A Novel Computational Tool to Inform Cost-Effective Nutrition Interventions in Sub-Saharan Africa

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Team 28

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A Novel Computational Tool to Inform Cost-Effective Nutrition Interventions in Sub-Saharan Africa

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1. Executive Summary

Malnutrition contributes to nearly half of childhood deaths, while treatment reaches a small fraction of those in need. Treatment delivery is hampered by costly ingredients and inefficient supply chains. Here we develop a three-component tool to inform acute malnutrition treatment interventions. First, we forecast the geospatial demand of acute malnutrition treatment using a machine learning algorithm. Second, we optimize low-cost recipes of specialized nutritious foods while meeting nutritional standards. Recipes were optimized for both international production and local production in 24 sub-Saharan African countries, and both achieved ingredient cost reductions of up to 60% compared to current recipes. Third, we model a supply chain of the optimal production and distribution of acute malnutrition treatment with both international and local factories while accounting for production and transportation costs. Three optimization scenarios were considered: using current factories to treat a set demand, building new factories to treat a set demand, and building new factories to maximize the number of cases treated on a budget. Our model suggests that optimized recipes could reduce total procurement costs by 25%, with additional reduction through optimizing supply logistics. The tool can assess relative location suitability for SNF production; compare the cost-effectiveness of different recipes; and identify cost drivers, such as the high import and export costs in sub-Saharan Africa. Used in conjunction, forecasting demand, optimizing recipes, and modelling efficient supply chains can better inform policy makers and donor organizations. Optimal supply chains could reach more children with life-saving treatment within existing budgets while supporting sustainable agriculture and future food security in developing countries.

2. 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 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 treatment coverage from under 10% to over 70% of children suffering from SAM. [4,5].

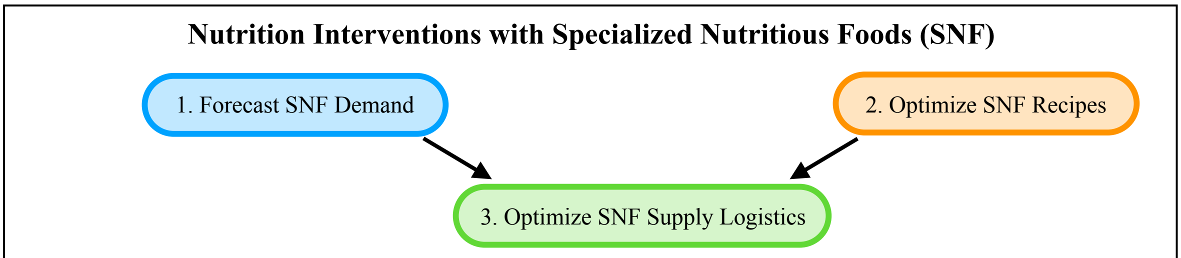
However, current RUTF, RUSF, and SC+ remain costly, largely due to expensive ingredients, transportation, and misaligned policy. The standard RUF recipes use milk powder and peanut paste with vegetable oil, sugar, and micronutrient supplements [6]. Expensive milk powder accounts for over half the final cost [7], thus stressing developing countries' limited health budgets. It has become a major obstacle for scaling up treatment of SAM and MAM [8], preventing the meeting of basic nutrition needs in developing countries and hindering integration of SNF in national health programs [2,9]. Thus, there remains a major need to reduce the cost of RUF through reduced use of milk powder and peanuts, while still meeting all macro and micronutrient requirements.

Transport and logistics are also costly, involving international shipments from manufacturing sites mainly in France and the United States [10]. Insufficient lead time of malnutrition forecasts often leads to crucial delays in policy negotiations, planning, producing, and trucking of SNF. This delay sometimes forces aid organizations to rely on air transport of SNF during emergencies, bringing transportation costs from 10% to 39% of the total treatment cost [9,11]. Greater lead time of SAM and MAM forecasts could help increase the cost effectiveness of SNF logistics, allowing more people to receive treatment.

Recent research supports context-specific approaches to the treatment and prevention of malnutrition, including localizing SNF production close to malnourished patients [12]. Local formulae can improve acceptability, while local production may enhance availability and supply chain efficiency [12]. However, current RUTF recipes rely on ingredients that are locally unavailable (e.g. milk powder, peanuts, oil) and subject to import tariffs in sub-Saharan Africa. Domestic RUTF cost currently averages at $50 per carton (150 servings), compared to $44 for internationally procured RUTF [12], meaning local production is currently less cost-effective. Using local ingredients could increase the cost effectiveness of local production for more cost effective treatment [13].

The cost of ingredients, logistics, and transport hinders developing countries from properly treating malnourished children. The current supply of SNF is insufficient, with RUTF meeting the needs of only 16% of children suffering from SAM [2]. This figure falls significantly short of the United Nation First 1000 Days goal to reduce malnutrition during the critical prenatal to 2-year-old time frame that "can cause irreversible damage to a child's physical growth and brain development." [14].

We aim to create a tool to inform policy makers on optimal production sites and distribution networks of SNF to best treat all malnourished children. By predicting future malnutrition prevalence, reducing ingredient cost, optimizing logistics, and localizing production, we aim to propose a more economic and sustainable system of acute malnutrition relief, aligned with long term development and food security goals.



	1. Forecast SNF Demand	**2. Optimize SNF Recipes**	**3. Optimize SNF Supply Logistics**
Input	33 training features (e.g. development, crop health, political situations)	Nutrient database and SNF nutrition requirements	SNF demand **(1.)**, optimized SNF **(2.)**, and variable costs (factory startup & running, transportation, etc.)
Method	Machine learning	Linear programming optimizer	Facility location model
Output	Forecasts of SNF demand across sub-Saharan Africa	Optimized SNF recipes for treatment of malnutrition	Supply logistics: quantity, type, and destination of SNF from each factory/ port

Figure 1. A flowchart detailing the three components of the computational tool.

3. Methods

The goal of this project is to inform SNF production decisions to sustainably increase treatment and reduce costs. It consists of three components: prediction of acute malnutrition prevalence (Section 3.1); optimization of SNF formulae (Section 3.2); and modeling the production and distribution of SNF (Section 3.3). The flowchart in Figure 1 illustrates an overview of all three parts of the project.

All of the python code for this manuscript was written by the authors and totalled to 2000 lines. The code can be found at https://github.com/lillianpetersen/Nutrition_Intervention.

3.1. Forecasting SNF Demand

The first step in this project is forecasting demand of SNF to feed into the supply chain model (Figure 1). Inaccurate or untimely forecasts of malnutrition prevalence often lead to crucial delays in planning and production of SNF, which can force aid organizations to use air transportation and dramatically increase the cost of treatment.

We used a machine learning algorithm to predict future geospatial malnutrition prevalence across sub-Saharan Africa based on 33 training features (Table 1). After performing a training and testing trial to validate the accuracy of the predictions, we predicted malnutrition prevalence across sub-Saharan Africa to year 2021.

3.1.1. Malnutrition Data and Training Features

The malnutrition data that we used as ground-truth synthesizes weight, height, and age data from numerous surveys across sub-Saharan Africa [15]. The released data set includes gridded acute malnutrition prevalence from 2000-2015 at a 5km resolution (Figure 2).

We assembled a training data set for machine learning of malnutrition prevalence. The 33 training variables may be split into five categories: development, economics, political situations, climate, and crop health. Table 1 lists the training features and Figure 3 highlights some examples.

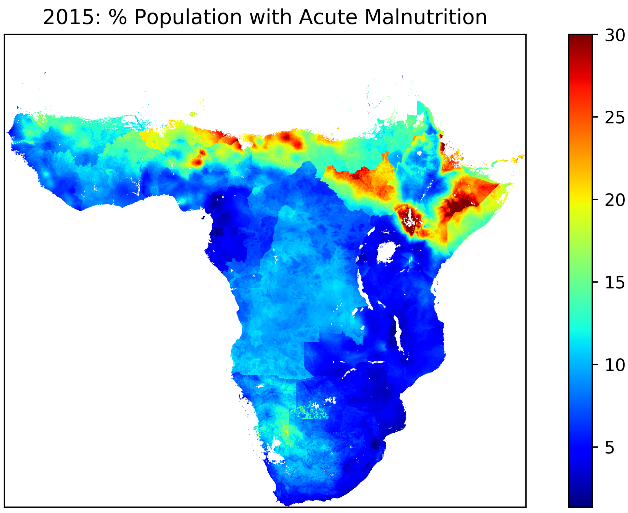


Figure 2. Acute malnutrition prevalence across sub-Saharan Africa in 2015. This data is used as ground-truth in our model. Malnutrition prevalence is highest in South Sudan, Ethiopia, Niger, Nigeria, and Kenya.

3.1.2. Scenarios using the Logistic Model

Before entering the features into the model, the data had to be processed into the correct format. Many of the variables came as tiff files and were already gridded. These variables were interpolated to the same grid as the malnutrition prevalence data using a bivariate spline approximation technique. Other data was retrieved by country (e.g. World Bank data). We used a national identifier grid [32] to overlay these variables onto a grid.

A few datasets came as latitude/longitude points or shapefiles (i.e. coastlines and fatalities from conflicts). We interpolated coastlines into a raster dataset of distance from coasts by calculating the

Table 1. Training features used in machine learning algorithm to predict acute malnutrition.

Category	Training Features
Development	1. Female education, years of attainment, gridded [16] 2. Percent of school-aged children in school [17] 3. Percent of population with access to electricity [17] 4. Percent of females with a secondary school education, national [17] 5. Human Development index [18] 6. Gridded population [19] 7. Travel time to the nearest urban center [20,21] 8. Low degree and high degree of settlements [19,22] 9. Built up land cover types [22]
Economics	1. Agriculture as a percentage of GDP [17] 2. Net official development assistance (ODA) per capita [17] 3. Gridded subnational estimates of GDP PPP per capita [18] 4. Imports per capita [17]
Political Situations	1. Political stability and absence of violence [17,23] 2. Government effectiveness [17,23] 3. Conflicts and fatalities from conflicts [24]
Climate	1. AVHRR-derived forest cover [25] 2. Distance to coasts and inland coasts [26] 3. Elevation [27] 4. Elevation roughness [27] 5. AVHRR-derived bare ground [25]
Crop Health	1. Mean annual precip [28] 2. Crop yield [17] 3. Crop production per capita [29] 4. Diversity of Crop Systems [30] 5. AVHRR-derived NDVI [25] 6. Irrigated area (area actually irrigated) [31] 7. Irrigated area (area equipped for irrigation) [31]

distance from the nearest coast for every pixel. To convert the conflict points onto a grid, we used a market potentials index. The market potentials equation applied to conflicts is

$$\mathrm{MP}_i = \sum_{j=0}^{J} \frac{\mathrm{fatalities}_j}{\mathrm{dist}_{i \to j}^{\theta}} \tag{1}$$

where i is the current pixel, j is the latitude/longitude point of the conflict, and fatalities is the fatalities at point j. The power θ in this calculation is chosen to be 1.2. In this way the conflicts database was converted into a raster dataset. All of the training features combined made a total of 13 gigabytes of input data for the malnutrition forecasting component.

3.1.3. Machine Learning and Predictions

Next we trained a random forest regressor, a machine learning algorithm in the python library scikit learn, on the features to predict malnutrition prevalence. The data was split into a training set of 80% and a testing set of 20%. To avoid overfitting by spatial correlation, the testing data was removed in boxes across sub-Saharan Africa. The model was trained on the previous year's indicators (e.g. 2015 prevalence was trained on 2014 features). We then validated the accuracy of the predictions by

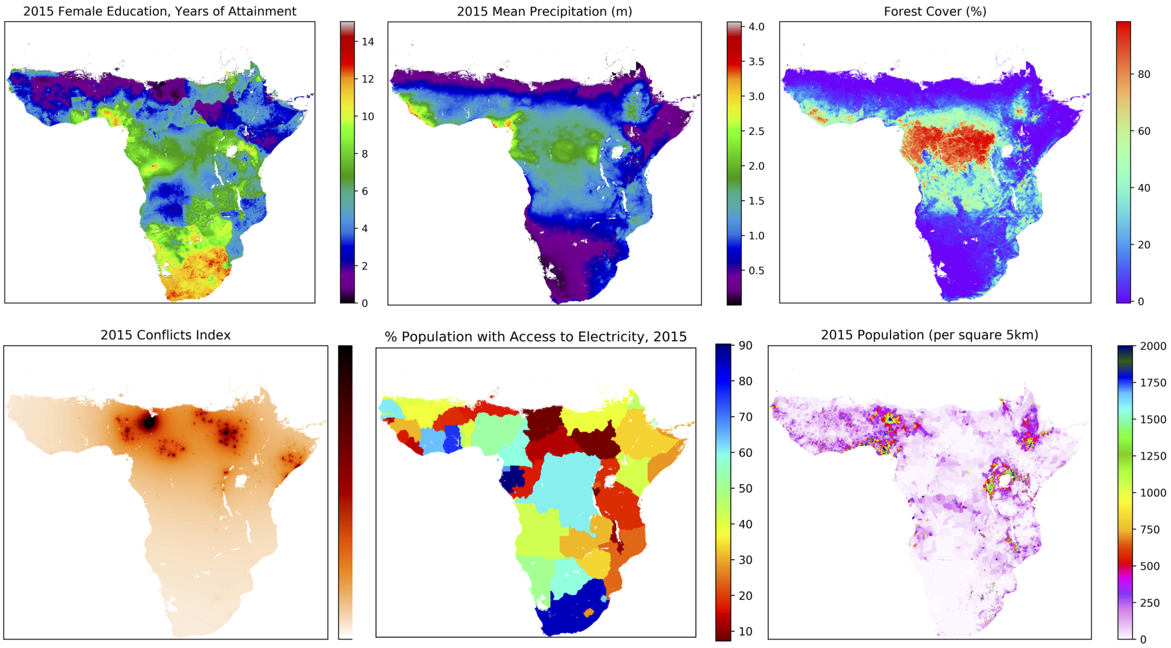


Figure 3. An example of six of the 33 training variables for prediction of malnutrition. The year 2015 is shown, but data was evaluated for each year, 1999–2020.

comparing the predicted malnutrition prevalence to the testing set. Validation data is presented in the results Section 4.1.

After validating the model, we predicted malnutrition prevalence for 2016–2021. When a training variable was missing for one of these years, we extended a trend from the previous years. The caseload of malnutrition was calculated by multiplying the prevalence by the population under 5 for each grid cell, and from the caseload the expected demand of SNF may be calculated (see Section 3.3.1).

3.2. *Optimizing SNF Recipes*

For the second component of the computational tool, we created optimized formulae for treatment of acute malnutrition by meeting all nutritional requirements while minimizing cost (Figure 4). First, we created optimized recipes using international ingredient costs. Then we created optimized recipes for 24 sub-Saharan African countries using local ingredients and prices. The optimized recipes are then fed into the third component of this project, the supply chain model of SNF production and distribution (Section 3.3).

3.2.1. Linear Programming Tool

Building on Brixi (2018) [33], we created a linear programming (LP) tool to optimize for low cost and local contexts in compliance with applicable nutrient and formulae composition standards. The

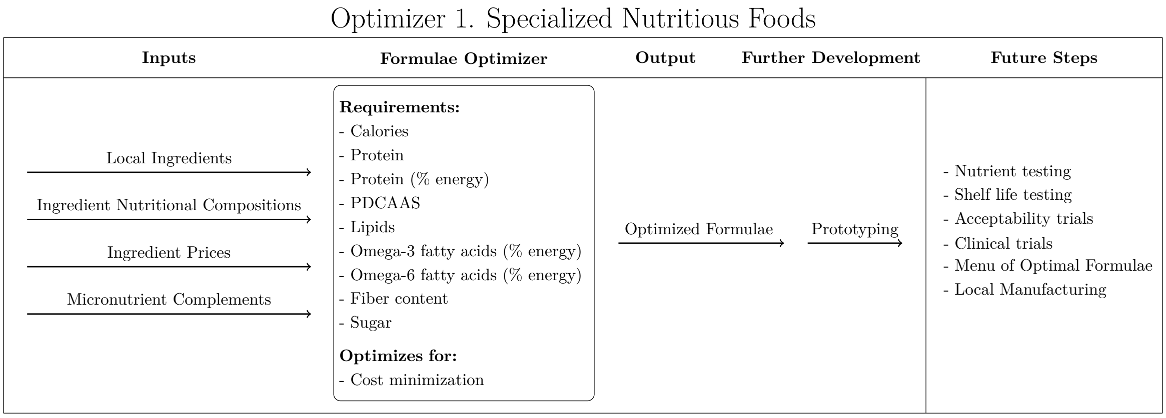


Figure 4. A flowchart of the inputs, constraints, and outputs of the SNF optimizer.

tool minimizes cost, specifying the optimal quantity of each ingredient for low cost while meeting established nutritional requirements and other constraints. The tool's linear objective function is

$$Y = \sum_{i=0}^{n} b_i \cdot B_i \tag{2}$$

where Y is the total cost of ingredients, b_i is the cost per gram of ingredient i, and B_i is the amount of ingredient i in grams.

Compared to previous optimization efforts, our tool includes an expanded range of ingredients and constraints. The optimization tool lets users set the macro and micronutrient constraints according to patient conditions. Protein Digestibility Corrected Amino Acid Score (PDCAAS), micronutrient supplements, and water efficiency optimization constraints are included.

PDCAAS is automatically calculated and constrained in order to ensure protein quality without the need for costly dairy ingredients. This is expressed as

$$Q_a = \sum_{i=0}^{n} C_i a_i d_i \tag{3}$$

where Q_a is total quantity of essential amino acid a, C_i is quantity of ingredient i, a_i is quantity of amino acid a per gram of ingredient i, and d_i is protein digestibility factor of ingredient i. The tool assures that protein quality is met using the criteria

$$\frac{Q_a}{P} \geq S g_a \tag{4}$$

where P is total protein quantity in the formula, S is the goal PDCAAS score expressed as a decimal, and g_a is goal quantity of amino acid a per gram of reference protein. The tool can automatically include amino acid supplements as ingredients to meet this goal PDCAAS. Furthermore, the tool is able to modify formulae in response to shifts in prices and availability.

For water efficiency, the tool limits the water footprint of ingredients using UNESCO-IHE water footprint data to facilitate local production in water scarce regions [34].

The tool's accuracy was validated using the ingredient composition of current peanut RUTF and previously published dairy-free RUTF [35,36]. The nutritional values calculated by our tool were compared with previously published laboratory analysis.

3.2.2. Optimizing SNF for International Production

SNF were developed using the optimization tool. We set constraints according to standards for each SNF product. To ensure satisfactory PDCAAS, we used measured amino acid profiles from previous laboratory analysis of RUTF, and estimated amino acid profiles based on composition of RUSF and SC+, alongside technical specifications. The constraints, shown in Table 2, reflect the current standards and practice, as well as clinical trials of recovery from SAM and MAM.

At this stage, we used the tool to optimize alternative RUTF, RUSF, and SC+ formulae for international production using average international commodity prices over the past five years, adjusted for processing.

3.2.3. Prototyping and Testing Optimized SNF

Prototyping and testing were conducted in collaboration with Valid Nutrition, a research NGO, and partner facility in Kenya. Optimized SC+ formulae were manufactured in Kenya with locally sourced soybeans and corn flour and imported sugar, oil, Ajinomoto amino acid supplements, and micronutrient premix. Samples were sent to SGS lab Nairobi for nutrient analysis.

3.2.4. Optimizing SNF for Local Production

After confirming the accuracy of the LP tool through prototyping, we optimized recipes in 24 sub-Saharan African countries with available local ingredient price data. For each country, we optimized RUTF, RUSF, and SC+ formulae using locally grown crops, and compared our optimized formulae with current products for nutrition, ingredient cost, and water efficiency. For the comparison, the ingredient cost and water efficiency value of current formulae were calculated using the same databases as the optimized formulae to ensure consistency.

3.3. Optimizing SNF Supply Logistics

Next, we created a computer model to optimize SNF production and distribution networks in sub-Saharan Africa based on the optimized local and international SNF formulae presented in the previous section (Section 3.2). The optimizer treats the demand of acute malnutrition while accounting for associated costs, including ingredients, production, and transportation of SNF. After minimizing cost, the tool returns the optimal placement and capacities of factories and ports; the type, quantity, and destination of SNF from each port and factory; and the total procurement cost (Figure 5).

We optimized supply logistics for three scenarios that reflect the possible uses of the tool:

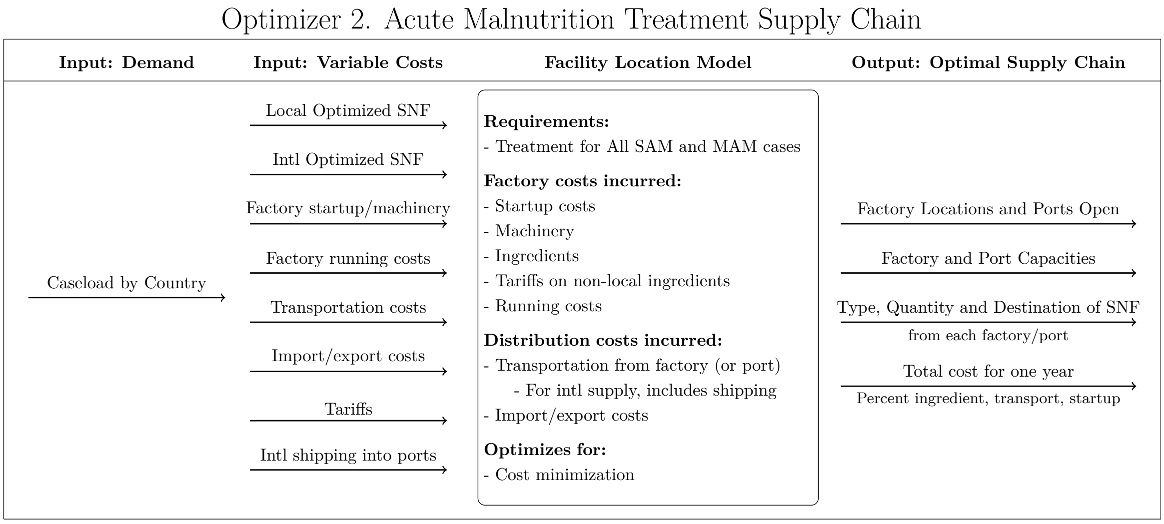


Figure 5. A flowchart of the inputs, costs, constraints, and outputs of the supply chain optimizer.

1. Current factories and prices; cost is optimized to treat all demand;
2. New factories can be established; cost is optimized to treat all demand;
3. New factories can be established; number of cases is optimized on a budget

3.3.1. Quantifying SNF Demand

The first step is to calculate the SNF demand for treatment of SAM and MAM for each country. We calculated the annual treatment demand to quantify demand by country in the model. Prevalence of severe and moderate acute malnutrition was obtained for 43 mainland sub-Saharan African countries using national surveys [2]. Although survey data is currently used for the demand, the facility location model is built to accept future demand forecasts from Section 3.1.

In order to account for the known underestimation of caseload based on prevalence, We adjusted prevalence using the incidence correction factor K [37–39].

$$\text{Incidence} = \text{Prevalence} \cdot K \tag{5}$$

$$K = \frac{\text{duration over which prevalence was estimated}}{\text{avg duration of untreated disease}} \tag{6}$$

$$\text{For SAM:} \quad K = \frac{365\text{ days}}{45\text{ days}} \tag{7}$$

For both SAM and MAM, survey data estimated prevalence over a one year period. Using current estimates for the duration of untreated malnutrition, we calculated the incidence correction factor K for SAM and MAM [37–39]. 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 [39–41]:

$$\text{Annual treatment demand} = \text{Incidence} \times \text{Duration of treatment} \times \text{Treatment Dosage} \tag{8}$$

The annual SNF demand was then increased by 10% to account for possible underestimation based on previous findings [37]. 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 6 displays the final by-country demand for treatment used in the model, where a sachet is a single serving packet.

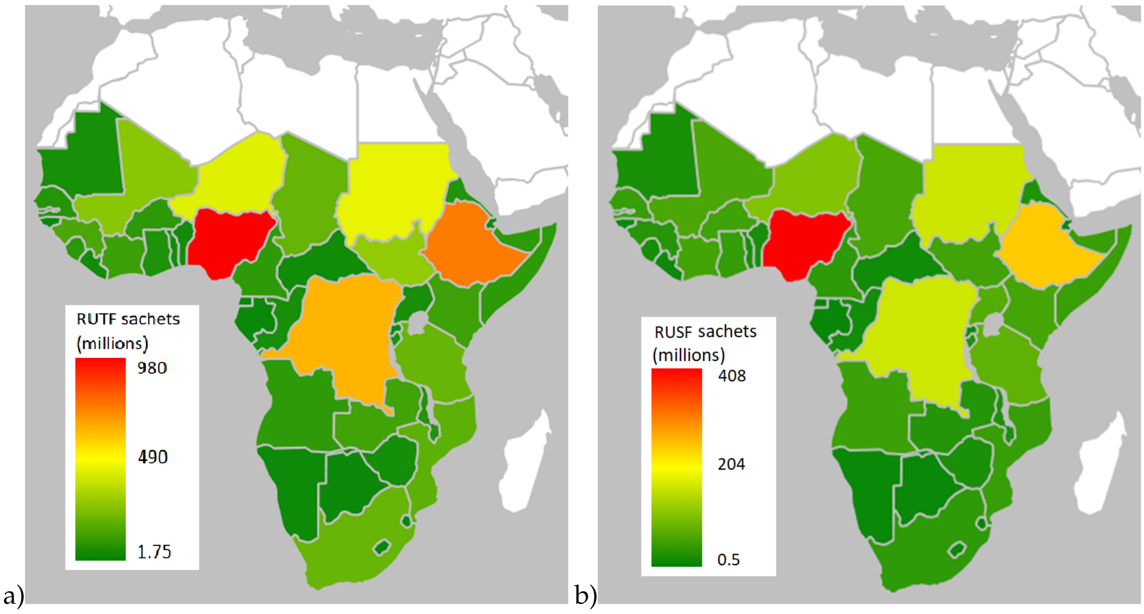


Figure 6. The estimated demand for treatment of severe (a) and moderate (b) acute malnutrition, based on UNICEF surveys [2].

3.3.2. Variable Costs

The optimizer is dependent on variable costs of SNF production and distribution. These include: ingredient costs of local and international optimized SNF, 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 [42]. The ingredient cost came from the optimized RUTF, RUSF, and SC+ formulae for each country (explained in Section 3.2). 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 [7,43].

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 [44,45]. Import and export costs per tonne of product were then added to the trucking cost, as document and border compliance costs in sub-Saharan are extremely high [17]. Import tariffs on non-local ingredients were also added to the model, and were estimated based on published tariff data [46]. Shipping costs on internationally-produced SNF were calculated to each major port in sub-Saharan Africa, and were based on published shipping costs [2].

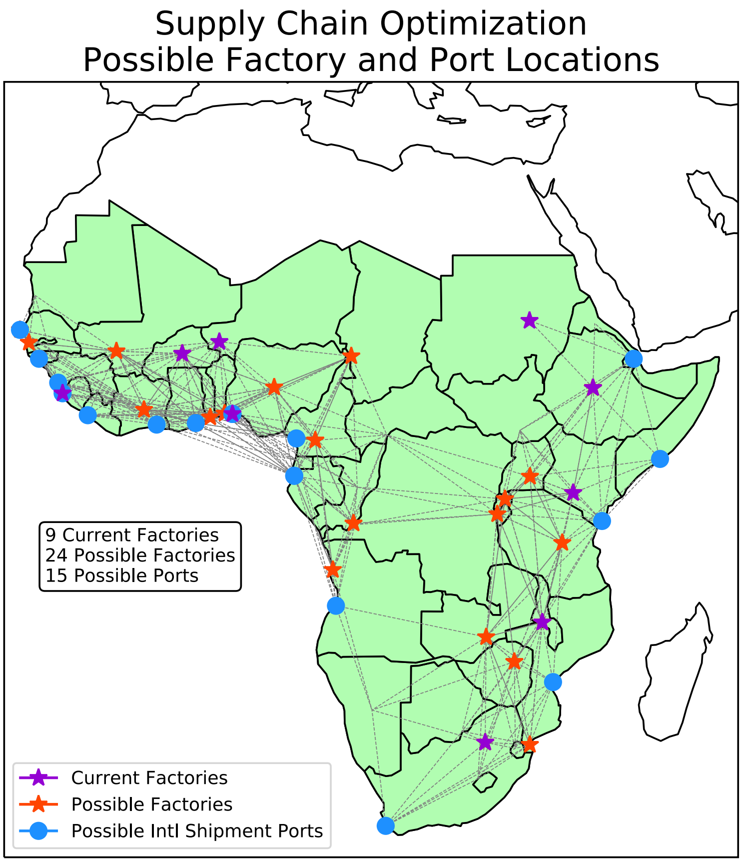


Figure 7. A skeleton of the supply chain optimizer. Every purple star is a current factory location, every red star is a possible factory location (in every country with sufficient price data), and every blue circle is a possible port for international shipments.

3.3.3. Supply Chain Model

A skeleton of the facility model can be seen in Figure 7. The model starts with the current factories and can build new ones. The cost of local production in African cities (stars) include factory start-up (for new factories), machinery, and running costs, plus the cost of producing the SNF in that country (includes tariffs on non-local ingredients). When treatment is shipped from that factory to neighboring capitals, the costs incurred include trucking, import, and export costs. Off-continent production costs include manufacturing internationally-optimized SNF, shipping into one of the major African ports (blue dots in Figure 7), and trucking to the final destination with import/export costs across borders.

In the end, the optimizer outputs include the factory and port locations and capacities, as well as the type, quantity, and destination of SNF from each factory and port, in order to either treat all malnourished children on the lowest budget or treat the highest number of children on a set budget.

3.3.4. Scenarios Using the Logistic Model

The different supply chain possibilities were ran to reflect the possible use of this supply chain tool. The model can be set to optimize the cost while meeting a demand or to maximize the cases treated on a set budget. By modelling to treat the full caseload, the model is able to identify the optimal supplier of treatment for each country, while maximizing cases treated allows users to see where interventions are least costly. The user can also set whether the model can build new factories or just uses the current ones. Within the scenarios, three SNF recipe levels were used to determine the cost reduction that could be achieved through optimization of recipes (Current recipe, local recipes optimized while international remains current, and all optimized recipes, Section 3.2). The total scenarios are:

1. Current factories and prices; cost is optimized to treat the full caseload;
    - Current prices used [47]
2. New factories can be established; cost is optimized to treat the full caseload;
    - Current recipes
    - Local Optimized
    - All Optimized
3. New factories can be established; number of cases is optimized on a budget
    - Current recipes
    - Local Optimized
    - All Optimized

High-quality local ingredients are sometimes not available locally, and must be imported. For this reason, estimated tariffs were added to the cost of imported ingredients.

3.3.5. 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 logistic model. The logistic model was run for approximately 700 cases, varying each of the following parameters independently: trucking costs, sea shipping costs, border and document compliance costs, factory start-up costs, tariffs, and budget (for the budget scenario).

4. Results

We built a tool to optimize treatment of acute malnutrition across sub-Saharan Africa. In this section we present the results from each of the three components, including forecasting SNF demand

(Section 4.1); optimizing SNF recipes (Section 4.2), and optimizing the supply chain of SNF distribution (Section 4.3).

4.1. Forecasting SNF Demand

The model predicted malnutrition prevalence with minimal error. The random forest regressor was trained on 80% of the data for each year, 2000 through 2015. It then predicted the 20% of the data it was not trained on. Figure 8a shows the training data for 2015 and Figure 8b shows the same data with the boxes filled in with predictions. The predicted and actual malnutrition prevalence across 2000–2015 had a correlation of 0.95 with an average difference of 0.83% prevalence (Figure 8c).

After validating the model, we predicted malnutrition prevalence from 2016 through 2021 (Figure 8d). It was found that the geospatial prevalence of malnutrition will likely remain the same over the following years, with the highest prevalence remaining in Ethiopia, South Sudan, Niger, and Kenya. Malnutrition prevalence forecasts show a decreasing trend in the future. Malnutrition prevalence has been decreasing since 2000, and our predictions suggest that this trend will continue. However, because of the growing population in sub-Saharan Africa, caseload of malnutrition and demand for SNF is expected to grow in the upcoming years.

Through the random forest regressor, we also find which training variables have the greatest influence on malnutrition. Ordered by importance, the top ten features are: (1) female education; (2) mean annual precipitation; (3) forest cover; (4) percent of school-aged children in school; (5) political stability and absence of violence; (6) crop yield; (7) crop production per capita; (8) access to electricity; (9) distance to coasts; (10) elevation.

Lack of education, especially female education, is highly correlated to malnutrition. Education has been shown to lead to better nutritional habits and food diversity, increased development, and decreased poverty. From this result, we can conclude that aid organizations should have a focus on education to improve long-term measures of living standards.

The environment also affects malnutrition prevalence. Forested areas are less vulnerable to acute malnutrition than semi-arid regions or deserts, likely because dryer regions are more susceptible to seasonal variability and droughts. Proximity to coastlines may temper malnutrition by providing easier access to fisheries and overseas markets for alternative food sources.

Malnutrition prevalence is also dependent on crop yield and crop production per capita, which indicate both the level of agricultural technology and amount of food available. As the population of Africa is projected to grow throughout this century, aid organizations should focus on supplying local farmers with better agricultural technology to increase food availability. Political instability and violence also may obstruct markets to limit access to food, thus increasing malnutrition.

4.2. Optimizing SNF Recipes

The linear programming tool successfully optimized SNF formulae and generated cost-effective RUTF, RUSF, and SC+ suitable for international and local production in sub-Saharan Africa. Compared

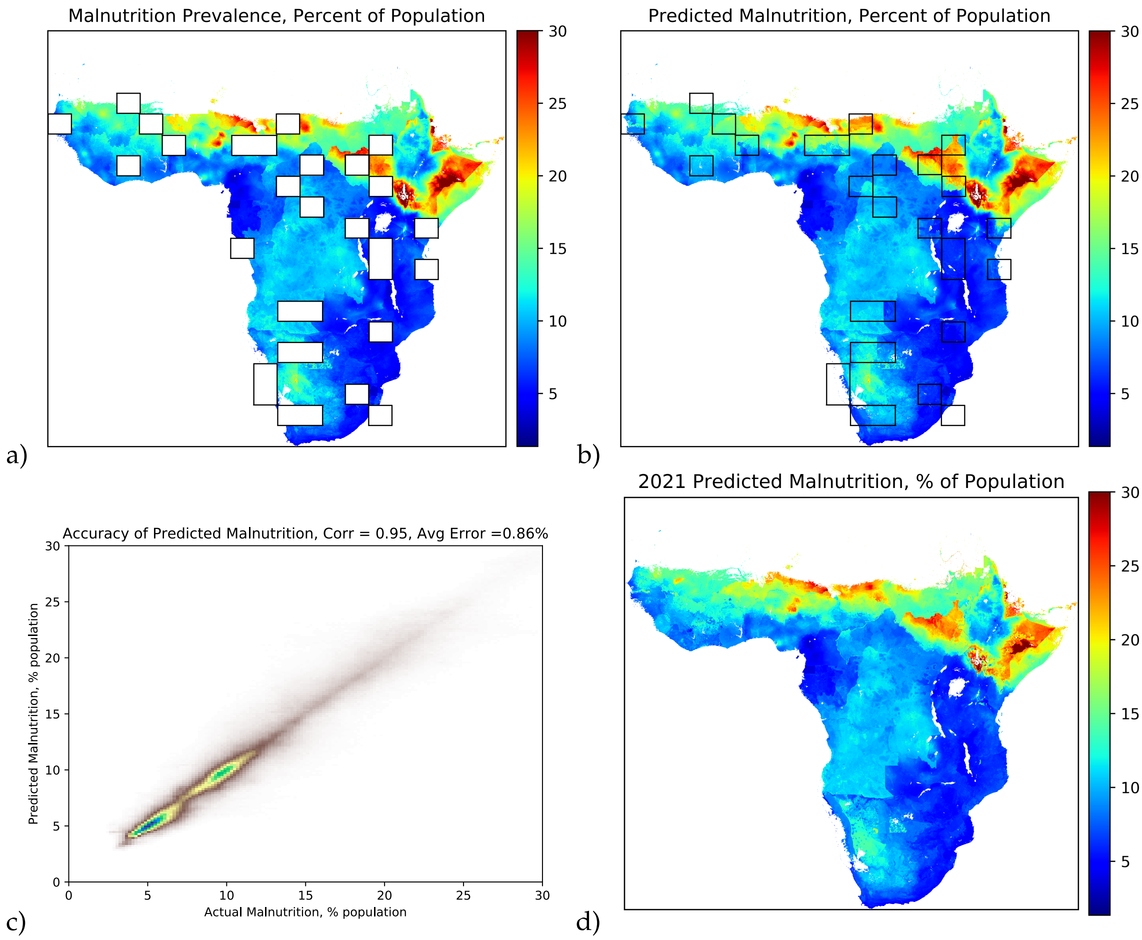


Figure 8. The malnutrition prevalence training data (a), and the same data with the boxes filled in with predictions (b), shown for 2015. The difference between the actual and predicted malnutrition prevalence (c) has a correlation of 0.95 with an average difference of 0.86% prevalence. After the model was trained, malnutrition prevalence was predicted to 2021 (d).

to current products, the optimized formulae have significantly lower ingredient cost and water footprint. The primary driver in ingredient cost was low-cost protein.

4.2.1. Linear Programming Tool

The LP tool generated cost-effective RUTF, RUSF, SC+ formulae meeting nutritional and technical specifications. The tool was found to accurately calculate recipe nutrition values: when we calculated the nutritional values of current recipes (peanut and dairy free RUTF), caloric value and PDCAAS were within 1% of actual values and percent energy from protein was within 5%. The amino acid profile (non digestibility corrected) was within 5% of the actual value, and within 1% for the limiting amino acid.

4.2.2. Optimizing SNF for International Production

Here we present the optimized SNF based on international commodity prices. The optimized RUTF, RUSF, and SC+ all include corn flour, palm or soy oil, soybean, sugar, and small quantities of leucine and lysine supplements (amino acids). For each formula, the tool calculated a complementary micronutrient premix and included the cost of the premix in ingredient cost. Following prototyping, adjustments may be made to the micronutrient premix to ensure goal nutrition regardless of losses during processing and storage.

As shown in Table 2, the proposed optimized formulae within nutritional requirements, lower ingredient cost, and lower water footprints compared to the current practice [48,49]. The LP tool created formulae with PDCAAS equivalent to current recipes by automatically balancing proteins with complementary quantities of the essential amino acids.

Table 2. Comparisons between current and optimized RUTF, RUSF, and SC+.

Formulae	Ready-to-Use Therapeutic Food		Ready-to-Use Supplemental Food		Super Cereal Plus (SC+)	
	Current (Plumpy'nut)	Optimized	Current (Plumpy'nut)	Optimized	Current	Optimized
Composition (g) *[descriptors below]	peanut sugar milk powder palm oil micronutrient premix	corn flour 28.8 palm oil 24.6 soybean 22.5 sugar 15 sorghum 7 leucine 0.199 lysine 0.170 valine 0.058 adjusted premix	peanut sugar milk powder palm oil micronutrient premix	corn flour 34.2 soybean 19.4 palm oil 23.5 sugar 15 sorghum 7 adjusted premix	corn flour soybeans milk powder Sugar soy oil micronutrient premix	corn flour 62.8 soybean 26 sugar 9 palm oil 1.8 leucine 0.0722 lysine 0.0353 adjusted premix
Total weight (g)	100	100	100	100	100	100
Total calories	520–560	520	510–560	510	410–430	410
Total protein (g)	13–16	13	11–16	11	≥16	16
Total fat (g)	26–36	30.85	26–36	29.39	≥9	10.10
Fiber (g)	<5	4.53	<5	4.7	6	2
Omega 6 (g)	2.03–6.75	5.29	2.03–6.75	6.10	4.73	4.04
PDCAAS	required: ≥95 actual: ~106	106	required: ≥70 actual: ~79	86	required: ≥70 actual: ~87	87
Total int'l ingredient cost (USD/100g)	0.126	0.04956	0.118	0.0422	0.04487	0.03116
Water footprint (gallons/mt)	11,551	2,762	10,123	2,675	4,444	1,717

Notes: Prices calculated using FAO, UNCTAD and GEM data. Water footprint calculated using UNESCO-IHE report [34].
* Descriptors for USDA nutrient database: soybean: (16111, soybeans, mature, dry roasted. roasted); palm oil: (04055, oil, palm); maize: (20017, corn flour, enriched, white).

The optimized SNF have a lower total international ingredient cost than current SNF. Optimized RUTF and RUSF reduce ingredient cost by 60% and optimized SC+ by 30%. Water footprint was also reduced significantly in the optimized formulae, largely due to the removal of milk powder.

Table 3. Results from the laboratory analysis of the prototyped SC+. The calculated values were very similar to the actual values, and all parameters were in compliance with WFP standards.

Parameter	Calculated Value	Actual Value	Compliance with WFP Standards?
Moisture (%)	3.1	2.75	Yes
Fat (%)	10.1	11.17	Yes
Fiber (%)	2	1.98	Yes
Protein (%)	15.99	16.57	Yes
Ash (%)	3	2.72	Yes
Energy (kcal/100g)	410	424	Yes

4.2.3. Prototyping and Testing Optimized SNF

The optimized international SC+ recipe was prototyped and analyzed in Kenya in collaboration with Valid Nutrition. The analysis confirmed recipe compliance with WFP standards for nutrition, composition, and texture. This analysis confirmed the LP tool's suitability for developing new recipes. Table 3 shows results from the laboratory analysis.

4.2.4. Optimizing SNF for Local Production

After validating the accuracy of the international recipe, we optimized RUTF, RUSF, and SC+ in 24 sub-Saharan African countries with local commodity prices while meeting WFP standards. All optimized recipes are more cost-effective than the current recipe for RUTF and RUSF (Figure 9).

For both RUTF and RUSF, the local optimized recipes ranged between about 60% and 3% ingredient cost reduction in South Africa and DR Congo, respectively, compared to the current international recipe (Figure 9). Locally optimized formulae likely reach the lowest ingredient cost in South Africa due to the lower cost of vegetable oils there.

For SC+, only two-thirds of countries had lower ingredient cost for locally optimized SC+ compared to the current international formula. This reflects the relatively low cost of current SC+. Again, the greatest cost reduction (25%) was achieved in South Africa. Due to high daily dose of 200g for SC+, the relative cost of one serving (92g) of optimized RUSF is lower than that for one serving (200g) of optimized SC+, making optimized RUSF the more cost-effective treatment for MAM.

Cost reduction is mainly facilitated by cost-effective protein quality. The compositions of each RUTF and RUSF recipe can be found in Figure 10.

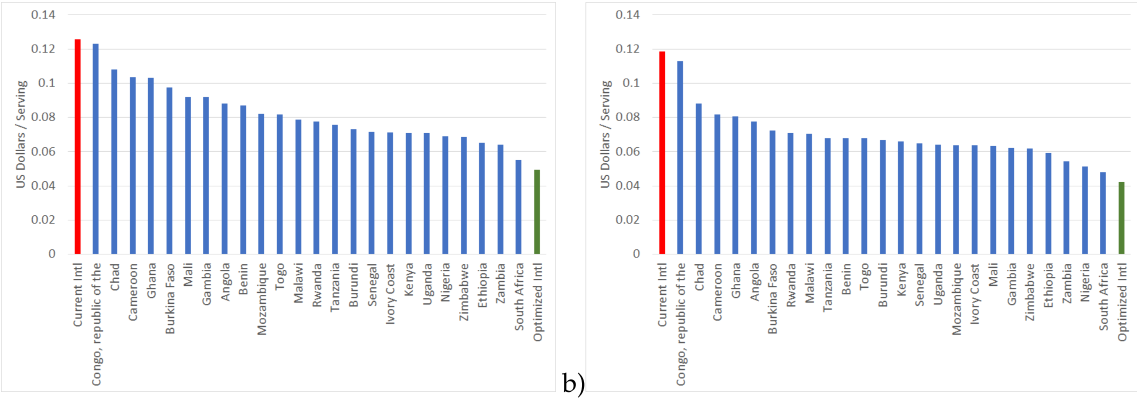


Figure 9. Ingredient cost comparison for optimized RUTF (a) and RUSF (b) arranged by cost.

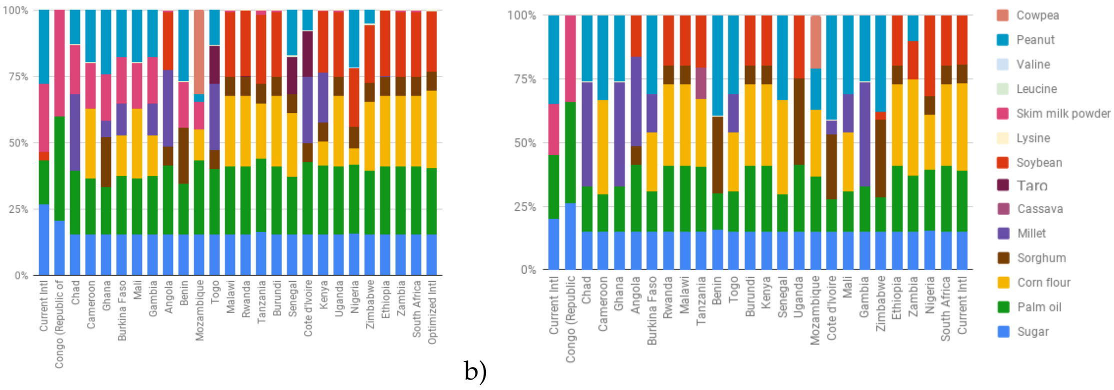


Figure 10. Ingredient composition comparison for local optimized RUTF (a) and RUSF (b) by cost.

4.3. Optimizing SNF Supply Logistics

The supply chain model effectively distributed acute malnutrition treatment through an optimized network of factories and ports. Here we will present the optimal supply logistics using only current factories to meet all demand (Section 4.3.1), building new factories to meet all demand (Section 4.3.2), and building new factories to treat the highest number of children on a budget (Section 4.3.3).

4.3.1. Optimizing Cost while Meeting All Demand: Current Factories

The supply chain model used existing factories in Africa and internationally in order to meet the current caseload. The model supplied 40% of the total demand from current factories in South Africa, Kenya, and Sudan, relying on international import to meet the remaining demand for treatment (Figure 11).

Although the model had the potential to use 9 factories without any startup cost, it only procured treatment from two because of the current high cost of local SNF. Local SNF remains more expensive because the countries must import expensive ingredients, such as milk powder or peanuts, and pay high tariffs on them. Because South Africa has relatively low tariffs and can produce some of these ingredients locally, it is much cheaper than the other local producers and supplies several countries with treatment.

To evaluate how the supply chain would change if local production became cheaper, we reduced the cost of local SNF (excluding South Africa) by 5% intervals. Even at a 5% reduction, 56% of SNF is procured locally with 5 local factories (Figure 11). This exhibits how using local ingredients or reducing tariffs could make local production economically competitive with international procurement.

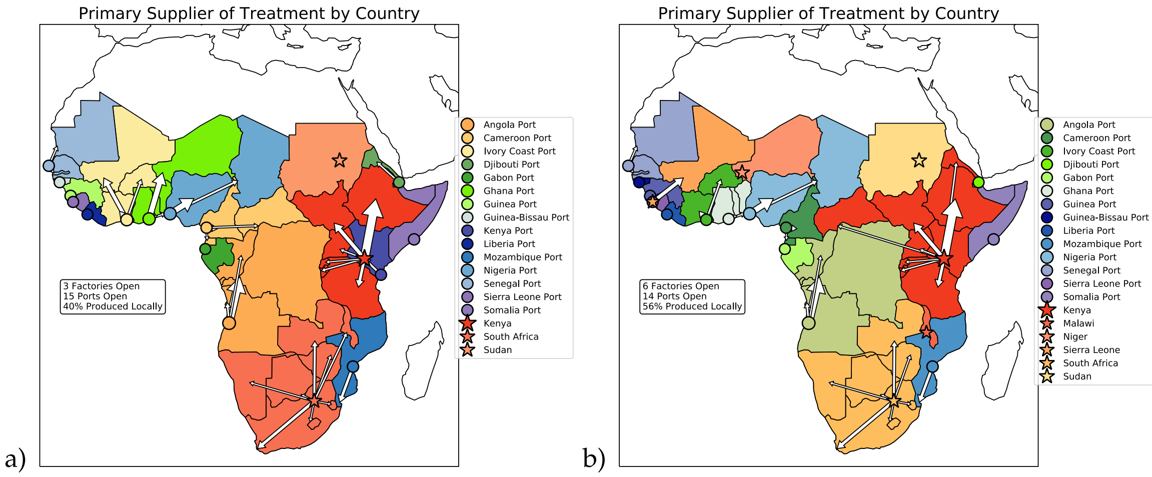


Figure 11. The primary supplier of SAM and MAM treatment using only current factories at the current cost (a) and when local costs are reduced by 5%. The arrows are scaled by the amount of treatment being shipped.

4.3.2. Optimizing Cost while Meeting All Demand: Building New Factories

The supply chain model effectively met the demand for acute malnutrition treatment through an optimized network of factories and ports. We optimized the supply chain for three scenarios: current recipe, local optimized recipes, and all optimized recipes. First, we present the results from the all optimized scenario.

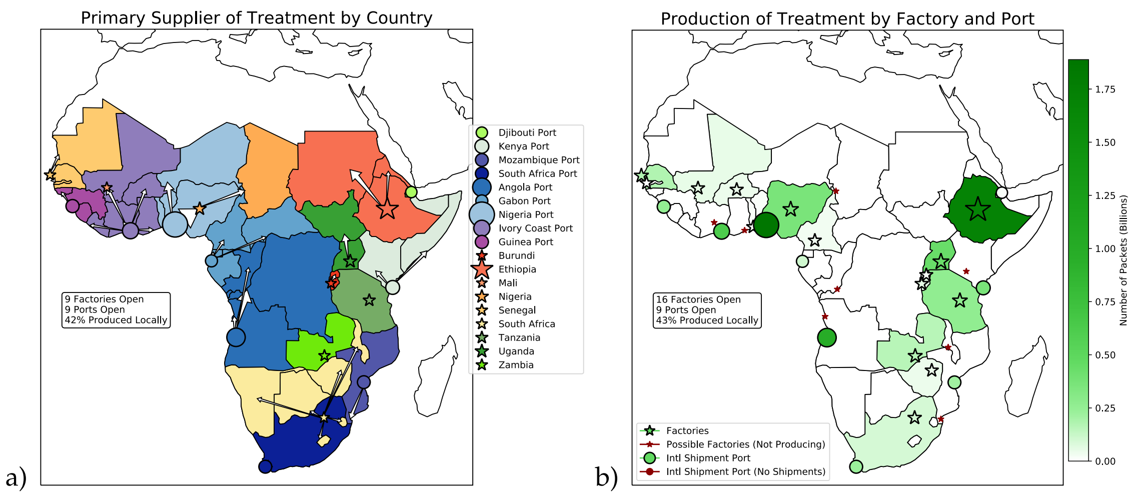


Figure 12. The primary supplier of SAM and MAM treatment (a) when all recipes are optimized. The arrows are scaled by the amount of treatment being shipped. About half of both products are produced locally. (b) shows the number of packets of RUSF produced or imported per year.

Figure 12a shows the primary supplier of RUF by country when all recipes are optimized, and Figure 12b 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.

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. For example, we altered the startup costs from 20% to 200% of today's prices, with 20% intervals. Figure 13 shows the optimal amounts of treatment provided by each port and factory as startup cost varies. At today's startup prices (100%), about half of the treatment for both SAM and MAM is produced locally (shown in warm colors). As startup cost increases, the local production cannot compete with the cheaper international product. If countries are able to lower their high startup costs, local production would 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 13, 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, only local optimized, 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 14), 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.

The total cost of procurement varies when changing the parameters of startup, import/export, trucking, and shipping cost (Figure 13). Even as the parameters change, the current recipes remain the most expensive while the optimized recipes are much cheaper.

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. As seen in Figure 14b, prices drop dramatically as import and export costs decrease. Thus, improving cross-border transportation should become a priority for sustainable development.

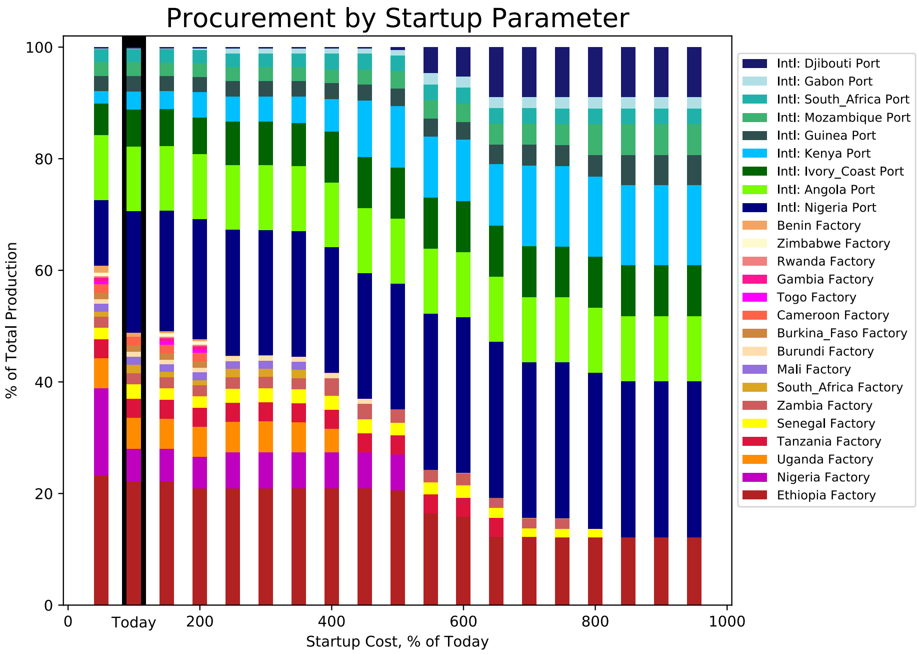


Figure 13. Optimal suppliers of acute malnutrition treatment, according to the changing startup parameter. Warm colors correspond to local production and cool colors correspond to international production.

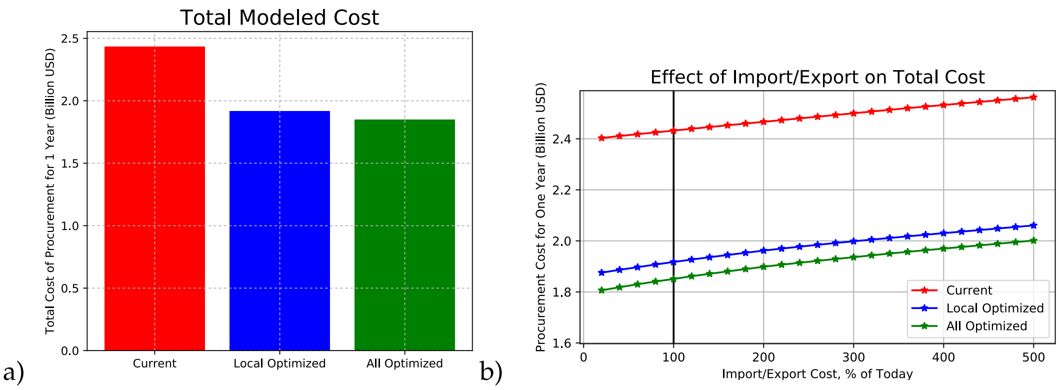


Figure 14. The cost of procurement for one year when all parameters are standard (a) and when varying the import/export parameter (b). The cost is shown for current SNF recipes (red), local optimized recipes (blue), and all optimized recipes (green).

4.3.3. Optimizing Cases Treated on a Budget: Building New Factories

The supply chain model optimized the number of children treated on a set budget. 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 each. As in Section 4.3.2, the supply chain was optimized using all optimized recipes, local optimized recipes, and the current recipes. First we discuss the scenario of all optimized recipes.

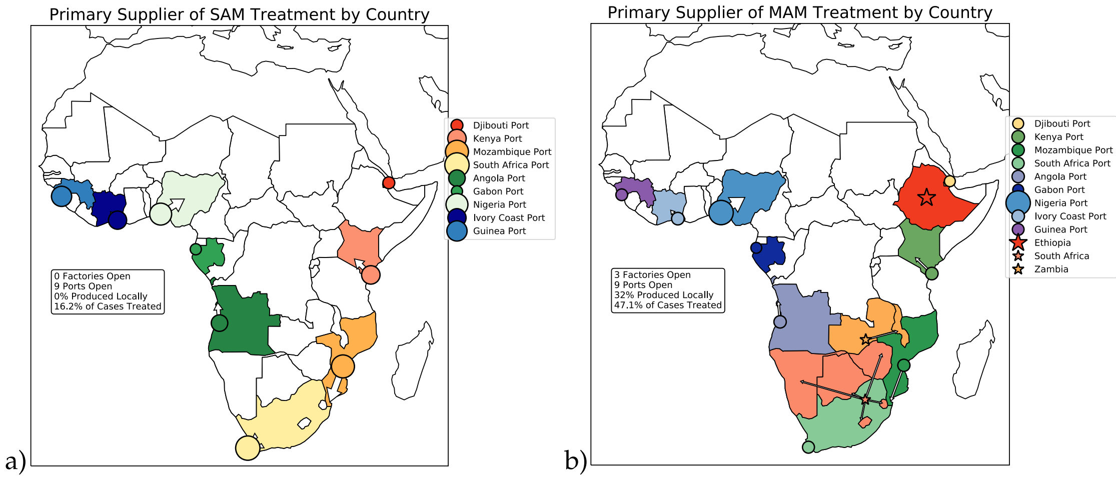


Figure 15. The primary supplier of SAM (a) and MAM (b) treatment under the current budget when all recipes are optimized.

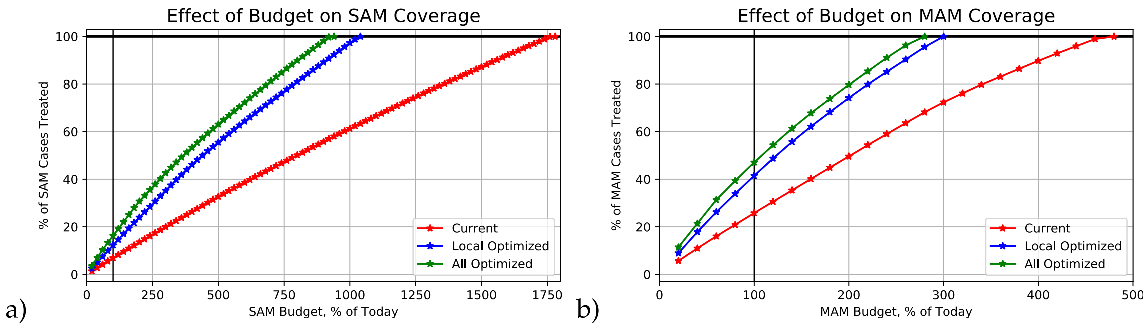


Figure 16. The percent of cases treated as the budgets for SAM (a) and MAM (b) treatment increases. To treat all cases using all optimized recipes, the MAM budget must be increased by 3 fold, while the SAM budget must be increased by 10 fold, due to the current small SAM budget.

Figure 15 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.

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 16). However, when considering only the current recipe, both budgets would need to be increased much more.

5. Conclusions

Due to difficulty in forecasting demand, the high cost of current treatments, and costly supply chains, acute malnutrition treatment reaches only a small fraction of children in need. Here we develop a tool to inform nutrition interventions in sub-Saharan Africa. This tool can forecast the caseload of acute malnutrition, optimize SNF recipes, and inform on cost-effective production and distribution of SNF.

Our analysis suggests that current treatment of acute malnutrition is inefficient and unnecessarily expensive. The development of SNF leveraging amino acid supplements complementary to local crops could play a major role in reducing costs. Furthermore, the supply chain model identified 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 donor organizations on cost-effective nutrition intervention. Improved forecasting of acute malnutrition can enable timely procurement, shipping, and distribution of treatment, thereby lowering logistical costs.

We are currently applying the supply chain model to further scenarios. For example, to reflect actual procurement more closely, we are running the model according to newly provided data of UNICEF's actual RUTF procurement per country. We are also applying the model to compare between the current SNF, previously proposed soy-based SNF recipes based on literature, and an optimized SNF recipe.

Bringing low-cost SNF into use has the potential to greatly reduce the total cost of acute malnutrition treatment, and thereby reach more patients within the current budgetary constraints. All parts of the tool developed here can be 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 this tool to adjust distribution networks according to real-time information.

Used in conjunction, the forecasted demand, optimized recipes, and optimized supply chain model could allow more children to receive life-saving treatment within existing budgets while supporting sustainable agriculture and future food security in developing countries.

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