcal{L}||\mathcal{T}|}\times 100\%, \tag{A.9}$$

$$LOC = \frac{\sum_{j\in\mathcal{N}_{LS}}\sum_{i,k,t} F_{ijkt}}{\sum_{j\in\mathcal{N}_P}\sum_{i,k,t} F_{ijkt}}\times 100\%, \tag{A.10}$$

$$CBT = \frac{\sum_{j\in\mathcal{N}_{LM}}\sum_{i,k,t} F_{ijkt}}{\sum_{j\in\mathcal{N}_P}\sum_{i,k,t} F_{ijkt}}\times 100\%, \tag{A.11}$$

$$ALT = \frac{\sum_{i,j,k,t} dur_{ijk}\times F_{ijkt}}{\sum_{i,j,k,t} F_{ijkt}}, \tag{A.12}$$

$$MLT = \max_t LT_t. \tag{A.13}$$

The usual optimization objective, the total operation cost, consists of the following components: the procurement costs (A.1), the transportation costs (A.2), the storage costs (A.3), the handling costs (A.4), the ODOC costs for food (A.5), and the ODOC costs for C&V (A.6). For WFP, this efficiency measure makes the most sense because a lower cost per beneficiary means that it is able to supply more beneficiaries from the available funding. The other measures usually are used as constraints (goals) in this paper to ensure that the resulting solutions are in line with the objectives of the operation that is being optimized.

A second efficiency measure is the full cost recovery (FCR) rate, the average dollars per metric ton that WFP spends on food. The FCR rate varies wildly between countries and is particularly high when countries are landlocked (e.g., more transport necessary to get the commodities to the beneficiaries) or when WFP is forced to adopt suboptimal strategies (e.g., sourcing, transfer modality) by donors or the local government. The global average FCR is about a dollar per kilogram of food.

We measure effectiveness using kilocalories and the nutritional value score (as developed by Ryckembusch et al. 2013). The number of kilocalories (A.8) that a food basket provides is very easy to capture and is still one of the most important and easy-to-understand performance measures when it comes to measuring effectiveness. For a more holistic view of all macronutrients and micronutrients we use the NVS (A.9). We know the nutritional profile of the targeted beneficiaries and the nutritional contents of our food basket; the NVS measures how close the current food basket is to the required nutrients. It is defined as the sum of the delivered percentages for each nutrient l, and we truncate the delivered nutrients at 100% (i.e., the score does not improve if you supply more than necessary). In practice, this means that we can just sum the (reversed) shortfalls. The maximum value for this statistic is then the amount of nutrients that are being tracked (11 for the applications in Iraq and Yemen), which is not a very intuitive measure. We adjust the measure slightly by dividing the original NVS by the amount of nutrients. To measure the NVS performance adequately across the time horizon, we also average it over the months. The NVS defined here, therefore, measures the average requirements supplied across all nutrients with a maximum value of 100% when we supply at least 100% of the requirements for each of the tracked nutrients in each of the months in the time horizon. Note that the NVS does not favor some nutrients over others, and the NVS score may hide the fact that one nutrient is not supplied at all. Because of these limitations, we are working with WFP's nutrition department to come up with better measures.

Humanitarian organizations prefer using local businesses to source and supply food as this contributes to the development of the country. As a performance measure, we consider the percentage of commodities purchased locally, either through wholesale procurement (A.10) or commodity vouchers (A.11). Note that even though the "percentage purchased" measure is nonlinear, upper and lower bounds (goals) for this measure can be included as linear constraints.

For the lead times (which are notoriously hard to capture in linear programming models) we use two proxy measures. One is a maximum lead-time proxy variable (A.13), which is used when WFP needs to respond to a disaster quickly (i.e., they need to get a food basket inside the country within x days). In practice, however, we generally apply this model to long-term recovery operations. This means that there is always food on its way to the recipient country, there are inventories in the warehouses, commodities with a long lead time are being prepositioned, etc. Maximum lead times are of less concern in such a scenario. Additionally, if one commodity has a long lead time, but the others can be supplied quickly, the maximum lead time does not reflect the agility of the supply chain well. The second proxy measure is, therefore, the average number of days that it takes for a metric ton of food to arrive at its destination after being ordered (A.12). Note that this is again a nonlinear measure that can be modeled as a linear constraint.

A.5. Constraints

In the implementation of the optimization model, we make a distinction between constraints that always hold and optional constraints. For the minimum working example, we focus on the former. Through a graphical user interface, WFP officers may impose additional context-specific constraints, such as beneficiary preferences, long-term supplier agreements, funding restrictions, etc. Most of those (optional) constraints are mathematically trivial though.

$$\sum_j F_{ijkt} = inv_{ikt} + \sum_{(j,i,k,t^*)\in\mathcal{A}(i,k,t)} F_{jikt^*} \quad \forall i \in \mathcal{N}_T \quad \forall k, t. \tag{A.14}$$

Constraint (A.14) is the traditional "flow in = flow out" constraint for the transshipment nodes. The parameter inv_{ikt} contains initial inventories and incoming shipments that are already underway when running the tool, and $\mathcal{A}(i,k,t)$ are pregenerated sets that contain the indices of all flow variables F_{ijkt} that arrive in transshipment node i with commodity k at time t, generated based on their lead times (dur_{ij}). They are currently defined as follows:

$$\mathcal{A}(i,k,t) = \left\{ \left(j,i,k,t^*\right) : t^* + f\left(dur_{j,i}\right) = t \right\} \quad \forall i,k,t$$
$$f(t) = \left\lfloor \frac{t}{30} \right\rfloor + \mathbb{1}_{\{t \bmod 30 > 20\}},$$

so we look at the duration of each arc and transform the lead time in days to a lead time in months, using a cutoff point of 20 days. This cutoff point is very context-specific and may need to be revised when applying this algorithm to non-WFP supply chains. In practice, we use this formula to generate the parameter initially, but users can override the "rounded" lead time for any arc themselves if the default cutoff results in poor behavior.

$$\sum_j F_{jikt} \times \alpha = dem_{ben,it} \times days_{ben} \times R_{kt} + \sum_{b \neq ben} dem_{bit} \times days_b \times rat_{bk} \forall i \in \mathcal{N}_{FDP} \quad \forall k, t. \tag{A.15}$$

Constraint (A.15) states that the flow into an FDP must equal its demand (number of beneficiaries times feeding days times daily ration for commodity k plus any additional requirements for that commodity from other beneficiary types). Note that we multiply incoming flows by $\alpha = 10^6$, converting the metric ton values to grams (which is how food baskets are specified).

$$\begin{aligned} \sum_j F_{ijkt} &\leq cap^P_{ikt} & \forall i \in \mathcal{N}_S \quad \forall k, t, \\ F_{ijkt} &\leq cap^P_{ikt} \times P_{ijt} & \forall i \in \mathcal{N}_S \quad \forall j, k, t. \end{aligned} \tag{A.16}$$

Constraint (A.16) specifies that the procurement flow must remain lower than its capacity. Multiplying the capacity by the binary variable P_{ijt} allows us to track maximum lead times as follows:

$$LT_t \geq P_{ijt} \times ltp_{ij} \quad \forall i \in \mathcal{N}_S \quad \forall j, t. \tag{A.17}$$

Recall that ltp_{ij} is a proxy for the lead time when purchasing commodities in node j from source i. We currently generate this value by applying Dijkstra's shortest path algorithm to get the fastest route to each of the FDPs and taking the maximum of those values. The lead-time proxy then reflects the shortest time it takes to reach all FDPs when a commodity is procured this way. If this is the only source for this commodity, the proxy value is accurate. If multiple sources are used to supply the same commodity in some month, this proxy is an upper bound. In practice, however, it is uncommon to have multiple sources for the same commodity in the same month (the sources do change over time to benefit from price seasonality).

$$\sum_k F_{ijkt} \leq cap^T_{ijt} \quad \forall i, j, t. \tag{A.18}$$

Constraint (A.18) bounds the flow between nodes so that the flow cannot exceed the (transportation) capacity of an arc. Note that arc capacities may change over time because of hazardous conditions (security, rainy seasons, etc.).

$$\sum_{jk} F_{jikt} \leq cap^H_{it} \quad \forall i \in \mathcal{N}_{DP} \cup \mathcal{N}_{EDP} \quad \forall t. \tag{A.19}$$

Constraint (A.19) bounds the flow through a node (based on handling capacity rather than transportation capacity).

$$\sum_k nutval_{kl} \times R_{kt} = nutreq_{ben,l} \times (1 - S_{lt} + O_{lt}) \quad \forall l, t. \tag{A.20}$$

Constraint (A.20) states that the supplied nutrients must cover the requirements. To ensure that the slack variables for shortfalls (S_{lt}) and overshoots (O_{lt}) are working as intended, we need to make sure that they are never positive at the same time. For this, we use the shortfall indicator:

$$\begin{aligned} S_{lt} &\leq SFI_{lt} & \forall l, t, \\ O_{lt} &\leq (1 - SFI_{lt}) \times 10 & \forall l, t. \end{aligned} \tag{A.21}$$

Note that S_{lt} is a continuous variable between zero and one, whereas the overshoot is only bounded from below (maximum nutrient intakes are not as well defined as minimum nutrient intakes).

When leaving all food basket choices up to the model, it chooses the most cost-effective way to supply all nutrients regardless of the palatability of the resulting food basket. This may mean that a daily ration consists of half a kilogram of peas, that it includes large amounts of fortified food (not very palatable and with limited supply), or even 200 milliliters of oil. All these instances and more were found during test scenarios. Intuitively, these solutions make no sense and are, therefore, not credible (despite being the *cost*-optimal way of delivering the nutritional requirements). Through interviews with nutrition experts and food basket designers, the "unwritten rules" for food baskets were brought to light and quantified. The following constraints result in sensible food basket outputs:

$$\begin{aligned} \sum_{k:group_k = g} R_{kt} &\geq minrat_g & \forall g, t \\ \sum_{k:group_k = g} R_{kt} &\leq maxrat_g & \forall g, t \\ R_{\text{Iodised Salt},t} &\geq 5 & \forall t \\ S_{\text{Energy},t} &\leq 0.1 & \forall t \\ S_{\text{Protein},t} &\leq 0.1 & \forall t \\ S_{\text{Fat},t} &\leq 0.1 & \forall t, \end{aligned} \tag{A.22}$$

Table A.1. The Sensible Food Basket Constraints (in Prams per Person per Day) for Each Food Group

Food group	$minrat_g$	$maxrat_g$
Cereals and grains	250	500
Pulses and vegetables	30	130
Oils and fats	15	40
Mixed and blended foods	0	60
Meat and fish and dairy	0	40

Note. These ration sizes are tailored for GFD, which is the bulk of WFP distribution.

with $minrat_g$ and $maxrat_g$ values as given in Table A.1. Following these constraints, the rations consist of plenty of staple foods (grains and pulses) to make two or three dishes per day, oil to satisfy fat requirements and for cooking, some fortified foods to prevent malnutrition, and iodized salt to satisfy iodine and sodium requirements. Additionally, we make sure that the three most important nutrients have at most a very small shortfall. Naturally, extra constraints should be added to capture the preferences of the targeted beneficiaries (that may differ a lot between different tribes or countries of origin). Note that these constraints are geared toward so-called GFD, which is the ration that we supply to most (if not all) targeted beneficiaries in a country. Beneficiaries with additional needs (children, pregnant and nursing women, newly arrived refugees, etc.) receive the required supplements on top of this GFD basket. These constraints are disabled when we optimize non-GFD baskets.

Finally, we add some nonnegativity constraints:

$$\begin{aligned} F_{ijkt} &\geq 0 \quad \forall i,j,k,t \\ R_{kt} &\geq 0 \quad \forall k,t \\ S_{lt} &\geq 0 \quad \forall l,t \\ O_{lt} &\geq 0 \quad \forall l,t \\ LT_t &\geq 0 \quad \forall t. \end{aligned} \tag{23}$$

Appendix B. Extension: Location Differentiation Approach

To track the choice between CBT and in-kind for each FDP, we create new binary variables CBT_{it}, which are one if FDP i receives CBT assistance in month t and zero if it receives in-kind assistance. We need to make a small adjustment to the demand constraint in the network flow model to account for this choice. For this, we need an auxiliary variable (continuous) that keeps track of the in-kind demand for the activity to be optimized:

$$SAD_{ikt} \geq dem_{it} \times R_{kt} - M \times CBT_{it} \quad \forall i,k,t, \tag{B.1}$$

$$OAD_{ikt} = \sum_b dem_{bit} \times rat_{bk} \quad \forall i,k,t, \tag{B.2}$$

where M is a sufficiently large number. The selected activity demand (SAD_{ikt}) is equal to the in-kind demand as per the optimized food basket (R_{kt}) if the FDP chooses in-kind and zero otherwise. The other activity demand (OAD_{ikt}) keeps track of the in-kind demand for the other activities (b) that still need to be supplied. Note that we do not need a variable for this; the explicit specification is just for notational convenience. Similarly, we are ignoring the conversion factors in these formulas (metric ton to gram conversion and daily ration to monthly ration conversion).

With these new variables defined, the new demand constraint becomes

$$\sum_i F_{ijkt} \geq SAD_{jkt} + OAD_{jkt} \quad \forall j,k,t. \tag{B.3}$$

Note that, in practice, we may need to limit the number of switches between IK and CBT assistance (to make the solution more implementable); for example, if we decide to switch, it should be at least for n months. A potential solution for this is to track the decision to switch as a(n) (additional) binary variable (by location, by month), for which the original CBT_{it} variables are now defined implicitly by these switch variables. The approach can be modeled using the following constraints.

We need new binary variables ST_{it} ("switch to") that are equal to one if location i swaps transfer modality (to CBT or IK) in month t:

$$ST_{it}^{CBT}, ST_{it}^{IK} \in \{0,1\} \quad \forall i,t. \tag{B.4}$$

For any location, in any month, we can swap at most once:

$$ST_{it}^{CBT} + ST_{it}^{IK} \leq 1 \quad \forall i,t. \tag{B.5}$$

We have to start with one of the two modalities:

$$ST_{it_0}^{CBT} + ST_{it_0}^{IK} = 1 \quad \forall i. \tag{B.6}$$

The original *CBT* variables are now determined implicitly by the new swap variables:

$$CBT_{it} = CBT_{i,t-1} + ST_{it}^{CBT} - ST_{it}^{IK} \quad \forall i, t, \tag{B.7}$$

$$CBT_{it_0} = ST_{it_0}^{CBT} \quad \forall i. \tag{B.8}$$

Ensure that swaps hold for at least n months (n would probably be something like four to six months):

$$ST_{it}^{IK} \leq 1 - \sum_{t_*=t-n}^{t} ST_{it_*}^{CBT} \quad \forall i, t, \tag{B.9}$$

$$ST_{it}^{CBT} \leq 1 - \sum_{t_*=t-n}^{t} ST_{it_*}^{IK} \quad \forall i, t. \tag{B.10}$$

During implementation of the location differentiation approach, we found that the solution speed increased drastically. The core model requires little branch and bound with the binary variables mostly impacting capacities but not the costs (e.g., if during branch and bound a binary variable is 0.7, increasing it to one would not affect the cost of the node). With the new binary variables governing the CBT decisions, the problem becomes significantly more difficult to solve. With our default solver, we were unable to find solutions for more than three months of demand. We were able to define a custom solver strategy using Gurobi that makes the problem tractable again even for large planning horizons, but there is still some research and experimentation to be done to reduce the optimality gap to reasonable levels. We will be refining our approach moving forward.

Appendix C. Author Biographies and Project History

Historically, WFP has had a siloed approach to managing and optimizing its supply chains. With humanitarian operations becoming increasingly complex, the need arose for cross-functional innovations that consider WFP's operations more holistically. Initial ad hoc analyses by WFP's logistics development unit (now called the supply chain planning & optimization unit) showed that there was a huge potential for savings in Syria by integrating the decisions of the procurement and logistics teams; a thorough cross-functional analysis of the sourcing strategy, corridor allocation, and supply chain network design led to savings of two million U.S. dollars. The analysis was performed in 2013 by modeling Syria's operation in Excel and using the built-in Excel Solver to find improvements.

From this initial analysis, two things became clear. First, although it was possible to optimize sourcing and delivery for a WFP operation using the Excel solver, it was a very labor-intensive and cumbersome process. Second, it was noted that the sourcing and delivery solution was heavily dependent on the project design, that is, the food basket that beneficiaries were supposed to receive and the way in which they were supposed to receive it (food, cash, or voucher). Changing even one commodity would have effects that rippled throughout the entire sourcing and delivery strategy. Integrating project design decisions into the Excel solver proved too difficult, however, so WFP reached out to its partner universities to develop a model and tool that could cope with the complexity of connecting project design decisions to traditional sourcing and delivery decisions.

In 2014, students from Georgia Tech (United States) and Tilburg University (Netherlands) developed a tractable prototype that connected the major decisions, and this was then piloted in Syria during a redesign of WFP's operation there. Through optimization, we were able to identify concrete savings opportunities, and we recommended a range of food basket adjustments that led to significant savings throughout 2015 (US$23 million). Our collaborative approach to optimization and our ability to rapidly analyze, quantify, and visualize key decisions resulted in traction for optimization initiatives. Since then, we have been focusing on improving the accuracy, scope, and user-friendliness of the prototype while institutionalizing optimization as a management tool and supporting WFP's biggest and most complex operations with ad hoc analyses using the model.

The project was initiated in 2013 by WFP by Rui Gonçalves and Sérgio Silva under the guidance of Mirjana Kavelj. Rui Gonçalves is a supply chain officer working in the humanitarian sector for more than 10 years. He is an engineer interested in lean principles and in the optimization of resources that benefit the most vulnerable and food-insecure populations in complex humanitarian emergencies. Sérgio is a graduate of mechanical engineering and management and has been working for the World Food Programme for more than ten years. He is currently the chief of WFP's supply chain planning and optimization unit and is the founder and current council president of G.A.S. Porto, an NGO with around 400 volunteers. Mirjana was the chief of WFP's logistics development unit and has been working for the World Food Programme for more than 20 years. She is currently the chief of the HR technology & analytics unit.

In 2014, WFP requested support from two universities, first Georgia Tech and then Tilburg University. A team of undergraduate students in the Stewart School of Industrial & Systems Engineering (Maria Ayers, Lakshmi Sangeeta Gadepalli, Ashfaque Kachwala, Tahsin Munir, Cane Punma, Gabriel Rodriguez, and Yuvraj Singh) from Georgia Tech worked on the first prototype, supported by Ozlem Ergun and Mallory Soldner, with the aim of integrating the various decision parameters into a single model. Ozlem Ergun is a professor in mechanical and industrial engineering at Northeastern University. Her research focuses on design and management of large-scale and decentralized networks, focusing on organizations that respond to emergencies and humanitarian crises around the world including the U.S. Agency for International Development, WFP, UN High Commissioner for Refugees, Centers for Disease Control, and many more. She currently serves as the area editor at the *Operations Research* journal for policy modeling and the public sector area. Mallory Freeman completed her graduate work with the Center for Health & Humanitarian Systems. She is now lead data scientist at the United Parcel Service (UPS) advanced technology group, where she works on research and development projects and consults within the company.

The next prototype iteration (also in 2014) was with Tilburg University with the aim of operationalizing the model by integrating it better with operational data and fine-tuning its decision granularity. This activity was conducted by masters student Koen Peters, supported by Hein Fleuren and Dick den Hertog. Koen Peters is a graduate of operations research & management science, pursuing a Ph.D. at Tilburg University's Zero Hunger Laboratory. He is currently the head of development for WFP's supply chain planning and optimization unit, where he has been working for more than five years. Hein Fleuren is a professor of application of operations research at Tilburg University. Over the past 35 years, he has been involved in many practical applications in production and transportation and, in the last years, also the humanitarian world. Hein shares the passion of applying data science and optimization to obtain a better world with Dick den Hertog and Koen Peters. Together with Perry Heijne, he is the founder of the Zero Hunger Lab. Dick den Hertog is a professor of operations research at University of Amsterdam. His research interests cover various fields in prescriptive analytics, in particular, linear and nonlinear optimization. He is specifically interested in applications that contribute to a better society.

Since 2015, WFP has taken ownership of the maintenance and development of the model, working together with internal experts and private sector partners to support its implementation. The main contributors (in terms of expertise and funding) from the private sector are Palantir, who supported us in the automation of our data feed through their Foundry platform, and UPS, who supported us with change management expertise related to the rollout of optimization tools.

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