Supply Chain Optimization for Acute Malnutrition Treatment in Sub-Saharan Africa

Abstract: Malnutrition is the leading cause of child death internationally and treatment reaches only a small fraction of those in need. Treatment is costly due to inefficient supply chains and expensive ingredients. Recent initiatives by aid organizations have demonstrated the potential cost savings in more localized supply chains. Here we develop a tool to inform production and distribution decisions of acute malnutrition treatment as a capacitated facility location model. The supply chain of acute malnutrition treatment is optimized based on published ingredient, factory, and transport costs to (a) minimize cost while treating the full caseload or (b) maximize cases treated on a set budget. A validation based on the current UNICEF supply chain returned values within 3.2% of actual costs. The model is able to evaluate the savings of using novel local treatment recipes instead of the current milk-based treatments. Our model suggests that scaling up implementation of novel recipes could reduce total procurement costs by 25% while supporting local economies. A parameter study of the variable costs identifies cost drivers and recommends countries that are suitable for investment in local production despite possible market shifts. This study demonstrates that supply chain modeling strategies can be applied to inform large-scale nutrition interventions.

Keywords: Nutrition Intervention; Acute Malnutrition; Supply Chain; Ready-to-use Foods; Facility Location Problem; Sub-Saharan Africa

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1. Introduction

Child malnutrition prevalence remains unacceptably high in developing countries, causing nearly half of all childhood deaths. Globally, 16 million children under the age of five suffer from severe acute malnutrition (SAM) and 51 million suffer from moderate acute malnutrition (MAM) [1,2]. SAM and MAM are measures of wasting, or weight for height, and are defined as the percent of the population below two and three standard deviations from a healthy population's average.

Children suffering from SAM previously required hospitalization and treatment with therapeutic milk. Due to the difficulty and expense of hospitalizing large numbers of patients, intervention coverage was commonly under 10% and mortality remained high. Since 2000, over 70 countries have implemented community-based management of acute malnutrition (CMAM) programs using specialized nutritious foods (SNF) [3]. These specialized food packets are pastes developed to meet correct macro and micronutrient compositions to help malnourished children under age five gain weight. Through outpatient care of children not suffering from complications, CMAM has improved treatment coverage and effectiveness. By using ready-to-use therapeutic foods (RUTF) to treat SAM and read-to-use supplementary foods (RUSF) or Super Cereal Plus (SC+) to treat MAM, CMAM led to major improvements in the survival of children with acute malnutrition. CMAM improved SAM treatment coverage from under 10% to over 70% in some areas, thanks to the efficacy of Read-to-use Foods (RUF) [4,5]. According to UNICEF, treatment currently reaches 28% of children suffering from SAM [6].

UNICEF currently procures over 80% of RUTF globally, with the World Food Programme procuring a similar percent of RUSF. A smaller percent of RUF is procured by different international aid organizations. RUF are purhcased from many independent manufacturers across the world, who often supply both RUTF and RUSF to aid organizations [6]. Fortified blended foods, including SC+, are procured by the World Food Programme and other aid organizations [7].

Although effective, current RUTF, RUSF, and SC+ remain costly, largely due to expensive ingredients. The standard RUF recipes use milk powder and peanut paste with vegetable oil, sugar, and micronutrient supplements [8]. Expensive milk powder can account for over half the final cost [9]. The high cost of treatment has become a major obstacle for scaling up treatment of SAM and MAM [10], preventing the meeting of basic nutrition needs in developing countries and hindering integration of SNF in national health programs [2,11].

Although procurement of RUTF is currently limited to costly recipes containing dairy, research testing the efficacy of low-cost dairy-free RUTF is promising [12–14]. If the efficacy of lower-cost recipes for SAM or MAM treatment is determined to be equivalent, it may reshape global SNF supply chains.

Transport and logistics are also costly. Supply of treatment relied has historically on international shipments from manufacturing sites mainly in France and the United States [15]. UNICEF has steadily expanded local procurement in recent years, achieving over 50% since 2016[16]. Transportation costs in sub-Saharan Africa are often several times higher than in developed countries [17], and the long travel time between the factories and the demand often delays response to emergencies. While localizing SNF production may improve the efficiency and timeliness of the supply chain, local production is currently less cost-effective than the international producers. Although research suggests local purchases of some ingredients, such as grains, can be of up to 50% lower cost, this has not translated to locally produced acute malnutrition treatments[18]. Current RUF recipes rely on ingredients that are locally unavailable (e.g. milk powder, peanuts, oil) and subject to import tariffs in sub-Saharan Africa. Thus, domestic RUTF costs currently average at $50 per carton (150 servings), compared to $44 for internationally procured RUTF [19].

Recent initiatives by aid organizations have demonstrated the potential cost savings in more localized supply chains [16]. Research suggests local production may enhance availability and supply chain efficiency while local treatment recipes can improve acceptability [19,20]. Currently, UNICEF primarily procures milk and peanut based RUTF. However, UNICEF expects that recipes using lower cost local ingredients will reduce the cost of treatment in the future [16].

The rapid growth of local production of SNF could give the opportunity for new, more optimized supply chains of acute malnutrition treatment distribution. However, there remains a need to model these supply chains in order to inform international aid and donor organizations on the best strategies to optimize logistics.

Our goal is to model and optimize the macro supply chain of acute malnutrition treatment based on published, accurate data. By incorporating both the current recipes and local, plant-based recipes, our model informs on how the supply chain may change with potential future formulas. A variety of parameters allows the user to fit the model to their needs and constantly update it with real-time information. Under a changing procurement system, from international to localized production, this model would be able to inform policymakers on treatment recipes, factory placements, and significant cost drivers.

There have been no previous studies that model or optimize supply logistics of SNF procurement. UNICEF publishes annual reports and data on current supply chains and there have been a few studies to model last-leg SNF distribution. For example, Rancourt et al (2015) [21] models last-leg distribution networks of food aid in the Garissa region of Kenya. Their model includes coverage, cost, beneficiary time, and coverage radius. Other articles model the distribution of general food aid, such as grains, and examine the largest cost barriers [22]. However, there remains a lack of a model that can optimize the macro supply logistics of acute malnutrition treatment.

We optimize the production and distribution of acute malnutrition treatment to identify potential cost savings in the supply chain and study the economic feasibility of local production and different treatment recipes.

2. Methods

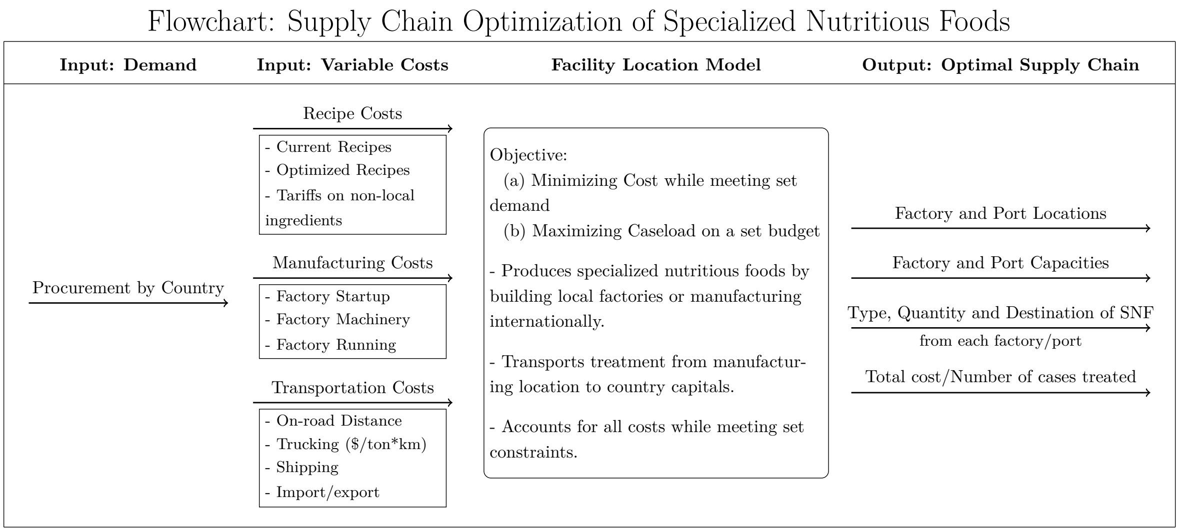

Figure 1. A flowchart of the inputs, costs, constraints, and outputs of the supply chain optimizer.

We created a capacitated facility location model to optimize SNF production and distribution networks in sub-Saharan Africa. The model meets the demand of acute malnutrition while accounting for associated costs, including ingredients, production, and transportation of SNF. The tool returns the optimal placement and capacities of factories and ports used; the type, quantity, and destination of SNF from each port and factory; and the total procurement cost (Figure 1).

We optimized supply logistics for several different scenarios that reflect the possible uses of the tool. The different settings that we explored are:

1. Optimization: (a) minimizing costs while treating demand or (b) maximizing cases treated on a budget.
2. Demand: (a) full caseload for SAM and MAM or (b) the caseload that UNICEF currently treats.
3. Factories: (a) only current factories and prices or (b) establishing new factories in countries with sufficient data.
4. Production sites: (a) international and local production or (b) only local production.
5. Recipes: (a) current recipe ingredients and prices or (b) optimized recipes.

2.1. Quantifying SNF Demand

We input the caseload of acute malnutrition from either the per country demand that UNICEF currently meets [23], or the entire caseload based on available surveys. These reflect the current actual demand for treatment and the maximum theoretical demand.

Prevalence of severe and moderate acute malnutrition was obtained for 43 continental sub-Saharan African countries using national surveys [2]. We used this data to calculate SNF demand for treatment of SAM and MAM for each country.

In order to account for the known underestimation of caseload based on prevalence, We adjusted prevalence using the incidence correction factor K. Due to lack of data, many different estimates of K exist, and K is expected to vary greatly between countries. We used higher estimates of K, based on data from Nigeria, to prevent underestimation [24–26].

$$\begin{aligned}
\text{Incidence} &= \text{Prevalence} \cdot K && (1)\\
K &= \frac{\text{duration over which prevalence was estimated}}{\text{avg duration of untreated disease}} && (2)\\
\text{For SAM:} \quad K &= \frac{365 \text{ days}}{32 \text{ days}} && (3)\\
\text{For MAM:} \quad K &= \frac{365 \text{ days}}{75 \text{ days}} && (4)
\end{aligned}$$

For both SAM and MAM, survey data estimated prevalence over a one year period. Using available estimates for the duration of untreated malnutrition, we calculated the incidence correction factor K for SAM and MAM. The incidence of malnutrition per country was then multiplied by the quantity of SNF needed per case to estimate the annual demand for the respective treatment product by country [24,26–28]:

$$\text{Annual treatment demand} = \text{Incidence} \times \text{Duration of treatment} \times \text{Treatment Dosage} \qquad (5)$$

Compared to SAM, MAM requires a lower amount of treatment, which reflects the lower incidence correction factor as well as lower amount of treatment needed per case. Figure 2 displays the final by-country demand for treatment used in the model, where each sachet is a single serving packet.

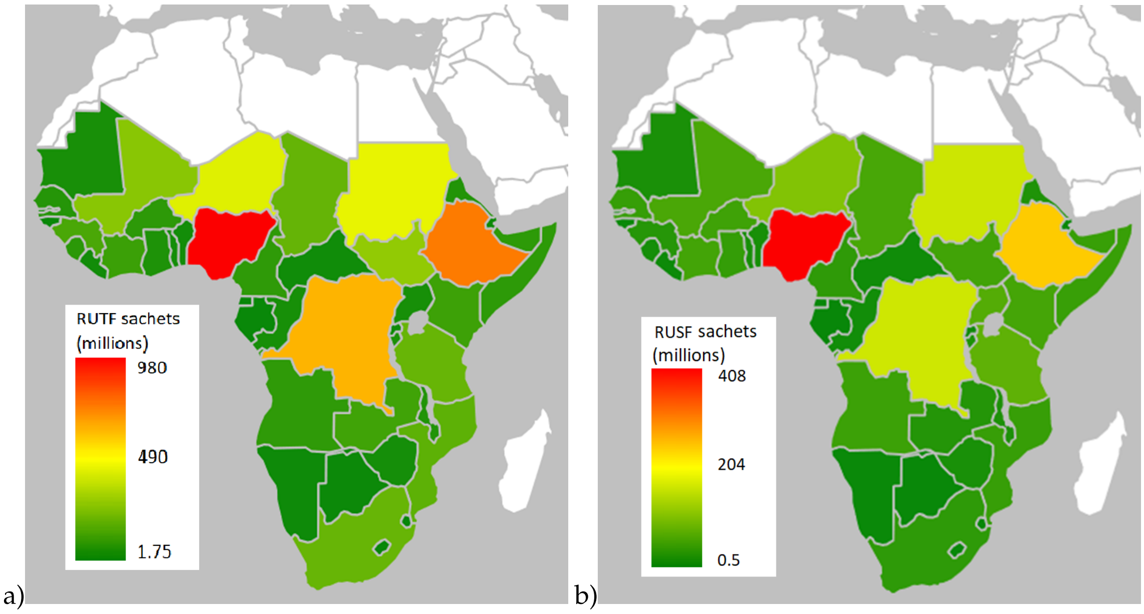

Figure 2. The estimated demand for treatment of severe (a) and moderate (b) acute malnutrition, based on UNICEF surveys [2].

2.2. Variable Costs

The optimizer is dependent on variable costs of SNF production and distribution. These include: ingredient costs SNF products, factory startup and machinery costs, factory running costs, transportation costs, import and export costs, tariffs on non-local ingredients, and shipping costs from international suppliers. These variable costs are sourced from literature, UNICEF reports, and personal communications with Valid Nutrition

The model includes local production cost information to quantify the fixed and operating costs. Interviews with SNF production experts indicated that ingredient cost is the most significant and most variable operating cost item, which should influence SNF facility location [29].

2.2.1. SNF Recipe Costs

We used local and international commodity prices [30] to calculate the ingredient cost of current RUTF and RUSF [31,32]. All factories in sub-Saharan Africa currently produce the same peanut and milk based RUF, but the ingredient cost differs due to local commodity prices and tariffs. We calculated the current RUTF and RUSF to have an ingredient cost of 12.6 cents and 11.8 cents per packet respectively on the international commodity market.

We next optimized treatment recipes to estimate possible future alternative formulas. The optimization of recipes was based on a paper previously published, in which a linear programming tool was used to optimize low-cost, dairy-free treatments for local and international production

[33]. The optimizer minimizes cost while meeting all nutritional requirements. Most importantly, it automatically ensures protein quality as protein digestibility corrected amino acid score (PDCAAS), meaning it can combine low-protein quality ingredients to form a high protein-quality output without the need for costly animal products.

We made improvements to the published recipe optimization tool in several important ways. First, we raised the protein quality requirement to match the PDCAAS score of the current recipes. We then used the tool to optimize locally sourced RUTF, RUSF and SC+ in 24 sub-Saharan countries with sufficient market data. These optimized recipes in each country could only import sugar, oil, and micronutrient premixes, as those ingredients are rarely found locally. All other ingredients had to be locally grown. The ingredient composition and price per packet of these RUTF and RUSF recipes is shown in Figure 3. Unlike the current recipes, optimized SC+ was much more expensive than the optimized RUSF, so we only used RUSF to treat MAM in our supply chains.

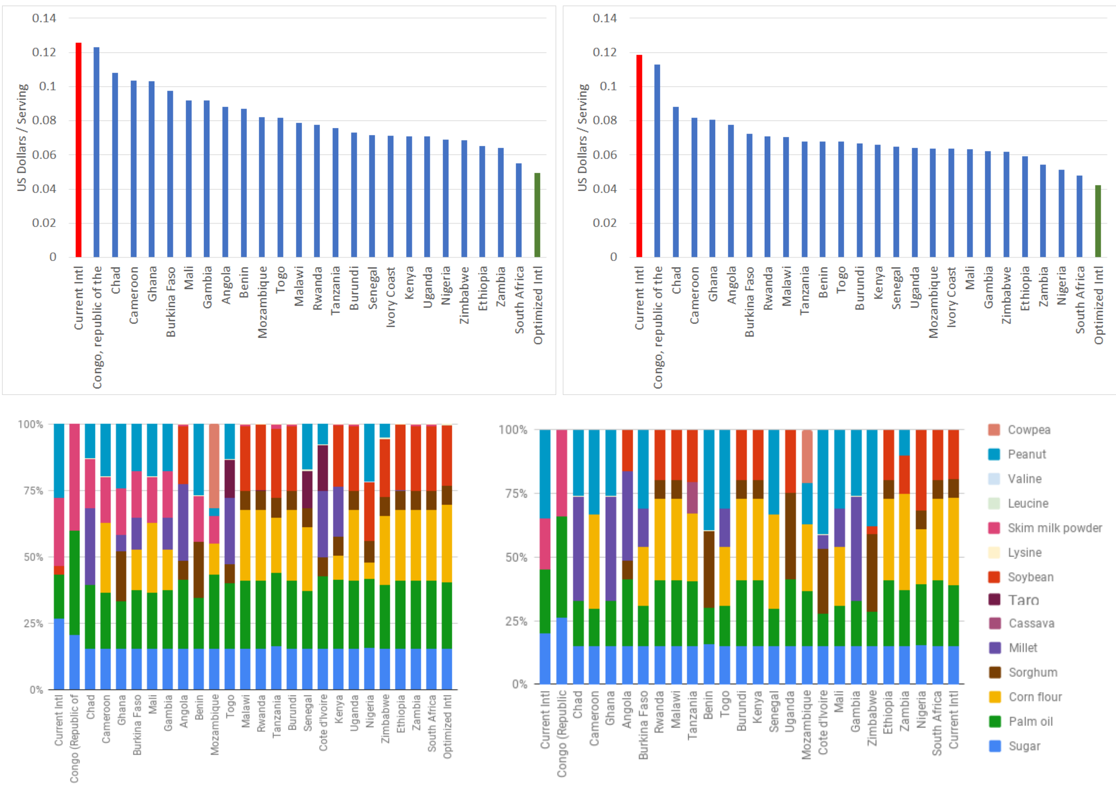

Figure 3. Ingredient cost (top) and composition (bottom) for optimized RUTF (right) and RUSF (left), arranged by cost.

2.2.2. Factory Costs

Fixed costs (e.g. factory startup, purchasing and upgrading machinery) were distributed over a five year period. Required equipment include cleaning/preparation machines and the mixing/bagging machines. Fixed costs were estimated based on literature, supplier catalogues of machinery, and personal communication with SNF manufacturers [9,29,34].

Running costs were estimated from personal communications with the Valid Nutrition factory in Malawi [29] and the product costs of the larger factories in Africa [35]. Running costs include labor, packaging, fuel and electricity, the profit margin, and other miscellaneous costs incurred through the running of the factory. The running costs of larger factories is consistent both temporally and across factories and is about 14.6 cents per packet. However, the running costs of the smaller factories are highly variable and difficult to predict. Our model assumes that all factories share running costs of the larger factories due to lack of country-specific data.

2.2.3. Transportation Costs

Transportation costs were estimated between each sub-Saharan African capital. On-road distances were calculated using the python Google Maps API. This distance was multiplied by estimated regional costs, to obtain the cost of transporting one tonne of packaged product between each capital [17,36]. Import and export costs per tonne of product, reflecting the high document and border compliance costs in sub-Saharan Africa, were then added to the trucking cost [37]. Import tariffs on imported ingredients were also included in the model, and were estimated based on published tariff data [38]. Shipping costs on internationally-produced SNF were calculated to each major port in sub-Saharan Africa, and were based on published shipping costs [2].

2.3. Supply Chain Model

A skeleton of the facility model can be seen in Figure 4. The cost of local production for current factories (purple stars) includes the cost of the ingredients, including tariffs on non-local ingredients, and running costs. Local production with new factories (red stars) has those same costs plus start-up and machinery. When treatment is shipped from a factory to neighboring capitals, the costs incurred include trucking, import, and export costs. Off-continent production costs include manufacturing international SNF, shipping into one of the major African ports (blue dots), and trucking to the final destination with import/export costs across borders.

The optimizer outputs include the factory and port locations and capacities and the type, quantity, and destination of SNF from each factory and port.

Our model focuses on the macro level production and shipment of SNF between countries, in order to inform the strategic development of manufacturing in locations where they have greatest potential. Due to the variance in existing health systems and unique regional and local challenges in last leg distribution, the model does not inform sub-National SNF distribution.

2.4. Parameter Study

To identify barriers in increasing access to treatment, as well as to account for the inaccuracy and lack of data in sub-Saharan Africa, we ran a parameter study using the supply chain model. The supply chain model was run for approximately 700 cases, varying each of the following parameters

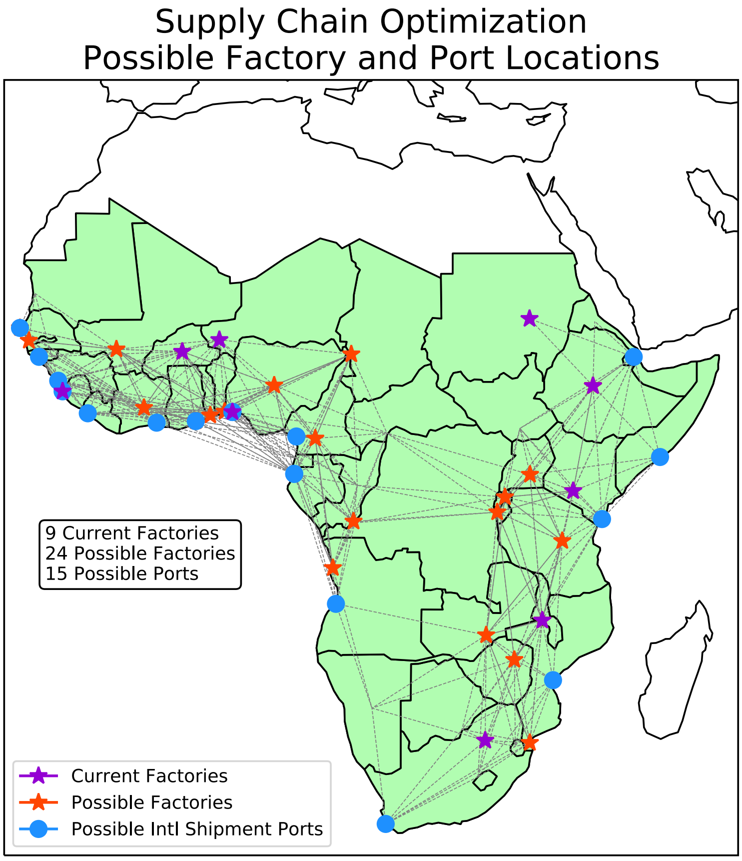

Figure 4. A skeleton of the supply chain optimizer. Every purple star is a current factory location, every red star is a possible factory location (in every country with sufficient price data), and every blue circle is a possible port for international shipments.

independently: trucking costs, sea shipping costs, border and document compliance costs, factory start-up costs, tariffs, and budget (for the budget scenario).

3. Results

The supply chain model effectively distributed acute malnutrition treatment through an optimized network of factories and ports. Fist, we validated the model with UNICEF's current supply chain (presented in Section 3.1). Results from cost minimization are presented in Section 3.2 and results from maximizing cases on a budget are presented in Section 3.3.

3.1. Supply Chain Model Validation

To assess the accuracy of the supply chain model, we modelled the UNICEF supply chain for treating SAM in 2018. Using the cost of product from different producers and the amount of treatment delivered to countries included in our model, we calculated UNICEF's cost of delivering RUTF to the 43 countries in our model during 2018.

To perform the validation, we applied our model to UNICEF's supply chain for RUTF while using our own calculations for ingredient, factory, and transport costs. The amount of treatment procured at each factory [35] and the amount delivered to each country was set according to UNICEF procurement reports [23]. We calculated UNICEF's supply chain by converting procurement to each factory in USD [39] and the price of RUTF by factory [35] to the amount of treatment produced in each country. The destination of this treatment was then optimized with our model, to meet the amount procured for each country. UNICEF currently distributes RUTF in sub-Saharan countries except Ghana, Gabon, Equatorial Guinnea, and the southern tip of Africa. 60% of RUTF is produced locally in nine African factories. UNICEF's supply chain in 2018 is visualized in Figure 5. When compared to the high estimate of incidence corrected caseload, only 6.3% of SAM cases are treated (Figure 5).

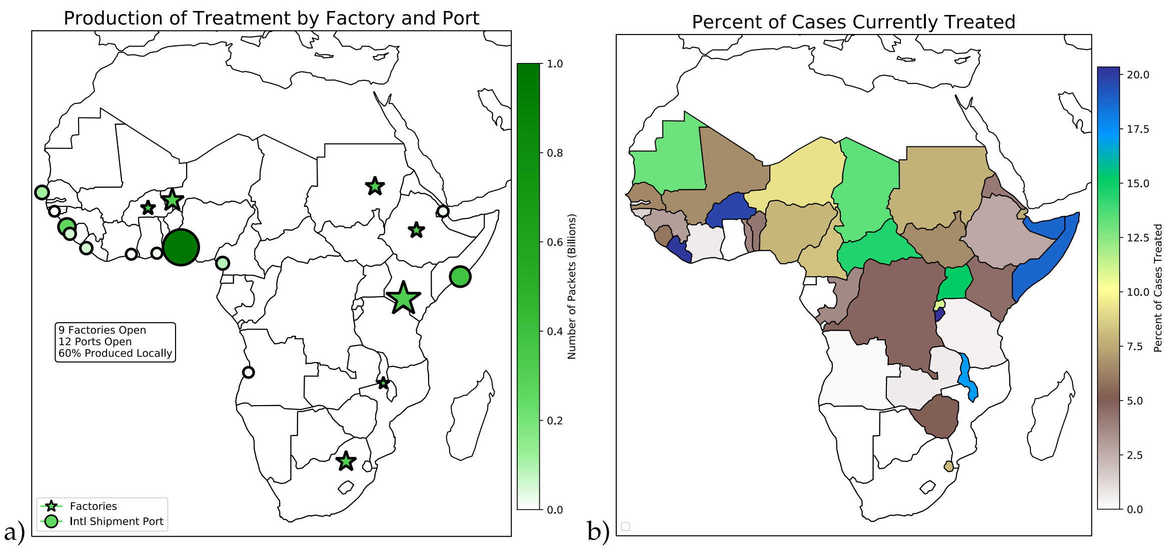

Figure 5. The amount of treatment produced at each factory or imported at each port (a) and the percent of cases treated in each country (b) in UNICEF's supply chain in 2018. The percent of cases treated is based on the adjusted caseload.

Our model calculated the total supply chain cost within 3.2% of UNICEF's RUTF budget in sub-Saharan Africa and an error of 0.9% for the average transportation cost of treatment (Table 1). The unweighted average of recipe costs, however, were much higher at 10%. The average recipe cost error was much smaller for the major producers (3%), but smaller factories have a much larger error due to difficulty in calculating running costs. Unlike the larger producers, the smaller factories have highly variable running costs between each other and temporally. Because our model only includes a set running cost, it cannot account for these differences.

Table 1. Results of the Validation.

	Total Cost	% Transport Cost	Avg Recipe Cost
Actual	121.5 million $/year	4.85 $/MT	0.314 $/serving
Modeled	117.6 million $/year	4.39 $/MT	0.287 $/serving
Error	-3.20%	-9.38%	-8.60%

This validation suggests that the supply chain model can accurately calculate the total and transportation costs even when estimating the cost of treatment products.

3.2. Minimizing Costs

We minimized the cost of the malnutrition treatment supply chain using either the current factories with caseload the UNICEF currently treats (Section 3.2.1) or building new factories to treat the full caseload (Section 3.2.2). For both scenarios we compared different recipes and conducted a parameter study.

3.2.1. Current Factories to Treat The Current Caseload

We next optimized a supply chain using the current factories to treat the demand that UNICEF currently treats in order to analyze the current supply logistics. Different scenarios were run for both the current and optimized recipes to examine how the optimal supply logistics may shift in the future.

Using the current recipes, the model supplied 31% of the RUTF locally in 2 factories (South Africa and Sudan) (Figure 6). UNICEF currently sources 60% locally from 9 factories. The loss in local production is reflective of the higher costs of most local producers. Because our model underestimates border costs, it may also truck treatment farther than it actually could. Today, UNICEF prioritizes local production in order to build more resilient and local supply chains. According to our estimates, this investment into local production costs UNICEF about 7 million dollars per year.

When all recipes are optimized, only 18% of RUTF is produced locally (Figure 6b) due to the significantly lower cost of international commodity prices. However, 100% of RUTF can be sourced locally at the cost of 5 million dollars compared to the fully optimized supply chain, still 28 million dollars cheaper than the current supply chain (Figure 2). Novel recipes using local, plant-based ingredients could make local production significantly cheaper. Even though many countries would still need to import sugar, vegetable oil, and micro-nutrient premix, novel recipes would allow UNICEF to more easily achieve its goal to source 100% of treatments locally.

Table 2. Comparisons of the supply chains to treat the current demand.

	UNICEF Current Recipe	Optimized Supply Current Recipe	Optimized Supply Optimized Recipes	Optimized Supply Optimized Recipes (Local)
Cost (Million USD)	121	116	86.6	93.5
% Reduction		4.44	28.8	23.0
% Produced Locally	60	31	18	100

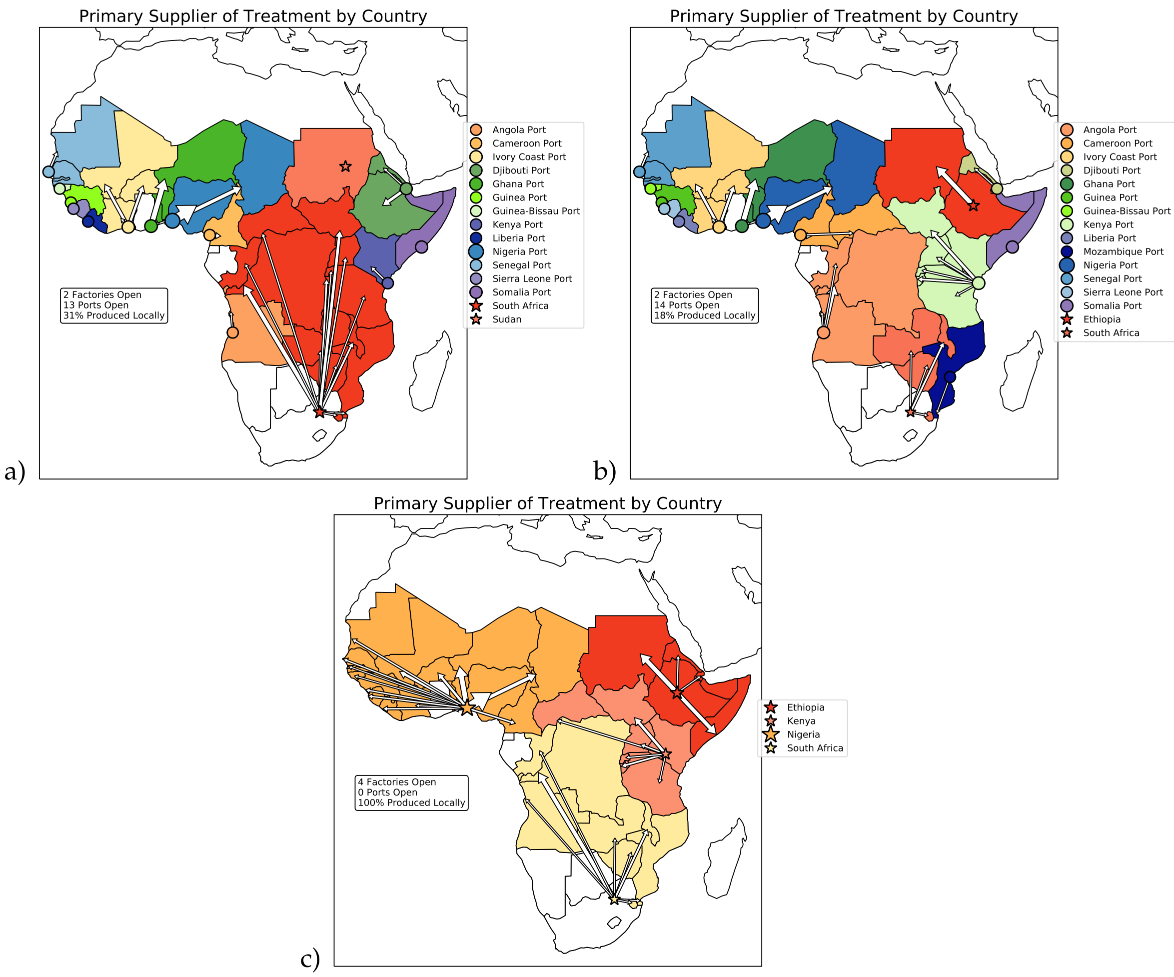

Figure 6. The primary supplier of RUTF using only current factories and the current recipes (a), optimized recipes (b), and optimized recipes with only local production (c).

3.2.2. New Factories to Treat The Full Caseload

The supply chain model met the estimated incidence corrected demand for moderate and severe acute malnutrition treatment through an optimized network of factories and ports. We optimized this supply chain for three recipe scenarios: current recipe, optimized recipes (only local production), and all optimized recipes. First, we present the results from the all optimized scenario.

Figure 7a shows the primary supplier of RUF by country when all recipes are optimized, and Figure 7b shows the relative amount produced at each factory or port. About half of the treatment is produced locally, with nine factories and nine ports open. Factories and ports typically supply between one and three countries, and supply the greatest quantity of treatments domestically.

A larger percent of treatment is produced locally when treating the full demand. This is likely because the model has the ability to build new factories in convenient countries instead of relying on only factories that currently produce. Also, a larger caseload must be met farther inland when treating the full demand. The high cost of trucking in sub-Saharan Africa makes it more convenient to produce locally.

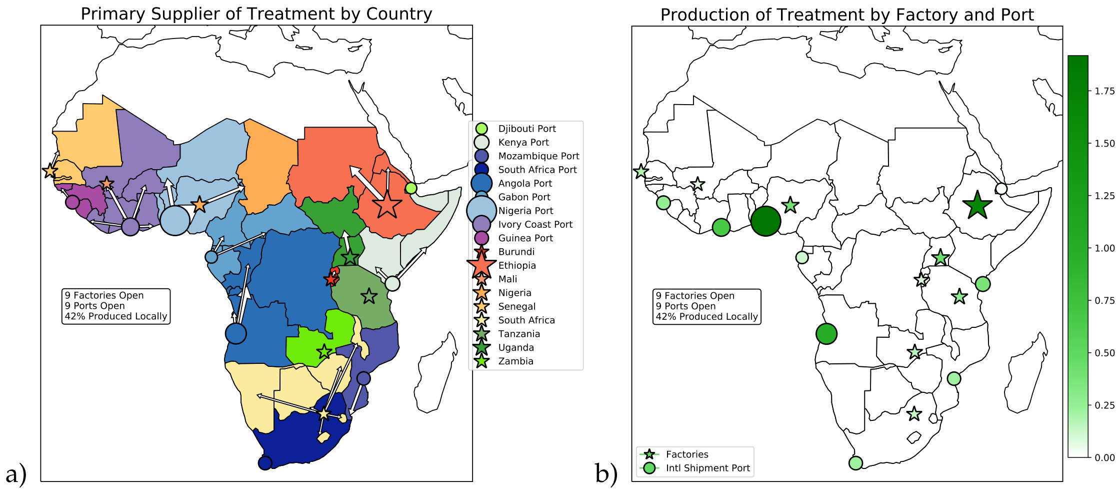

Figure 7. The primary supplier of SAM and MAM treatment (a) when all recipes are optimized. The arrows are scaled by the amount of treatment being shipped. About half of both products are produced locally. (b) shows the number of packets of RUSF produced or imported per year.

It is notable that most of the local producers of both SAM and MAM treatment are placed in inland countries. Because of the high startup and factory running costs in sub-Saharan Africa, it more cost-effective to import treatment on the coasts. However, the high trucking cost causes local production to be more cost-effective farther inland.

To examine how each variable cost affects the supply chain, we ran a parameter study in which we changed the relative costs of startup, import/export, trucking, shipping, and tariffs between 20% and 500% of today's costs in 20% intervals. For example, Figure 8a shows the optimal amounts of treatment provided by each port and factory as tariffs vary. At today's tariffs (100%), about half of the treatment is produced locally (shown in warm colors). Even with optimized recipes, local factories must import oil, sugar, and amino acids. As tariffs increase, the local production cannot compete with the cheaper international product. This analysis suggests that a more open market would cause local production to become more economically viable.

The parameter study may also help identify countries suitable for long-term investment, despite possible changes in variable costs. For example, when examining Figure 8a, we can see that Ethiopia remains a major producer of SNF even with extremely high startup costs. The amount of SNF produced in Ethiopia remains fairly constant regardless of changes in any of the 5 parameters, suggesting it to be an optimal supplier regardless of exogenous changes.

Next, the logistical model optimized SNF supply chains for all three recipe scenarios: current recipes, optimized recipes (only local production), and all optimized recipes. From these calculations, we may evaluate the effect of optimized SNF formulae. Optimized SNF reduces the total modelled cost by 25% compared to the current recipe (Figure 8a), reinforcing the importance of low ingredient cost. Interestingly, the total modelled cost is similar between only local optimized and all optimized recipes, suggesting the feasibility of local manufacturing.

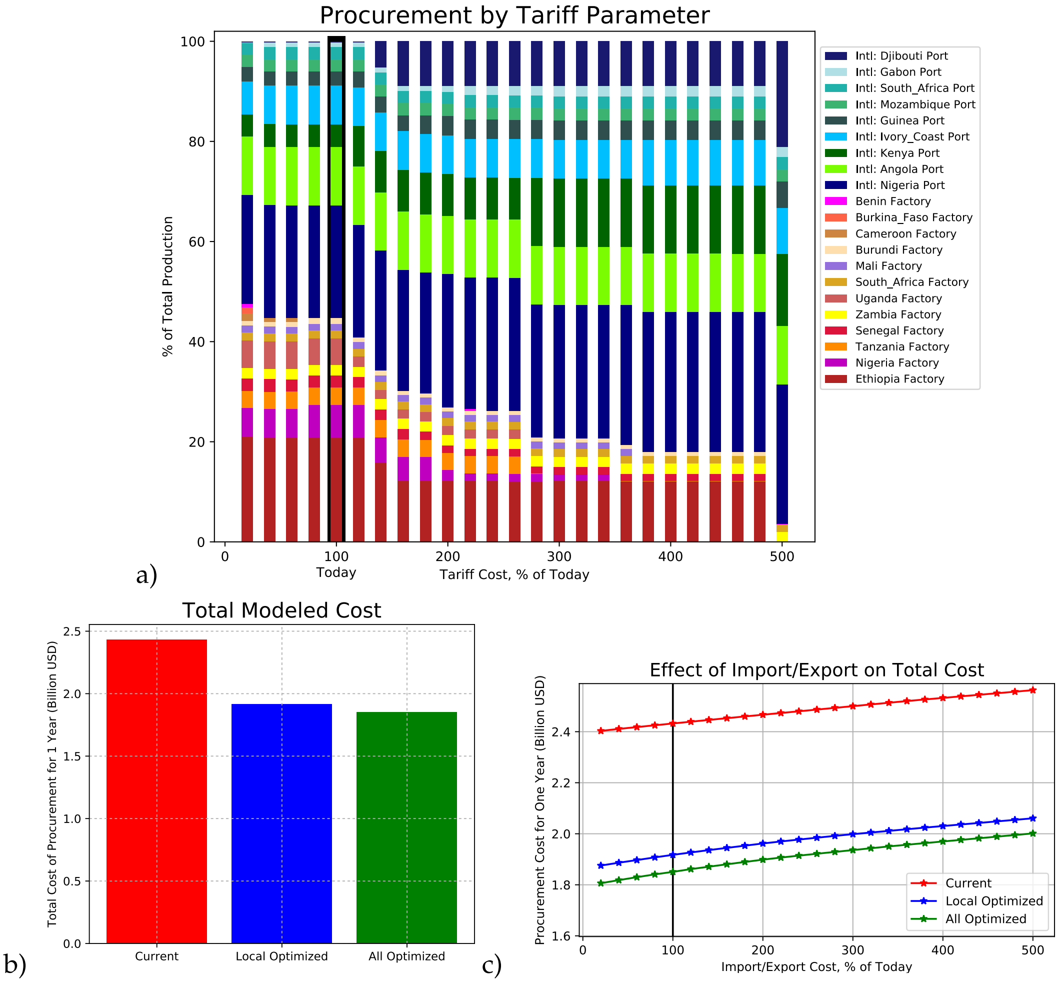

Figure 8. The cost of procurement for one year when all parameters are standard (a) and when varying the import/export parameter (b). The cost is shown for current SNF recipes (red), optimized recipes (only local production) (blue), and all optimized recipes (green). (c) shows the optimal suppliers of acute malnutrition treatment, according to the changing tariff parameter. Warm colors correspond to local production and cool colors correspond to international production.

Import and export costs are exceptionally high in sub-Saharan Africa, with the cost of trucking across a border averaging at \$1700 per 15 tons of material, or about half a truck of SNF. Although border costs do affect the price of the total supply chain, their contribution is actually relatively low compared to the difference in recipes (Figure 8c), reinforcing the fact that ingredient costs are the largest contributor to malnutrition treatment.

3.3. Maximizing Cases Treated

The supply chain model optimized the number of children treated on a set budget while building new factories. We optimized the treatment logistics of SAM and MAM separately, reflecting their current budgets. Based on UNICEF and WFP reports of current procurement of treatment, we estimated the budget of SAM and MAM treatment associated with costs included in our model to be 54 million

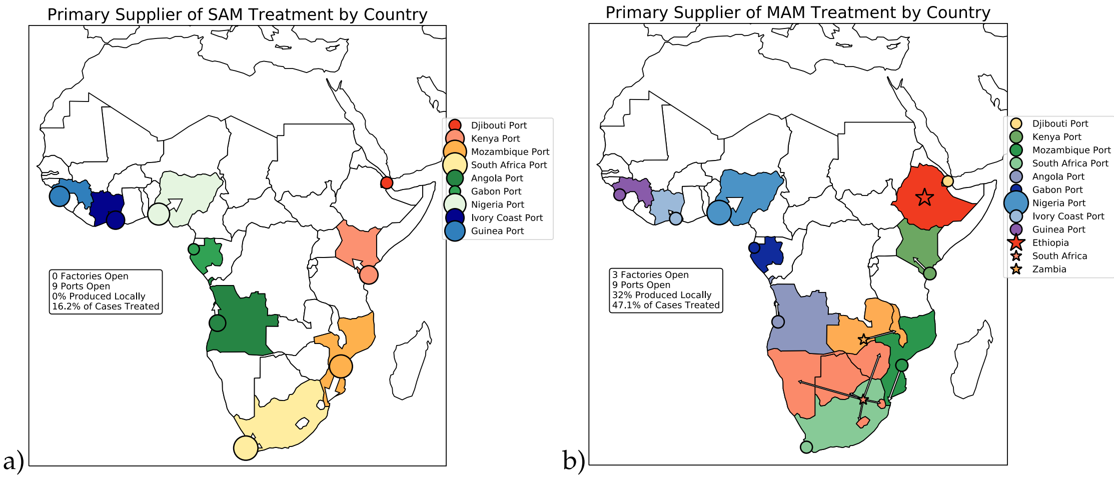

Figure 9. The primary supplier of SAM (a) and MAM (b) treatment under the current budget when all recipes are optimized.

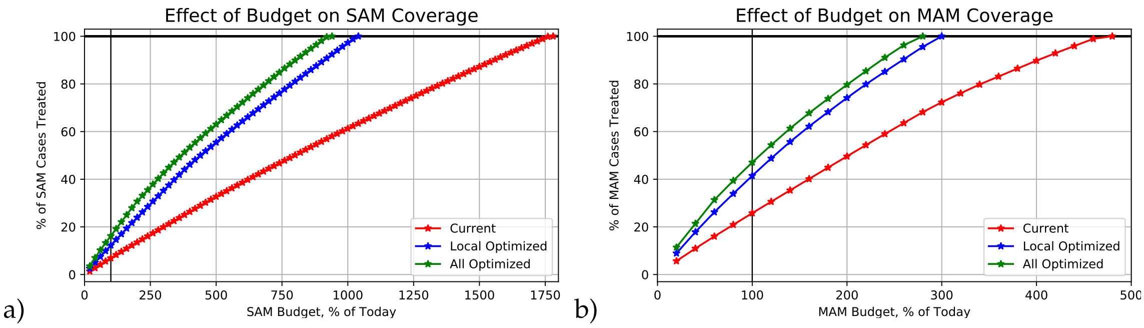

Figure 10. The percent of cases treated as the budgets for SAM (a) and MAM (b) treatment increases. To treat all cases using all optimized recipes, the MAM budget must be increased by 3 fold, while the SAM budget must be increased by 10 fold, due to the current small SAM budget.

each. As in Section 3.2, the supply chain was optimized using all optimized recipes, optimized recipes (only local production), and the current recipes. First we discuss the scenario of all optimized recipes.

Figure 9 shows the primary supplier of treatment for SAM (a) and MAM (b) treatment under the current budget. It is notable that most of the countries that are supplied with treatment are on the coasts, suggesting that international procurement is cheaper for coastal countries. In fact, severe acute malnutrition was only treated with international production with the current budget.

Under the current budgets, about 15% of SAM cases and 45% of MAM cases could be treated using all optimized recipes, and about half of that when using the current recipes. The numbers for current treatment compare well with with the number of cases actually treated: UNICEF estimates that 3 million children suffering from SAM in sub-Saharan Africa receive treatment [2], and our model treats 2.9 million SAM cases when set to use current budget and treatment. To meet the full caseload with optimized recipes, the SAM budget would need to be increased by 10 fold, due to the low current budget, while the MAM budget would need to be increased by 3 fold (Figure 10). However, when considering only the current recipe, both budgets would need to be increased much more.

4. Conclusions

Due to the high cost of current treatments and inefficient global supply chains, acute malnutrition treatment reaches only a small fraction of children in need. Here we develop a mathematical model to inform cost-effective production and distribution of specialized nutritious foods in sub-Saharan Africa. A validation of this tool showed that this model can accurately estimate the cost of distributing food aid in sub-Saharan Africa.

Our model has the power to recommend strategies to international aid and donor organizations to improve the efficiency of their interventions. We conclude that the ingredient cost of current animal-based RUF is the largest cost driver in the supply chain: once fully developed and implemented, optimized plant-based recipes have the potential to reduce total costs by 25%. Other costs, such as transport, border, and tariff prices, have smaller impacts on the total price, and would require sustained development to improve. Local production is currently much more expensive than international manufacturing due to high tariffs on imported ingredients. However, recipes with local, plant-based ingredients could allow local production to be more cost-effective. Therefore, aid organizations should focus on implementing more cost-effective plant-based recipes.

All of these results agree with previous studies and reports on acute malnutrition treatment. Studies have found that almost half of the landed costs of RUF come from milk powder [9] and there have been sustained attempts to create effective plant-based treatments [14,40,41]. A recent study in the Horn of Africa found that local production improved the economic, environmental and social sustainability of treatment supply chains while responding to crises with greater ease [16].

The supply chain model can be used to identify countries with the optimal combination of low production costs and proximity to demand to support cost-effective local production. This proposed model can help assess relative location suitability for SNF production; compare local, regional, and international supply chains; identify barriers to low-cost treatment; and better inform policy makers or aid organizations on cost-effective nutrition intervention.

Our tool can be easily adjusted by the user to include up-to-date information on ingredient costs, variable costs, and political situations, thus allowing aid organizations using this tool to adjust distribution networks according to real-time information.

The supply chain model presented here does have several limitations. The largest limitation is the quality of the input data. Data from sub-Saharan Africa, such as commodity, production, and transportation costs, are often difficult to find, coarse, and of limited accuracy. For example, we were only able to obtain factory running costs from personal interviews with the Valid Nutrition factory in Malawi and had to extend these costs to all factories in Africa. Using a single running cost means we can not capture the variance between countries in cost of fuel, electricity, labor, water, regulatory compliance, and profit margin. Similarly, trucking costs, in dollars per ton kilometer, were only available at the regional level, missing subnational variation [17,36]. Other models have also found it difficult to model logistics in Africa due to the lack of data [22]. Despite this limitation, the validation with UNICEF's cost breakdowns suggests that the model has reasonable accuracy in modelling SNF logistics.

The second limitation of this model is difficulty in implementation. Treatment production and distribution of different SNF is handled by several multiple companies and organizations. Factories for producing SNF are not centrally managed. For example, UNICEF procures from many different independent manufacturers of RUTF [42]. Additionally, donors can have a large impact on the procurement and supply chains of aid organizations [7].

Within this context, our model could be used to inform aid organizations on the cost of achieving a goal percent of local production, and suggest countries to invest in towards this goal. Additionally, it can help new manufacturers considering beginning production or established manufacturers considering introducing new products. In this way the model could assist different organizations in their efforts to be more competitive, instead of recommending a single system of production and distribution.

Finally, this model does not inform distribution of treatments sub-nationally because of the different national health systems in place and varied challenges between each country.

We are not aware of any previous literature on supply chain optimization of acute malnutrition treatment. A few studies model the supply chain of last-leg SNF distribution in select regions [21], and there are many studies on optimizing supply chains for businesses and environmental footprint [43–46]. This model focuses on the large-scale distribution networks of SNF in order to treat more children suffering from acute malnutrition.

This tool could be used by aid and donor organizations to decide how to most efficiently add and modify existing supply chains. It could inform on countries that are most suitable for investment in local production, where different regions should be sourced from, and assess the potential of new factories and products.

Comprehensively modelling the supply chains for SNF could ultimately allow more children to receive life-saving treatment within existing budgets while supporting sustainable agriculture and future food security in developing countries.

Acknowledgments: We would like to thank Dr. Steve Collins for feedback and guidance on current practices, Peter Akomo of Valid Nutrition for data on local production, and Mary Doyle of Valid Nutrition for helping obtain data on the current RUTF supply chain.

Conflicts of Interest: Declarations of interest: none.

Funding: This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

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