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Managing the Inventory of Ready-to-Use Therapeutic Food: The Case of UNICEF Kenya

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(Global Supply Chain Management)

Thesis Submitted in Partial Fulfillment Of the Requirements for the Degree of Master of Science (M.Sc.)

April 2015

ABSTRACT

Disasters of both natural and man-made origins increasingly threaten the safety and welfare of human beings worldwide. In response to such challenging tendencies, humanitarian relief operations have been studied intensively since the 1970s. However, while major attention was paid to disaster management, especially the response stage of natural disasters, long-term development issues remained a less developed area in the literature. It is also pointed out that compared with facility location and distribution problems, inventory management received very little attention.

In this thesis, by studying UNICEF Kenya's supply chain of Ready-to-Use Therapeutic Food (RUTF), we focus on inventory management issues for long-term humanitarian development programs, such as Integrated Management of Acute Malnutrition (IMAM).

The goal of our research for UNICEF Kenya case is to ensure the adequate service level of RUTF while keeping the whole supply chain cost-effective and efficient. To achieve this goal, we will develop standardized demand forecasting models at three different levels and an inventory management model at national level. These models should serve as decision support tools to improve the inventory management of the RUTF supply chain.

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LIST OF ABBREVIATIONS

AFDM	African Flood and Drought Monitor
APICS	American production and inventory control society
ARIMA	Autoregressive Moving Average
CNO	County Nutrition Officers
CO	Country Office
CTC	Community Therapeutic Care
DC	Distribution Center
DHIS	District Health Information Software
DM	Disaster Management
EM-DAT	International Disaster Database
EOQ	Economic Order Quantity
FAO	Food and Agricultural Organization of the United Nations
FEMA	Federal Emergency Management Agency
FIFO	First In First Out
GIS	Geographic Information System
HL	Humanitarian Logistics
IFRC	International Federation of Red Cross and Red Crescent Societies
IM	Inventory Management
IMAM	Integrated Management of Acute Malnutrition
IMC	International Medical Corps
KNBS	Kenya National Bureau of Statistics
LLSM	Lagrangian L-Shaped Method
LTD	Long-Term Development
MA	Moving Average
MDG	Millennium Development Goals
MSE	Mean Square Error
MUAC	Mid-Upper Arm Circumference
NDMA	National Drought Management Authority
NDMC	National Drought Mitigation Center
NDVI	Normalized Difference Vegetation Index
NGO	Non-Governmental Organization

PO	Pre-positioning Optimization
RMSE	Root Mean Square Error
ROP	Reorder point
RUTF	Ready-to-Use Therapeutic Food
SAM	Severe Acute Malnutrition
SD	Supply Division
SKU	Stock Keeping Unit
SMIP	Stochastic Mixed Integer Program
SNO	Sub-county Nutrition Officer
SP	Stochastic Programming
SPI	Standard Precipitation Index
UN	United Nations
UNICEF	The United Nations Children's Fund
UNOPS	United Nations Office for Project Services
UNSSCN	United Nations System Standing Committee on Nutrition
WFP	World Food Programme
WHO	World Health Organization
WVI	World Vision International

“To all those not content with mediocrity and

those who have not lost their enthusiasm”

- George Mc Guire

ACKNOWLEDGEMENT

At the final stage of my research project, looking back, there are times of difficulties, but the most memorable are the excitement of discovery, the fulfillment of contribution, the warm encouragement and generous help from all the people directly or indirectly involved in this project.

I would like to express my sincere thanks to my two academic supervisors, Professor Ola Jabali and Professor Marie-Eve Rancourt, without who I would never have this opportunity. Despite the long distance, time difference and other difficulties, they always do their best to provide me with guidance and supports in time, and give me the needed encouragement.

I would also express my special gratitude to my supervisors and colleagues at hosting organization, the nutrition section and logistics section of UNICEF Kenya country office, including Ms. Grainne Moloney, Mr. Christopher Adomati, Mr. Henry. N. Neufville, Ms. Olivia Agutu, and my supervisor in charge, Mr. Mathieu Joyeux.

My heartfelt thanks also goes to the jury of the Bursary IDEOS, who kindly provide me with financial support to carry out field study in Kenya.

Last but definitely not the least, I want to take this opportunity the say “thanks” to my lovely classmates, friends and colleagues in Montréal, Nairobi and Chengdu. Without their help, I will never complete this journey.

It is still early to say what changes this research project will bring to my career life, but it is certain that it has already to great extend restructured my values of life. I might not be working in the humanitarian sector, but I will definitely keep participating in humanitarian activities and doing my contribution share.

CHAPTER I

INTRODUCTION

Due to environmental, political and economic reasons, Severe Acute Malnutrition (SAM) represents an increasingly serious threat to young children in Sub-Saharan regions (WHO, WFP, UNSSCN and UNICEF, 2007). In Response to such situation, in order to enlarge the demographic and geographic coverage of beneficiaries, organizations such as UNICEF have strategically shifted from hospital treatment to community-based programs. The framework of such programs, Ready-to-Use Therapeutic Food (RUTF) is distributed to families in need through a multi-echelon supply chain composed of procurement center at Copenhagen, a national central distribution center (DC) at Nairobi, sub-county DCs and end facilities where RUTF is distributed to caretakers. To ensure the service level while controlling the costs, more research is required to improve the supply chain management of RUTF.

In this chapter, we will first introduce the different categories of disaster as well as long-term development issues in Section 1.1, followed by an overview of humanitarian logistics (HL). Then we will contextualize our research by discussing food insecurity and SAM in Section 1.2. Humanitarian operations led by UNICEF fighting against SAM will be described in Section 1.3. The supply chain management of RUTF in Kenya will be introduced in Section 1.4. Our research objectives and research questions will be clarified in Section 1.5.

1.1 General Overview of Disasters and Humanitarian Logistics

In 1998, 400 natural disasters were reported by the International Federation of Red Cross and Red Crescent Societies (IFRC), affecting more than 144 million people and left 90,000 deaths and five million temporarily displaced. Then from 1999 to 2003, the average number of disasters rose to 707 per year, with 213 million people affected annually (Beamon & Kotleba, 2006a;Collins et al., 2006). As we can see in Figure 1, the number of recorded disaster occurrence has significantly increased in recent decades.

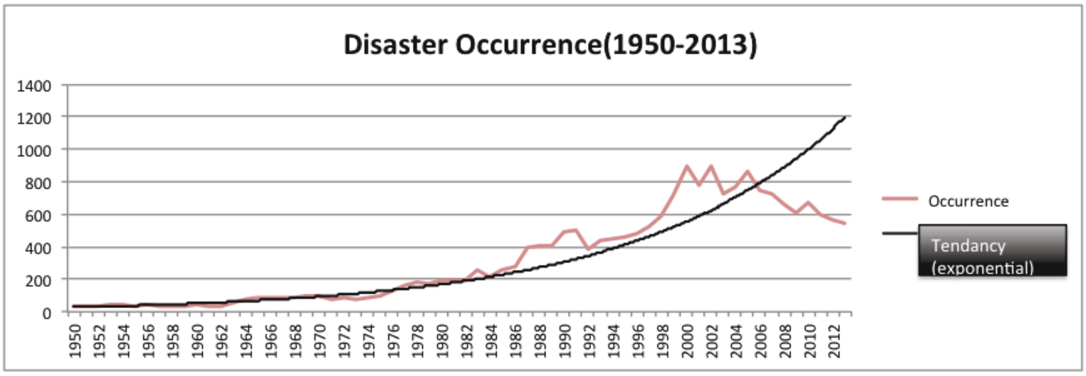

Figure 1: Disaster occurrence (1950-2013), generated from The International Disaster Database (EM-DAT, 2014).

According to IFRC (2009), a disaster is "a sudden, calamitous event that seriously disrupts the functioning of a community or society and causes human, material, and economic or environmental losses that exceed the community's or society's ability to cope using its own resources". Its origins can be either natural or man-made. As shown in Figure 2, "natural disasters" are composed of "slow-onset" ones, such as famine and poverty and "sudden-onset" ones, such as earthquakes; so are man-made disasters, that are comprised of " slow-onset" ones, such as political crisis and refugee crisis, and "sudden-onset" ones, such as terrorist attacks, coup d'état.

	Natural	**Man-made**
Sudden-onset	Tornados, tsunamis, floods, earthquakes, volcanic activities, etc.	Terrorist attacks, stroke states, transportation accidents, chemical leaks, etc.
Slow-onset	Famine, droughts, etc.	Political Crisis, Refugee Crisis, etc.

Figure 2: Types of disasters, developed from Van Wassenhove (2005).

Since occurrence of both natural and man-made disasters has significantly increased for the past several decades, humanitarian operations have become a major concern in the international community (Kent, 2004). Humanitarian assistance has been called the "fourth pillar" of United Nations and its associated organizations; many Non-

Governmental Organizations (NGOs) [1] also actively involve themselves in humanitarian operations to promote their values.

“The extent of the effectiveness and efficiency to which logistics activities are carried out largely determines the performance of humanitarian relief operations” (Çelik et al., 2012), and approximately 80 percent of operations are related to logistics (Trunick, 2005) . Therefore, HL has become a rich domain of research.

As illustrated in Figure 3, academic researches on humanitarian operations are normally classified into two categories: Disaster Management (DM) and Long-Term Development (LTD). DM usually deals with sudden-onset or slow-onset disasters. LTD issues can be those lead to human suffering or economic damage, spanning over long terms and cannot be traced back to a specific catastrophic event (Çelik et al., 2012). Typical long-term development issues can be food insecurity and mortality of young children in critical regions, such as Sub-Saharan Africa.

Figure 3: Types of humanitarian operations.

1.2 Food Insecurity and Severe Acute Malnutrition Among Young Children

Despite continuous progress on agriculture and food production, hunger and malnutrition are still the greatest risks to human health worldwide, even greater than

[1] In this thesis, we also cover non-for-profit organizations under the name of NGOs.

AIDS, malaria and tuberculosis combined (World Food Programme, 2012). Various facts such as “zonal climatic events and natural disasters, wars and political turmoil, lack of resources and education, and poor environmental management” (Dunn, 2013) play a role in explaning such a paradox.

According to the Food and Agricultural Organization (FAO) of the United Nations, “in 2011-13, a total of 842 million people, or around one in eight people in the world, were estimated to be suffering from chronic hunger, regularly not getting enough food to conduct an active life” (FAO, 2013). While significant reduction of hunger and poverty has been achieved in Eastern and South Eastern Asia and Latin America, Sub-Saharan and West Asia remain the regions most vulnerable in term of food insecurity, with modest progress in recent years (FAO, 2013).

In regions highly characterized by food insecurity, SAM[2] has been a threat for its most vulnerable population – children, especially those between six to fifty nine months old (Collins et al., 2006). SAM affected 13 million children under the age of five years (Collins et al., 2006), caused one million to two million preventable child deaths each year (WHO et al., 2013). Other Studies unveil the worsening tendency of the situation, stating that more than 20 million children worldwide nowadays suffer from SAM, and high attention should be paid to the most critical countries in the Horn of Africa (Komrska et al., 2013).

This research will therefore focus on SAM in East Africa by taking Kenya as a sample country, and will study how humanitarian operations can better respond to such a long-term development issue.

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[2] SAM is defined as a weight-for-height measurement of 70% or less below the median, or three SD or more below the mean National Centre for Health Statistics reference values, the presence of bilateral pitting edema of nutritional origin, or a mid-upper-arm circumference of less than 110 mm in children age 1–5 years (Collins et al., 2006)

1.3 UNICEF Kenya and RUTF

UNICEF, as a "driving force that helps build a world where the rights of every child are realized" (UNICEF, 2012), is actively involved in fighting against food insecurity, especially SAM among young children. Traditionally, affected children were treated in medical facilities in a centralized way, but the coverage was limited while cost was high. Since 1970s, attempts to treat SAM in a decentralized way have been continuously made. These attempts to decentralized treatment were coupled with development of RUTF. A picture of widely used RUTF, branded "Plumpy' Nut", can be found in Figure 4.

Figure 4: Picture of RUTF (Plumpy' Nut) (Nutriset, 2015).

RUTFs are portable, shelf-stable, single-serving foods that are used in a prescribed manner to treat children with SAM, and can be found in various forms and packages. The most used ones are in the form of paste, made of peanuts mixed with milk powder, oil, sugar, and fortified with vitamins and minerals. Many studies confirmed the effectiveness of RUTF in treating SAM affected children, one example could be the eight-week test carried out by Amthor et al. (2009) in Malawi in 2006, in which 93.7% of 826 SAM affected children recovered after eight weeks of treatment with RUTF.

In addition to its effectiveness, RUTF has some other advantages. As it is not water-based, it does not grow bacteria even when accidentally contaminated and it can be kept unrefrigerated in simple packaging for several months. It can also be served uncooked so that heat-labile vitamins are not destroyed. In addition, since the production process is simple, it can be made from crops available locally with basic technology available in developing countries.

In 2007, the Community Therapeutic Care (CTC) approach has been introduced for the sake of larger coverage of beneficiaries and cost control (WHO et al., 2007). Following this new strategy, which is illustrated in Figure 5, community members primarily scan nutritional status of children in critical areas by using a marked armband that associates arm circumference with level of malnutrition. Children diagnosed with SAM are then further diagnosed at health facilities, and depending on the severity of their situation, they will be treated in hospital or be taken care at home with following periodic check-ups.

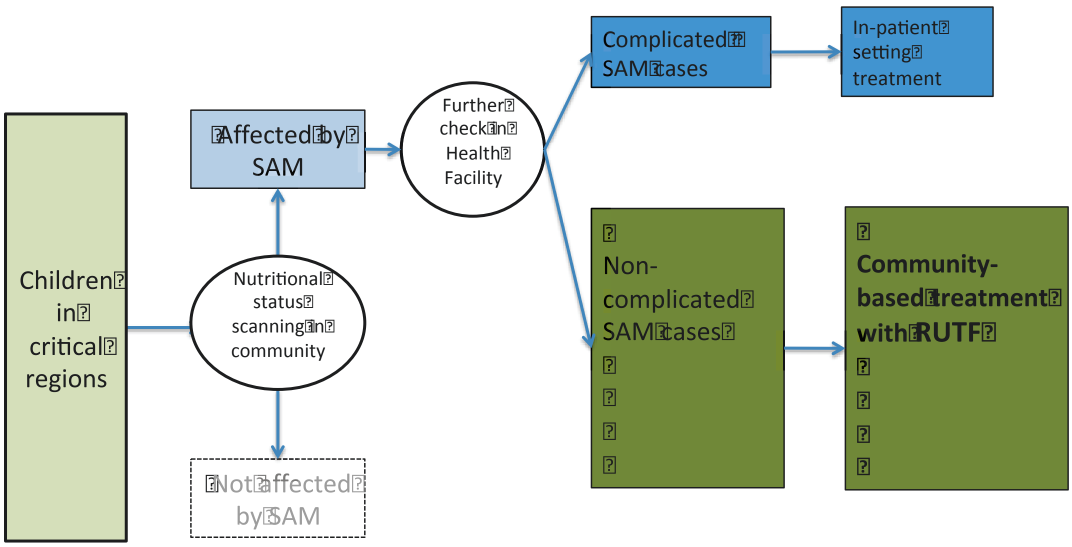


Figure 5: Children's nutritional status identification process under CTC approach.

The success of CTC heavily depends on two factors: the identification of SAM affected children and their level of SAM, and the provision of RUTF (UNICEF, 2009). As illustrated in Figure 6, the procurement of RUTF by UNICEF started in 2000. The shift to CTC in 2007 resulted in increasing of the global demand for RUTF through UNICEF to nearly 30,000 MT. In 2013, the figure was estimated to be 32,000 MT, and 34,000 MT for 2014.

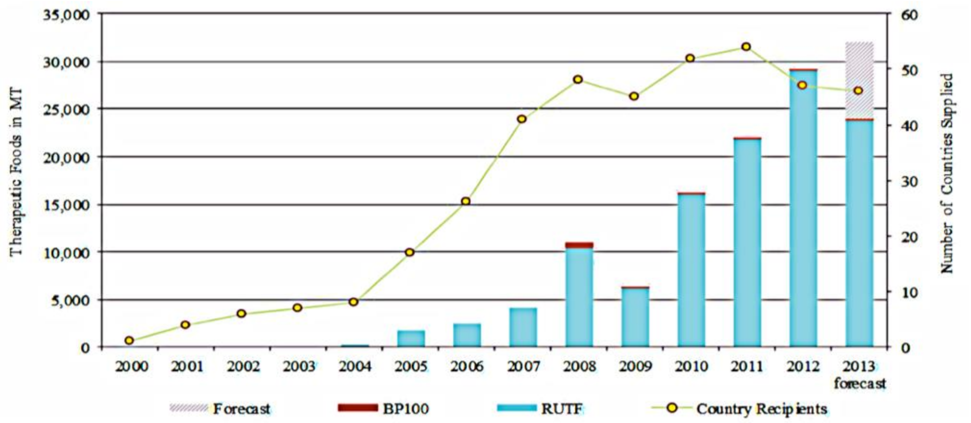


Figure 6: UNICEF Procurement and countries supplied 2000-2013 (UNICEF, 2013).

Although RUTF is delivered to more than 50 countries in the world, the majority of demand is concentrated in a few countries constantly experiencing large-scale food insecurity such as Ethiopia, Somalia, Kenya, Niger, Pakistan (Komrska et al., 2013). As one of the country constantly vulnerable of food security and typically characterized with HL complexities, Kenya is a representative region for research on RUTF supply chain management.

1.4 Supply Chain Management of RUTF in Kenya

Humanitarian supply chains should support three types of flows: material, information and financial flows (Van Wassenhove, 2005). In the case of Kenya, within UNICEF supply chain, the information and financial flow start from Country Office (CO) in Nairobi. Orders are placed once a year from CO to UNICEF Supply Division (SD) located at Copenhagen once the funds to cover relevant orders are available. The material flow starts from France, where the main RUTF supplier is located. The RUTF is transported to Mombasa port at Kenya by sea or to Nairobi by air, then through a multi-echelon distribution network composed of one national warehouse at Nairobi, sub-county Distribution Centers (DC), local health facilities (mainly clinics and dispensaries), RUTF is finally distributed to care takers, normally mothers. At the county level, there is no physical material flow, but as an important administrative level, information and data are collected and communicated at this level. Figure 7 illustrates the RUTF supply chain in Kenya.

As in most other humanitarian supply chains, last miles are usually the most difficult. Delivery from the sub-county DCs to local facilities mostly depends on local authorities and partner NGOs. If no budget is available or NGOs withdraw their activities, the delivery has to be arranged by local nutrition officers by all means, such as passenger shuttle vehicles. For some remote households, mothers have to spend a whole day walking to the closest facilities to obtain their rations of RUTF, which usually last two weeks for their children.

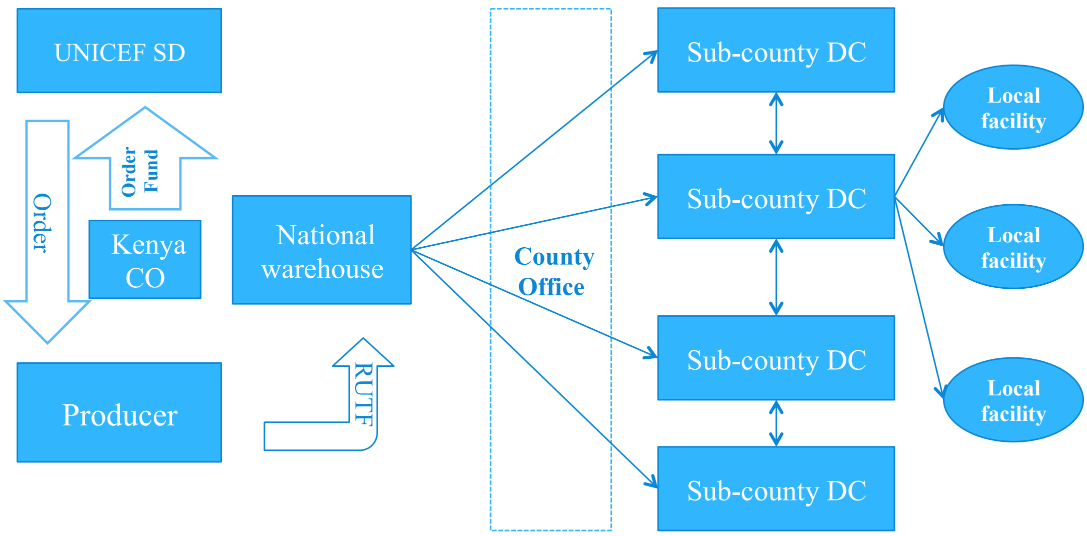


Figure 7: Illustration of RUTF supply chain in Kenya.

The RUTF supply chain in Kenya has been significantly influenced by following factors (UNICEF, 2009): absence of modern information processing and communication advices, uncertainty in demand and supply, the lack of coordination in production and delivery networks, and the different incentives of stakeholders. The critical factors are detailed in the following.

1) Multiple agents involved in the supply chain: RUTF manufacturers, global transport entities, local governments, international NGOs, donors, as well as UNICEF offices from SD in Copenhagen to CD Nairobi. Figure 8 illustrates the involvement of different agents.

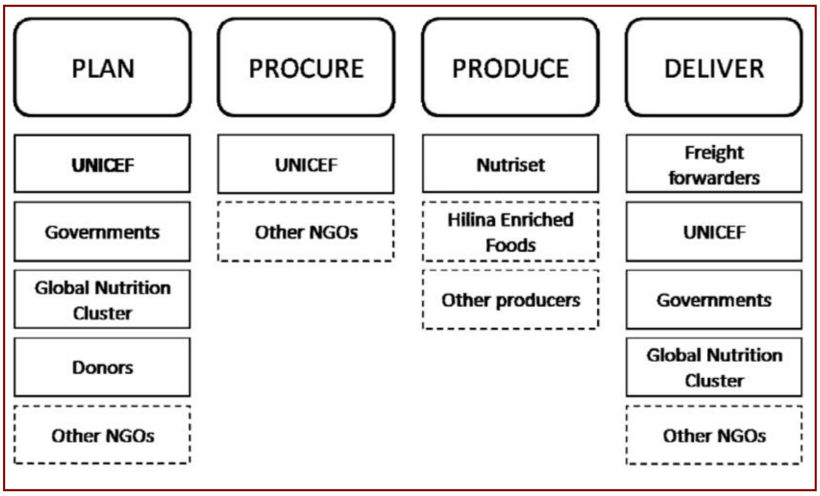


Figure 8: Stakeholders in the RUTF supply chain (UNICEF, 2009).

2) *Uncertainties in demand*: an important increase in demand of RUTF has been observed in recent years (UNICEF, 2013). The demand patterns differ from region to region, from period to period, and can reach spikes in emergencies such as famine. Additionally, children's needs of RUTF cannot be considered as "effective demand" unless the funding is available to UNICEF. The discontinuity and uncertainty in funding make the stabilization of RUTF demand more difficult to achieve.

3) National-level instability: Instabilities can be political, economic, environmental or demographic. In Kenya, post-election violence from end of 2007 to 2008 blocked imports and hindered transport, triggered tremendous increases in food prices (more than 40%) and large-scaled shortages of food (Nzuma, 2013).

1.5 Research Aims and Questions

Many Operations Research/Management Science (OR/MS) studies have been recently carried out in the humanitarian sector, nevertheless, academic research in humanitarian logistics and supply chain management is still in its "infancy" (Tatham et al., 2009). We noticed that the majority of research focuses on disaster management, leaving a very limited number of papers tackling the issues on long-term development. Moreover, compared with facility location, network design, distribution and routing, inventory management is a much less discussed subject.

By study the RUTF supply chain of UNICEF Kenya, we aim to propose decision support models that will enhance the performance of humanitarian logistics in the context of long-term development project. In particular, we focus on the inventory management of RUTF supplies, for which a balance between service level and cost will measure its effectiveness.

To achieve the aims, we divide our inventory management problem into two sub-questions:

- Can we set up a mechanism to better forecast the uncertain demands of RUTF?
- Can we identify a cost-effective inventory management model that fit better the distribution of RUTF?

In answering the first question, a statistical model for demand forecasting will be set up. An inventory model dealing with the second question will also be developed through simulations. In addition to their academic research value, both models will serve as decision support tool to optimize inventory management of RUTF for field operations, to maximize the coverage and availability of such a product, and thus to save more lives from SAM.

CHAPTER II

LITERATURE REVIEW

To have a good understanding of HL, the literature review first surveys the papers discussing HL in general in Section 2.1. Then, based on the classification mentioned in the Section 1.1, we survey papers dealing with DM in Section 2.2, followed by researches on LTD in Section 2.3. After summarizing the classification of HL problems in Section 2.4, we will review in more details the papers in HL domain tackling demand forecasting issues in Section 2.5 and inventory management issues in Section 2.6. By comparing these papers, we will better define our research in terms of objectives, scope, methodology and deliverables.

2.1 Humanitarian Logistics

In this section, we will introduce different definitions of HL and the involved stakeholders, the key complexities of HL and how it is different from commercial logistics.

2.1.1 Definition, Scope and Involved Stakeholders in Humanitarian Logistics

As many other emerging sciences, the definition of humanitarian logistics is still on the way of development. We list below the definitions proposed in the literature that are broadly discussed and accepted:

"A special branch of logistics managing response supply chain of critical supplies and services with challenges such as demand surges, uncertain supplies, critical time windows and vast scope of its operations."

-Apte (2010)

"The process of planning, implementing and controlling the efficient, cost-effective flow and storage of goods and materials, as well as related information, from the point of origin to the point of consumption for the purpose of meeting the end beneficiaries' requirements.”[3]

-Thomas and Mizushima (2011)

“Logistics activities related to preventing, reducing, preparing for, responding to recovering from human suffering and environmental and financial effects due to a disaster or a long-term development issue.”

-Çelik et al. (2012)

One improvement proposed by Çelik et al. (2012) in their definition is the inclusion of mitigation and recovery operations in the definition of HL since logistics plays a role in these phrases that are also important in disaster management. The other improvement is the emphasis on long-term development, an aspect that received little attention in previous researches.

The scope of humanitarian logistics encompasses a vast range of logistics activities, including preparedness, planning, procurement, transport, warehousing, tracking and tracing, customs clearance (Thomas & Kopczak, 2005). The various goods HL has to copes with include rescue materials, first aid set, medical equipment and supplies, medicine, water, food, shelters and cloths. Stakeholders involved in humanitarian logistics are typically governmental authorities and organizations, military institutions and forces, donors, NGOs, commercial institutions, affected populations or beneficiaries. Table 1 lists the main tasks of these different stakeholders.

[3] This definition is also used by United Nations World Food Programme (WFP) and Doctors Without Borders (Médecins Sans Frontières).

Stakeholders	Tasks
Governmental organizations	Carry out activities such as strengthening the infrastructure or providing education to the community; coordinate the preparedness, response and recovery activities
NGOs (local or international)	Participate in all activities at all stages (usually more than one NGO works on the same task)
Donors	Provide in-kind donations of relief commodities, financial aid or services
Military force	Provide manpower, equipment and services in various activities, such as transportation and last-mile delivery
Commercial instítues	Provide products and services in various activities, such as transport, warehousing, constructing

Table 1: Main tasks of different stakeholders in Humanitarian logistics, adapted from Çelik et al. (2012).

The main complexities of HL, as proposed by Overstreet et al. (2011), are summarized in the following in order to have a better understanding of its important characteristics.

Uncertainties: “Humanitarian logistics are always faced with unknowns” (Van Wassenhove, 2005). The greatest unknowns are the time, the place, the severity of a disaster in terms of both people and property; the usability of infrastructure; the quantity of equipment and materials required.

Qualified logisticians: There is constant shortage of qualified logisticians who can “plan, assess, and coordinate human and material resources” (Chikolo, 2006) in humanitarian logistics. According to Fritz Institute (2006), logistician turnover in humanitarian sector can be as high as 80 percent, mainly due to unclear career perspective, professional association and community of practice.

Timing: While a delay in the commercial supply chain may influence the productivity, profit, customer satisfaction, delays in humanitarian supply chains could mean the difference between life and death. A preliminary appeal for donations of cash and relief supplies is often made within 36 hours of the onset of a disaster.

The media and funding: “Media involvement and the way funds are raised for relief operations are inextricable” (Overstreet et al., 2011). Donors generally react generously to well-publicized disasters, but show little interest to unreported ones.

Equipment and information technology: Because money and materials are normally donated to directly help people affected by disasters, funding for necessary and up-to-date equipment and IT has been limited (Oloruntoba & Gray, 2006; Thomas & Mizushima, 2011). While the need for equipment may be obvious, the need for an inventory tracking system is often not recognized by donors (Whiting & Ayala-Öström, 2009).

Interference: It is stated by Thomas and Fritz (2006) that corruption has plagued almost every disaster relief efforts in the developed as well as developing world. Other forms of human interference include political grand standing and dishonesty among the individuals distributing supplies (McEntire, 1999; McLachlin et al., 2009).

2.1.2 Comparison with commercial logistics

Discussion on similarities and differences between humanitarian and commercial logistics can be found in many researches. Van Wassenhove (2005) emphasized on the "cross learning" potential between these two branches, and the need of better collaboration between industry, academia and humanitarian organizations to achieve more effective supply chains. Table 2 summarized the main differences between these two sectors, as proposed by Gill (2012).

	Commercial Supply Chain	Humanitarian Relief Chain
Goal	To make profits and provide satisfactory financial returns to shareholder interest (Boland & Fowler, 2000).	To achieve its social purpose and mission (Baruch & Ramalho, 2006; Moore, 2000).
Strategic Objectives	To produce high quality products at low cost to maximize profitability and achieve high customer satisfaction.	Minimize loss of life and alleviate suffering.
Main objectives	6 Rs (having the right item in the right quantity at the right time at the right place at the right price for the right customer) (Rutner & Langley Jr, 2000).	To meet the end beneficiaries' requirements (Thomas & Mizushima, 2011).
Source of income	Customers.	Donors (suppliers).
Demand	Products.	Supplies and people.
Demand Pattern	Stable, predictable demand patterns in terms of locations and quantities. Follows demand-supply relationships.	Purely random and unpredictable events in terms of timing, location, type, and size. Demand requirements are estimated after an event.
Lead Time	Lead times determined by the supplier- manufacturer-distribution cycles and driven by competition.	Zero lead-time requirements between the occurrence of event and the need, but actual lead time are determined by the material flow.
Distribution Network Configuration	Well-defined methods for determining the number and locations of distribution centers.	Challenging due to the nature of unknowns (locations, type and size of events), politics.
Inventory Control	Well-defined methods for determining inventory levels based on lead time, demand and target customer service levels.	Inventory control is difficult due to high variation in lead times, demand, and locations.
Information System	Generally well defined, using advanced technology.	Information is often unreliable, incomplete or non-existent.
Performance Measurements	Focused on resource performance and financial measures.	Focused on output measures such as response time or ability to meet the needs of an event of a certain magnitude.

Table 2: Differences between commercial and humanitarian supply chains, adapted from Gill (2012).

2.2 Disaster Management

We will briefly go through the four phases of DM as defined by Altay and Green (2006), shown in Figure 9, and the roles of logistics in different phases.

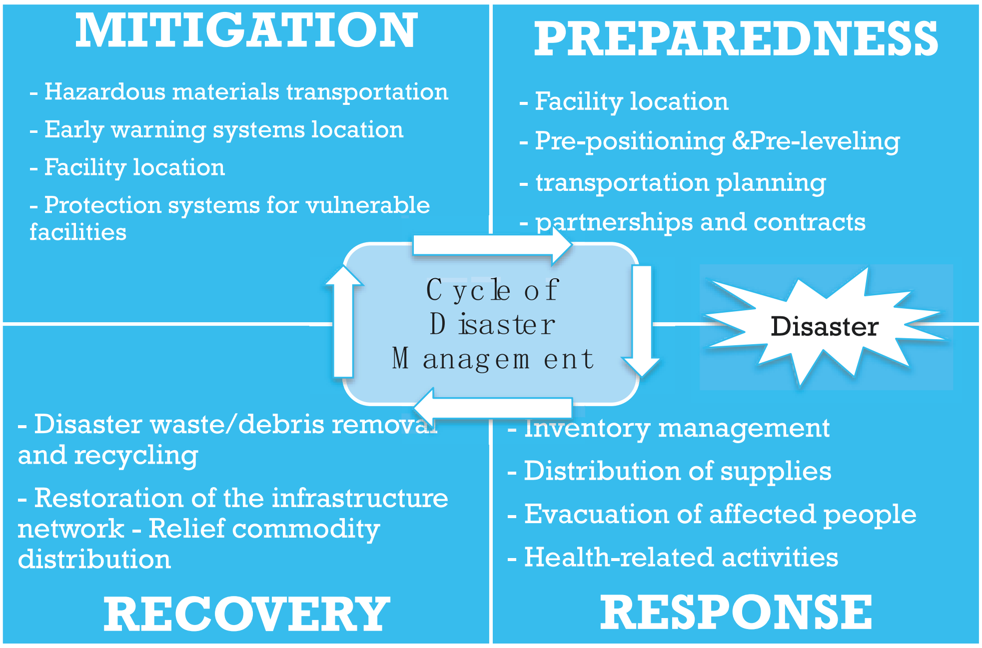


Figure 9: Cycle of disaster management, adapted from Altay and Green (2006).

Phase I-Mitigation: Strategic activities aim to either prevent the disaster from happening or to reduce its potential effects. Measures can be structural (e.g. building levees to prevent floods and retrofitting of building to prevent damages from possible earthquakes) and nonstructural (e.g. enforcing building codes). Lindell et al. (2006) pointed out that mitigation activities address long-term issues in the disaster life cycle and make efficient and effective management of these activities all the more important. Examples of logistics problems addressed within the literature are hazardous materials transportation, early warning systems location problems, facility location problems and the highly relevant problems of setting up protection systems for vulnerable facilities (Çelik et al., 2012).

Phase II-Preparedness: Proactive preparedness activities aim to facilitate response and recovery actions taken after disasters happen, which mainly comprise facility location, pre-positioning of assets, pre-leveling of resources, transportation planning, partnerships and contracts in advance for possible disasters (Altay & Green, 2006).

The World Meteorological Organization (2012) stated "one dollar invested in disaster preparedness can save seven dollars' worth of disaster-related economic losses". Due to the great uncertainties that must be taken into consideration, many of the models for activities in this phase are "two-stage stochastic programming models" supporting two stages of decision-making: first-stage decisions ("here and now" decision), such as location of warehouses and allocation of supplies; second-stage decisions ("wait and see" decision), such as the distribution of supplies (Noyan, 2012).

Phase III-Response: Activities in this phase start while the disaster is still in progress, with objective of efficiently managing the available resources so as to minimize the suffering of impacted communities. Timeliness is essential; conditions can be highly dynamic and uncertain, and information can be very limited. Inventory management, distribution of supplies, evacuation of affected people and health-related activities are aspects drawing most attention at this stage (Altay & Green, 2006).

Phase IV-Recovery: The main objective of the activities in this phase is to restore the system and re-stabilize the involved communities. Efforts are more in long-term and can be classified into three categories: disaster waste/debris removal and recycling, restoration of the infrastructure network, and relief commodity distribution (Altay & Green, 2006).

2.3 Long-Term Development Issues

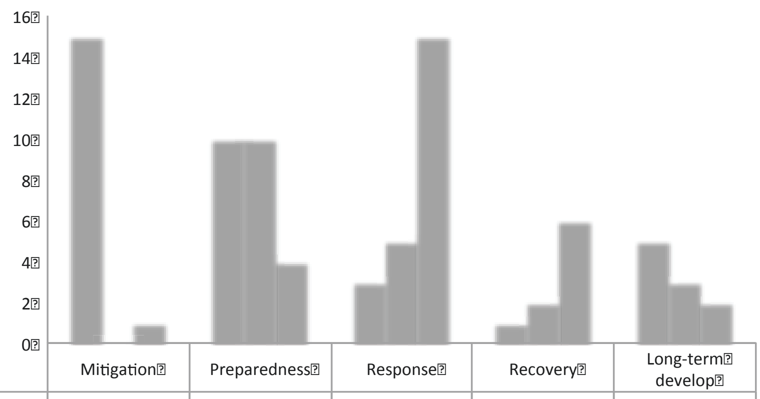
The guidelines and frameworks of LTD have been inspired and drawn from the Millennium Development Goals (MDG), which is written in the Millennium Declaration (United Nations, 2000). The eradication of hunger and reduction of child mortality are among the top priorities in the LTD issues. To fight against hunger globally, the inventory management of food supply chain in South Sudan has been studied by Beamon and Kotleba (2006a), so have been the WFP's supply chain capacity in Ethiopia by Sujin Kim and Singha (2010). Some other LTD issues for research could be facility location problems for education and health care in developing countries (Pizzolato et al., 2004; Rahman & Smith, 2000), cooperation between humanitarian and commercial sectors (Cozzolino, 2012), international shipment of humanitarian supplies (Oloruntoba & Gray, 2006), supply allocation at multiple levels of governments (Malvankar-Mehta & Xie, 2012).

2.4 Classification of Humanitarian Logistics Problems

The research problems on HL normally fall into three groups (Overstreet et al., 2011):

- Network design and pre-positioning;
- Inventory management;
- Transportation.

The first group focuses on the structure of the supply chain, the second on forecasting demand and pre-leveling of inventory, and the third is about delivery of goods or routing problems (Duran et al., 2011). Based on the information given in the HL tutorial by Çelik et al. (2012), the literature reviews of Overstreet et al. (2011), Caunhye et al. (2012), and Leiras et al. (2014), we have surveyed 147 papers in HL, out of which 72 are relevant to our research questions. We categorize them by two criteria: groups of discussing topics and types of disasters and phases of DM. The findings are depicted in Figure 10[4].



	Mitigation	Preparedness	Response	Recovery	Long-term develop
Facility location/Network design	15	10	3	1	5
Inventory management	0	10	5	2	3
Distribution/Routing	1	4	15	6	2

Figure 10: Number of papers contributed to groups of topics and DM phases.

While we notice that the network design problems and inventory management problems are highly interconnected and interdependent, and are often studied together and solved with a single mathematical model, the statistics in Figure 10 explicitly

4 The total number of papers classified in Figure 10 is not 72 because there are overlaps in research topics and phases.

confirms that LTD issues are still at early stage of research and need more attention. Moreover, compared with other two categories of problems, inventory management is the least studied one. Such observations confirm the necessity of our research, which tackles the inventory management issues in LTD as well as preparedness and response phases of DM.

2.5 Demand Forecasting in Humanitarian Logistics

Our literature survey unveils the fact that little research was conducted on demand forecasting in HL, especially the forecasting of relief materials for slow-onset disasters, such as drought and famine. In this section, we will focus on the papers discussing the forecasting of food aid demand or emergency response in Africa.

Tall (2010) have studied how climate information can be used by local vulnerable communities in West Africa and can serve to help the decision making process of the Red Cross in that region. At national level, rich climate information provided by authorities such as the Regional Climate Outlook Forums (RCOFs), National Meteorological and Hydrological Services (NMHSs) and West Africa's Seasonal Outlook Forum is available. However, there is no tailored information available or accessible at the user community level. The author suggested that some early actions should be taken: 1) "early warning early action", which move forward the funding process and pre-positioning of materials; 2) overcome the language and communication system barriers, and bridge the climate information providers with vulnerable groups and users; 3) develop trust between user communities and information providers; 4) integrate climate information using education in other humanitarian development projects. The authors have shown that early warning early action plan linking weather forecasting to early humanitarian actions yield remarkable improvement for Red Cross in response time and cost reduction in 2008, compared with precedent year when no such link was setup.

Verdin et al. (2005) also have studed the relationship between climate science and famine early warning. Due to the global climate change, the climate variability increases and extreme events occur more frequently (IPCC, 2001). The authors have observed that due to the lack of "access to modern methods of data capture, data management, telecommunication, modeling and analysis", countries like Ethiopia are more and more vulnerable given that a large number of people dependent on agriculture and pastoralism. Aiming to support the food security assessment, which is measured by availability, access and utilization of climate information, the authors suggested that remote sensing and modeling should be further developed and that innovated agricultural practices and natural resource management techniques should be adopted.

Since the need for food aid in Sub-Saharan Africa is increasing these years, a new strategy of aid is required (Haile, 2005). Haile (2005) has pointed out that the key for food aid supply is "not only how much, but also when and in what form" it should be delivered. The author focused his research on how current advances in the understanding of climate variability, weather patterns and food security could contribute to improved humanitarian decision-making. He proposed new approaches for triggering humanitarian responses to weather-induced food crises. Firstly, the author studied the agricultural monitoring system and has suggested bringing forward the need assessment and funding raising process, leaving beneficiaries the time to adjust their agricultural and financial planning with potentially available aid. Secondly, regarding humanitarian response systems, the author have highlighted that improvement should be done in need assessment, emergency appeal and resources mobilization, planning delivery, and managing surplus production of good years. Finally, as humanitarian aid has an insurance function, to better respond to extreme weather-induced food crisis, we need to bring forward the needs assessment and set up a new financing system.

Taking into consideration resource scarcity, normal delay in action, merely perceivable relevance between rainfall and needs of humanitarian aid, Mude et al. (2009) have developed an accurate statistical forecasting tool using empirical methods. The tool aimed at forecasting the needs of vulnerable populations in slow-onset disaster such as drought. They used household data collected over several years by the Arid Lands Resource Management Project (ALRMP) of the Government of Kenya, and study the following explanatory variables: trends in rainfall and forage availability rates, herd dynamics (livestock), Mid-Upper Arm Circumference (MUAC), food aid response whose intensity varies across time. Root Mean Square

Error (RMSE) has been used for evaluating a series of rolling of one to three months ahead forecasts. The results indicate that MUAC is significant as a variable, and that the models can accurately give policy makers a reasonable three-month early warning window to mitigate the consequences of impending disasters.

2.6 Inventory Management in HL

In this section, we focus on articles tackling inventory problems in both DM and LTD issues. The review has been organized based on the order from the least relevant to the most relevant paper to our research project, which focuses on the inventory management of humanitarian supply in LTD, and preparedness and response phases of DM.

Beamon (1999) has introduced performance metrics applicable for HL. Resource metrics indicate the level of efficiency and effectiveness of HL, mainly looking at "how better we can do with less". The metrics measure the response time and the number of items supplied (supply availability). The flexibility metrics measure the ability to respond to different magnitudes of disasters (volume flexibility), the time needed to respond to disasters (delivery flexibility), and the ability to provide different types of items (mix flexibility). Beamon and Balcik (2008) have compared HL with commercial supply chains, and have further tailored commercial metrics into a specific measure system for HL. The systematic performance measurement of HL is essential for our following discussion on models and solutions for HL inventory management.

Chang et al. (2007) have proposed a two-stage stochastic programming (SP) model that determines the location of facilities by minimizing the expected shipping distance at the first stage, then minimizes the facility setup cost and equipment average cost as well as the expected transportation cost, supply shortage cost, and demand shortage penalty during rescue operations at the second stage. The model runs under different scenarios based on different rainfall situations, and is solved by sample average approximation. Compared with the mean-value model, the SP model "has better capability to give adequate decision support for government agencies in both theory and practice" (Chang et al., 2007).

Salmerón and Apte (2010) have addressed the problem of strategic planning and resource allocation for humanitarian aid in order to minimize the expected casualties in cyclic natural disasters (e.g., hurricane and wild fires). They have developed a pre-positioning optimization (PO) model as a two-stage stochastic mixed integer problem. The authors classify the affected population into three categories in terms of fragility: 1) critical population, those in need for emergency medical evacuations to relief locations (RLs); 2) stay-back population, those who may stay in affected areas but require certain commodities from RLs for survival; 3) transfer population, those who need only evacuation to RLs. In the first stage, the PO is determined by minimizing the expected casualties resulting from non-rescued (and rescued but not surviving) critical populations and the stay-back casualties due to unmet commodities. In the second stage, the PO is determined so as to minimize unmet demand of population that should be transferred. A baseline case is undertaken under various scenarios in term of severity or location of the disaster. By analyzing the scenarios, it is suggested by the authors that authorities must match existing transportation capacity and health capacity for critical populations. The authors also conclude that the expansion of warehouses and delivery of commodities should take priority once more budget is available since the "cost for additional special transportation and health facilities for the last pockets of critical population is too expensive" (Salmerón & Apte, 2010).

In order to provide an emergency planning tool that can determine the most accessible relief supply locations and the optimal quantities of resource, in the context of uncertain demand and unreliable information network, Rawls and Turnquist (2010) have proposed a two-stage stochastic mixed integer program (SMIP). The objective function of the model minimizes the expected costs over all location-allocation and scenarios. The model is solved by the Lagrangian L-shaped method (LLSM). The model and the algorithm are then tested on two sets of scenarios that are developed based on historical records of hurricane storms. According to the experimental findings, the authors conclude that the LLSM is a very effective way for solving pre-positioning problems and suggest using this model for other problems, such as preparation of shelters.

Rawls and Turnquist (2012) have studied the problem of relief materials pre-positioning for urgent demands at shelter locations that should be delivered during the first 72 hours after an event. A dynamic allocation model has been designed, for which the objective is to minimize the total cost taking into account the pre-positioning locations and facility sizes, the commodity acquisition and the stocking decisions, the transport of the supplies to the demand points, unmet demand penalties and holding costs for unused material. The model includes uncertain demands and uncertain locations. This model also includes requirements for reliability in the solutions, and reveals the interaction between reliability constraints and preset penalties on unmet demand.

Mete and Zabinsky (2010) have also built a two-stage SP model for the medical supply storage and distribution problem at city level for the preparedness and response phases of DM. The objective is to minimize the cost and unmet demand of medical supplies. The first stage focuses on facility location and inventory level, whereas the second stage aims to handle aggregated delivery and vehicle routing issues. They have solved the SP model using the deterministic equivalent of the model and validate it with a simulation taking an earthquake in Seattle as a case study. The model is proved to be efficient and applicable to other cities.

In order to coordinate a multi-echelon system of humanitarian relief with, multi-stakeholders, it is important to develop a model that provides centralized operation plans, which can eliminate delays and assign the limited resources in an optimal way. Afshar and Haghani (2012) have studied the complex supply chain of the Federal Emergency Management Agency (FEMA). They have developed a mathematical model that optimizes the location and allocation of scarce resources as well as vehicle routing, taking into account facility capacity constraints and transportation constraints. The objective of this model is to minimize the total unmet demand over all commodities, periods and demand points. To evaluate the model, a numerical experiment under several scenarios of natural disaster is undertaken. The results confirm that the model is capable of handling large-scale problems with high level of transparency and control.

Another specific problem in HL is supplying relief items to affected areas after the occurrence of a sudden change in demand or supply during ongoing humanitarian actions, which can be characterized as “overlapping disasters”. Under such circumstances, relocation of goods between neighboring depots and transshipment is an efficient solution. Rottkemper et al. (2011) have discussed questions related with overlapping disaster scenarios. They have designed a linear multi-period MIP model to minimize the unsatisfied demand by incorporating penalty costs for unsatisfied demand and future uncertainties. The evaluation of the model shows that unsatisfied demand can decrease significantly by taking uncertainty into account using the appropriate penalty cost parameters, which should be determined specifically for each scenario.

Ozbay and Ozguven (2007) have also studied the problem of how to ensure supply of relief materials without disruptions during and after disasters. They account for the "probability of disruption". They have developed a stochastic model and have determined optimal safety stock (SS) by minimizing the sum of storage, surplus, and shortage costs. They have solved the model with the pLEPs (p-level efficient points) algorithm and validate it with a single commodity case study. According to the base case and sensitivity analysis, the number of deliveries, probability of disruption, amount of consumption and initial safety stock are all parameters that influence additional safety stock levels.

Based on data from World Vision International (WVI) on the food aid distribution in south Sudan, Beamon and Kotleba (2006b) have developed a multi-supplier, single-item and stochastic demand model to optimize the reorder quantities and reorder levels. The model allows two options of reorder quantities dealing with two reorder levels corresponding to normal and emergency levels of food aid supply. The authors also suggest that more researches should analyze the back-order cost in HL as it does not represents financial profits, or potential reputation and reliability, but potential suffering (or loss of lives) endured by a potential recipient.

Often the humanitarian relief operations require joint efforts from more than one organization, a universal cross-organization inventory management model is required to better cooperate. Based on the same case study of Beamon and Kotleba (2006b), Beamon and Kotleba (2006a) have developed, tested and compared three types of inventory management strategies that determine order quantities and re-order points for pre-positioned stocks: 1) a continuous inventory review system with two options for re-supply (normal mode and emergency mode); 2) heuristic method that determines order quantities using the Silver-Meal Heuristic and re-order levels calculated by using the mathematical model; 3) Naïve model, where the reorder level is calculated based on replenishment lead-time, and the order quantity is the average value of monthly demand. A simulation has been designed to test the three strategies, followed by performance measurement based on the performance metrics of Beamon (1999): 1) response time, (i.e., the amount of time it takes to provide the appropriate relief supplies to areas of need or to beneficiaries); 2) annual cost, which should be within the budget constraints of each project, since "repeated budget overruns will negatively affect an organization's ability to acquire future donor funding" (Beamon & Balcik, 2008); 3) maximum proportion of emergency order cycles, which represents the flexibility within a supply chain and its capability to "respond to shifts and fluctuations in the volume and schedule from suppliers, manufactures, and customers"(Beamon & Balcik, 2008). In addition, the results are tested with an ANOVA in order to determine the interrelationship between parameters of the models. The authors conclude that mathematical model achieved the best solution, whereas the heuristic method is most time-efficient and applicable.

The research of Consuelos Salas et al. (2012) have focuses on inventory management of perishable products (food) under threat of hurricanes. A mixed integer programming (MIP) model is developed with the objective of minimizing total cost. It addresses the multi-period stochastic inventory problem for perishable products using a first-in-first-out (FIFO) system. The ordering cost is time-varying as it may increase sharply when disasters approach. The shortage cost is much higher than the purchase cost because it represents a refugee not fed, and will increase significantly after two days since such delay of supply starts to threaten the life of refugees. Disposal cost is also included since the products have an expiration date. The model has been tested and solved by transforming stochastic programming model into a deterministic MIP model with a non-convex objective function. The authors suggest that the properties for the conditional expectation were very useful to better handle the stochastic programming problems, and that parameters such as shortage cost should be carefully defined.

Aviles et al. (2008) have executed an optimization project in conjunction with the supply chain optimization team of the WFP, focusing on two supply chain problems: 1) lack of smooth operations due to variability in donations; 2) inexistence of a standardized inventory management methodology. Some common characteristics of UN family organizations (e.g., WFP and UNICEF) are discussed, such as: 1) pull procurement system, in which the procurement process cannot begin until a donation is confirmed; 2) working capital financing (WCF), an funding mechanism aiming to facilitate a quicker initiation of the procurement process (a solution for disadvantages of Pull procurement system); 3) borrowing, a method that COs and lower layer facilities use often to prevent pipeline breaks; 4) the norms of "on spot procurement" and "spending entire donations on commodities for the country as soon as possible, regardless of the estimated future demand for those commodities". After a comprehensive analysis, a mathematical model has been developed tackling above-mentioned issues faced by WFP, introducing the possibility of using WCF and pre-positioning as mechanisms to smooth the variability in donations and to stabilize pipeline flow. A standardized periodic review model with optimal order quantity and reorder point is proposed. The authors estimate that WFP would have saved around 70 million USD in 2007 by using the proposed model.

CHAPTER III

UNICEF KENYA RUTF SUPPLY CHAIN

To better understand the field operations of UNICEF Kenya and to collect data and information effectively, we have conducted a two-month field study from the end of August to the end of October 2014. The field study has been mostly conducted in the Nutrition section and Logistics section of the KCO at Nairobi. Interviews have been arranged with concerned UN and local governmental officers and partners' employees. A one-week trip to the counties of Laikipia and Kitui has also been done to study the sub-county DCs and end facilities.

In this chapter, we will introduce in more detail the stakeholders of RUTF supply in Kenya and their information sources in Section 3.1, the organization of UNICEF Kenya and concerned UN institutions in Section 3.2. The field study and the data collected are presented in Section 3.3, and some issues in the existing system that we have discovered during the field study are discussed in Section 3.4.

3.1 Stakeholders of RUTF in Kenya and Information Sources

In Kenya, the RUTF is procured and distributed by three "consortiums" differentiated by different means of funding, as illustrated in Figure 11. The first is UN organizations, such as UNICEF supported by UNOPS[5] and certain NGOs, raising funding by themselves from donors on a continuous basis. The second is the government of Kenya, i.e., the Ministry of Health (MoH), receiving funding and loans from donors or organizations such as the World Bank, and outsourcing the distribution to the Kenya Medical Supplies Agency (KEMSA), a specialized state-own medical logistics provider. The third is composed of the NGOs, such as USAID, whose funding is highly unpredictable.

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[5] The United Nations Office for Project Services (UNOPS) is an operational institution of the United Nations, supporting the implementation of its partners' peace building, humanitarian and development projects around the world (UNOPS, 2015).

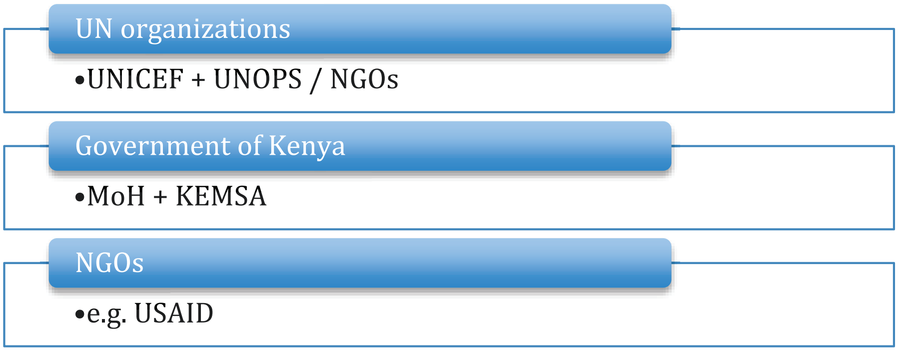
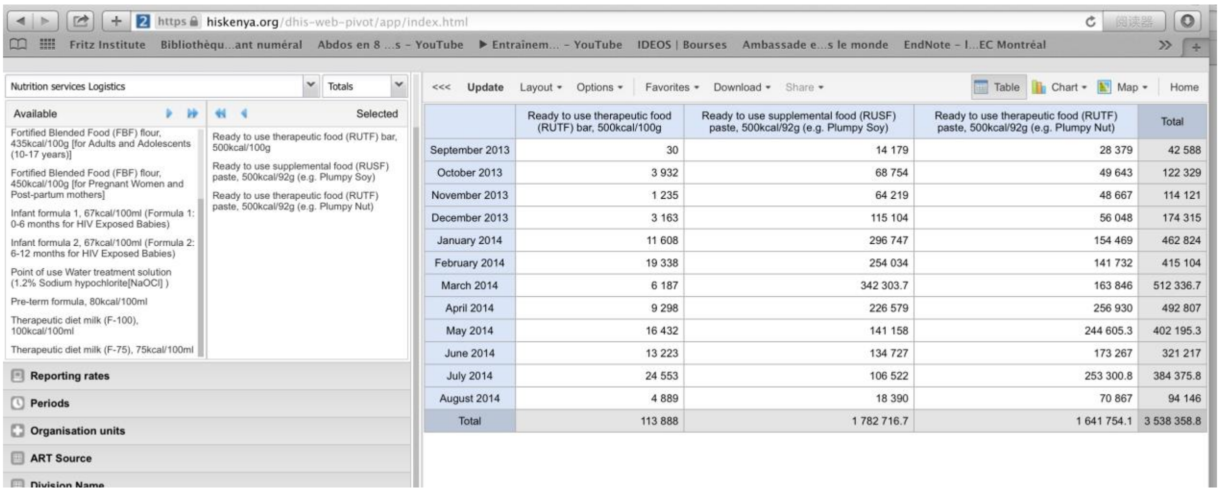


Figure 11: Three consortiums of RUTF stakeholders in Kenya.

At a strategic level, these three consortiums coordinate their activities by a nutrition sector conference that is held twice a year. The action guideline for such coordination is the *Nutrition Sector Preparedness and Response Plan*. At an operational level, the procurement and logistics are to some extend centralized, and the supplies are often distributed along the same logistics infrastructures and operators. It is not unusual the same type of RUTF stored at one clinic but bookkept separately and distributed to different groups of beneficiaries, as they belong to different programs and donors.

The nutrition sector participants have mainly two sources of nutrition status and RUTF information: the Nutrition Survey and District Health Information System (DHIS). Nutrition Surveys are sponsored by UNICEF and NGOs such as Action Against Hunger and World Vision, and are carried out at a county level normally on an annual basis (depending on the availability of funding). The survey reports provide overall nutrition assessment as well as social and economic data of a given county at a given year. The DHIS is an open source software platform used in more than 40 countries (in Asia, Africa and Latin-America), and it facilitates collecting, sorting and analyzing data for health programs. The system covers two types of data, routine ones and event ones. Routine data include information on health facility, staffing, equipment and infrastructure etc., and event data are nutrition status surveys, patient records, disease outbreaks, etc. Since 2008, the system has been upgraded to DHIS 2, with more visualizing and analytical functions and interfaces with other software. A screen shoot of the DHIS 2 user interface can be found in Figure 12.



	Ready to use therapeutic food (RUTF) bar, 500kcal/100g	Ready to use supplemental food (RUSF) paste, 500kcal/92g (e.g. Plumpy Soy)	Ready to use therapeutic food (RUTF) paste, 500kcal/92g (e.g. Plumpy Nut)	Total
September 2013	30	14 179	28 379	42 588
October 2013	3 932	68 754	49 643	122 329
November 2013	1 235	64 219	48 667	114 121
December 2013	3 163	115 104	56 048	174 315
January 2014	11 608	296 747	154 469	462 824
February 2014	19 338	254 034	141 732	415 104
March 2014	6 187	342 303.7	163 846	512 336.7
April 2014	9 298	226 579	256 930	492 807
May 2014	16 432	141 158	244 605.3	402 195.3
June 2014	13 223	134 727	173 267	321 217
July 2014	24 553	106 522	253 300.8	384 375.8
August 2014	4 889	18 390	70 867	94 146
Total	113 888	1 782 716.7	1 641 754.1	3 538 358.8

Figure 12: Example of user interface of DHIS 2.

3.2 Organization of the RUTF Supply Chain led by UNICEF

In Section 1.4, we have briefly introduced the UNICEF Kenya RUTF supply chain, which supports three flows (funds, information and material) and involves the Supply Division in Copenhagen and producers from France. In this section, we will focus on the national distribution network within Kenya, and clarify the actors at different layers (or echelons) and their practices, especially those at sub-county and end facility level, as illustrated in Figure 13.

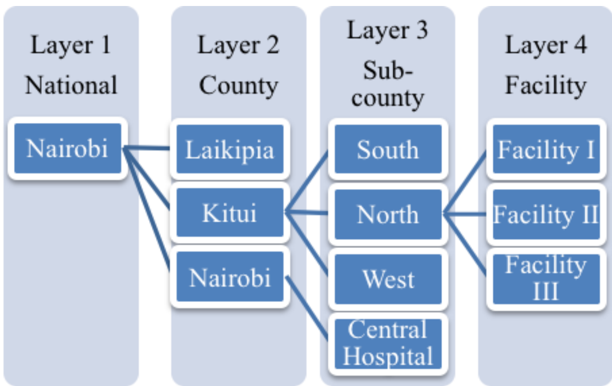


Figure 13: Four layers of RUTF supply chain led by UNICEF Kenya.

At Nairobi Gigiri UN complex there are three UNICEF institutions, the Eastern and Southern Africa Regional Office (ESARO) that coordinates and supervises UNICEF's work in 21 countries, the Kenya Country Office (KCO), and the Somalia County office. The office directly in charge of RUTF supply in Kenya is the KCO. Within KCO, there are two sections dealing with RUTF, the Nutrition Section and the Logistics Section. The Nutrition Section coordinates the nutrition and health programs including IMAM, and is responsible for the funding, demand forecasting, procurement and distribution planning of RUTF. The Logistics Section works as the supporting force, taking care of the order placing, shipment tracking, warehousing and delivery monitoring, etc. The commercial logistics service provider (LSP) Kuehne+Nagel (K&N) is granted the contracts of freight brokerage, central warehousing and re-delivery to local destinations in Kenya.

Currently, there is no physical material flow at the county level. According to the central warehouse inbound/outbound record from K&N, the RUTF supply is shipped from the central warehouse at Nairobi directly to sub-county warehouses. However, as an important administrative layer in Kenya, much data and information is collected at the county level, e.g. the Nutrition Surveys. The IMAM program in-charge at this layer are the County Nutrition Officers (CNOs), who will collect data from the Sub-county Nutrition Officers (SNOs) and report to Nutrition Support Officers (NSOs, from UNOPS) and also possibly to the Nutrition Section of KCO.The end distribution facilities of the RUTF supply chain can be in several forms, such as dispensaries, clinics or hospitals. The nutritionists are responsible for the patients screening, outpatient (OTP) registration and reporting (to Recording officer and SNO), they also report the distribution of RUTF to OTPs. We summarize the mechanism of information flow (both patient and commodity information) in Figure 14.

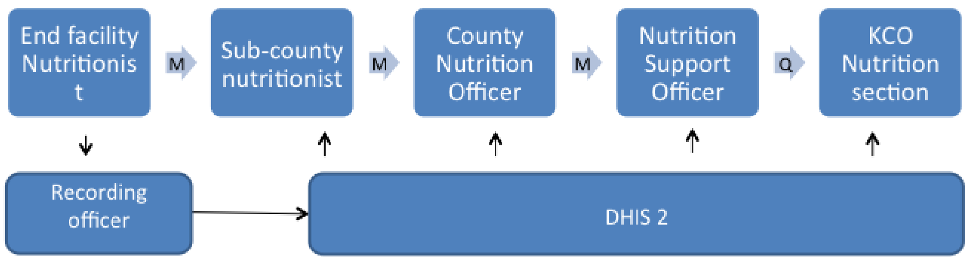


Figure 14: Mechanism of information flow in UNICEF Kenya RUTF distribution network, where “M” represents monthly reporting and “Q” represents quarterly reporting.

3.3 Data Collection and Field Studies in Kenya

At the national level, large quantity of data concerning nutrition status of children and RUTF supply has been collected from the KCO Nutrition Section, the Logistics Section and UNICEF SD. Detailed RUTF warehousing and shipping records since 2011 are collected from K&N. In addition to quantitative data, much qualitative information and insights have been shared during the interviews with UN and Kenya government officers and commercial partner employees. An exhaustive list of documents can be found in Figure 15.

Most of our data regarding RUTF inventory and shipment used in this thesis have been provided by K&N and extracted from their warehouse inbound and outbound records (2011-2014). The information regarding logistics cost of RUTF in Kenya has also been collected in quotes from K&N. The data regarding SAM caseloads of a given county have been mainly extracted from the DHIS2 system and the IMAM database of MoH. Other nutrition status data, such as children's MUAC, have been collected from nutrition surveys of studied counties and the Drought Monthly Bulletin (DMB), updated by the National Drought Management Authority (NDMA). Furthermore, the metrological data used in this thesis, such as the Standard Precipitation Index (SPI), have been mainly extracted from Drought Monthly Bulletin. It is also worth mentioning that all data and information explicitly cited and extensively used in this thesis are available through public channels. For confidential reasons, certain documents, especially the unpublished research papers and records from the LSP, cannot be cited extensively.

Auther/owner	Date	updating frequancy	Title	Content & Remarks	National	County	Sub-county	End facility
Research and consulting project papers								
Kimetrica	Sep 2014		Nutrition Scalability Methodology Report	Demand forecasting and scalability feasibility studies	X	X		
Deloitte	Apr 2014		Inception report for assessment of parallel nutrition logistics chains for intergration into the GOK national SCM system	Overall assessment of RUTF SC in kenya, qualitative	X	X	X	X
Unicef SD	Oct 2013	Yearly	Ready-to-Use Therapeutic Food: Current Outlook	Brief outlook of global RUTF demand, supply, usage, challenges and issues	X			
Nutrition Status Studies								
Nutrition sector, Kenya	Jul 2011 Apr 2012 Apr 2013 Apr 2014	yearly	Nutrition sector preparedness and response plan	Overall assessment of current and near future (about 6-12 month) nutrition situation, rate emergency and response level, coordinate efforts of stakeholders	X	X		
KCO, MoH, partners	May 2011 Jul 2012 Jul 2013 Jan 2014 May 2014	Yearly	Nutrition survey Turkana	Overall nutrition situation assessment in given county		X	X	
KCO, MoH, partners	Aug 2012	Yearly	Nutrition survey Laikipia	Overall nutrition situation assessment in given county		X	X	
KCO, MoH, partners	Oct 2009 Apr 2011 Sep 2013	Yearly	Nutrition survey Kitui	Overall nutrition situation assessment in given county		X	X	
MoH	2009-2014	Monthly	IMAM database	Inpatient, outpatient, SAM caseload, reporting rate, etc	X	X	X	
RUTF supply and distribution record								
Unicef SD	2008-2014	Daily	Purchase order record	PO placed from Copenhagen SD to international suppliers for KCO account	X			
Unicef KCO	2011-2014	Daily	Sales order record	PO placed from Unicef Kenya to Copenhagen SD	X			
Unicef KCO	2012-2014	Quarterly	Quarterly Distribution Plan	request from sub-counties and distribution plan			X	
K&N warehouse	2011-2014	Daily	warehouse inbound / outbound record	item, date, quantity, destination, etc	X		X	
Local Network Mapping								
Unicef & Unops	2014	yearly	Turkana County health facilities list	list of sub-county warehouses, end facilities, distances between them.		X	X	
Unicef & Unops	2014	yearly	Kitui County health facilities list	list of sub-county warehouses, end facilities, distances between them.		X	X	
Unicef & Unops	2014	yearly	Turkana County health facilities list	list of sub-county warehouses, end facilities, distances between them.		X	X	
LTA with RUTF and logistics service supplies								
Unicef SD		bi-yearly	LTA with RUFT suppliers		X			
K&N	2012	bi-yearly	Road transportation and related services contract	Transport, warehousing, customs clearance services contract	X	X	X	
BOLLORE (SDV)	2012	bi-yearly	Long Term Agreement for services	Land transport service contract	X	X	X	
NDMA	2012-2014	monthly	Drought monthly bulletin Turkana			X	X	
NDMA	2012-2014	monthly	Drought monthly bulletin Kitui	Monthly precipitation, climate, nutrition status , socio-economic situation assessment		X	X	
NDMA	2012-2014	monthly	Drought monthly bulletin Laikipia			X	X	
UNESCO & USAID		Daily /monthly /yearly	African Flood and Drought Monitor	Meteorological, hydrological indices historical record and short term forecast, spot data. (SPI included)				X
Diverse Information								
ZENG KE	2014		Weekly report	diverse information collected, including qualitative infos, such as interview with KEMSA, K&N, Unicef	X	X	X	X
Unops	2011-2014		Doldol, Segera and Kwavonza RUTF distribution record	imcomplete record of RUTF intake, stock and distribution at given end facility				X
Unops	2011-2014		Doldol , Kitui Central warehouse RUTF stock record	imcomplete record of RUTF intake, stock and distribution at given sub-county warehouse			X	
Unicef	2014		Local nutrition support officers contact list				X	X

Figure 15: List of documents collected during field study in Kenya.

In this research project, due to limited resources and time, also for safety consideration (unstable political situation in border counties, e.g. Mandera, Turkana, Wajir and Garissa in 2014), we were not able to investigate all the 22 counties involved in the IMAM program. We have selected a few sample regions. Nairobi county is selected as it represents the urban area which are "marginalized" in the IMAM program, whereas Laikipia and Kitui cover both agricultural favorable and arid and semi-arid land (ASAL) areas,. These two counties are not well studied compared with remote arid counties such as Turkana and Mandera. The regions and facilities we visited are listed in Figure 16. The locations of sample counties are mapped in Figure 17.

County	Sub County	Facilities
Laikipia	Nanyuki	1) *Nanyuki teaching & referral hospital;* 2) Likii dispensary; 3)Segera dispensary
	Doldol	1) *Doldol missionary;* 2) Doldol health center
Nairobi	Embakasi	1) Makadara health Center; 2) Mama Lucy hospital
	Kamukunji	1) Pumwani Hospital
Kitui	Kitui Central	1) Kitui central nutrition department; 2) *Kitui district hospital*
	Kitui rural	1) Yatta health center; 2) Kwavonza dispensary

*In italic are sub-county level central warehouse

Figure 16: The counties, sub-counties and end facilities visited for field study.

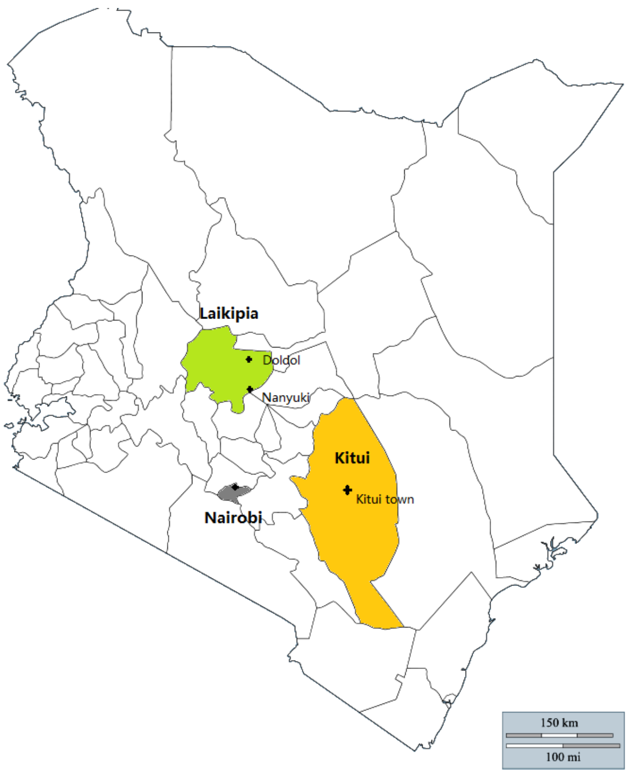


Figure 17: The samples counties visited for the research project.

3.4 Issues Discovered during Field Study at Selected Counties

During our field study at the end facility, sub-county and county level, some general issues cross counties are noted. Supply shortage is critical in areas where the economy is relatively developed, i.e., the urban area. In the county of Nairobi, a large portion of the population still lives in poverty and approximately 5000 children are in need of RUTF according to the SNO at Makadara health center. However, due to relatively better economic status compared with other remote and rural areas, this county is often ignored by donors and thus suffers constantly from supply shortage in the IMAM program.

The transport from sub-county warehouses to end facilities is a big challenge at certain counties. The end facilities have no transport means or financial resources. The decentralized medical care system, i.e. the county administration (each county is responsible of the medical care), does not have budget either. The supply delivery from sub-county DCs to end facilities is highly dependent on supports from NGOs. In counties where NGOs are not actively present, passenger cars of SNOs often carry the RUTF when there are mission visits.

In some ASAL counties, e.g., Laikipia, where the IMAM program is not well implemented and NGOs are not actively involved, nutrition status data are very limited. In Laikipia, the only available nutrition survey dates back to August 2012. It was conducted International Medical Corps (IMC), who withdrew activities from the county in 2013. The data management of the IMAM program in urban areas is no better than in remote rural areas, despite the fact that most facilities are equipped with computer and have Internet access. It is therefore both a managerial issue and IT infrastructure problem.

Instead of being stocked with medical supplies, it is not uncommon to find the RUTF stored with rice, flour and other kitchen supplies in food storage. As a consequence, RUTF stock might be excluded from regular stock checking and later neglected. The effectiveness of OTP treatment is challenged due to improper use of RUTF, according to nutritionists from Kitui, SAM affected OTP gain weight behind the schedule, compared with those inpatient taking F-100 (intensified milk powder). It is not uncommon that the family members share RUTF rations prescribed to one affected child. In certain counties, e.g., Wajir and Garissa, RUTF is a popular “snack” for adults, and illegal RUTF trade is of considerable scale.

Compared with human nutrition status data, which have been shared on computerized platforms such as DHIS2, commodity data, i.e., the stock level of RUTF, are not well recorded and shared. Some important commodity data, such as receipt quantity and date, distribution quantity and date, the patients and their rations, are supposed to be recorded on Stock Control Record and on the OTP health facility monthly report. However, they are not computerized in the DHIS2, only sub-county recording officers document hard copies. Except certain facilities in Nairobi that record quantity of sachet given each visit, on the widely used OTP registrar sheets (the patient status record sheet used for IMAM program), no data on quantity of RUTF distributed is recorded.

The rule of FIFO is not well practiced at end facilities due to poor training received by nutritionists. During the field study, in certain end facilities, we noticed that some stocks are at the edge of expiration.

CHAPTER IV

DEMAND FORECASTING MODELS

"The need to make decisions based on judgments about the future course of events extends beyond the profit-oriented sector of economy... Social service agencies such as the Red Cross and the Easter Seal Society must also base their yearly plans on forecasts of needed services and expected revenues." (Wilson & Keating, 2009)

In this chapter, we first review the different forecasting methods in Section 4.1. Then we discuss in detail our forecasting models for each layer of the Kenya RUTF supply chain in Section 4.2. Conclusions are drawn in Section 4.3.

4.1 Overview of Forecasting Methods

According to Makridakis et al. (1998) and Charles W (2013), there are quantitative and qualitative forecasting methods. Quantitative methods are used when sufficient quantitative information is available and when past pattern will continue into the future. The two categories of such methods are time series methods and causal methods. Time series methods predict the continuity of historical patterns, including Naïve Method, Moving Average (MA), Exponential Smoothing, Decomposition (Additive, Multiplicative). Causal methods predict the results by explanatory variables, including Linear Regression (simple or multiple) and Integrated Autoregressive Moving Average (ARIMA) models. Qualitative methods are used when little quantitative data is accessible but sufficient qualitative knowledge is available. According to Armesto et al. (2010), the efficacy of forecasting methods mainly depends on two factors, the nature of the information to be forecasted and the information available to perform forecasting.

4.2 Forecasting Methods for Different Layers in Kenya

In the case of Kenya RUTF supply chain, since each layer has its specific features (information availability, resources constrains and ordering policies), we have selected the proper forecasting methods for level. According to Mukattash and

Samhouri (2011), when developing forecasting models, we have to take into consideration the availability and quality of data for quantitative methods and availability of expertise for qualitative methods. The forecasting horizon, the complexity and the cost of developing forecasting models also have to be considered. For the different levels of the supply chain, these aspects have been considered in order to determine the best-fitted forecasting approach.

4.2.1 Forecasting Models at End Facility Level

As shown in Figure 18, the end facilities are the last layer of RUTF supply chain, where the RUTF is distributed to caretakers. Facilities at this level are mainly local clinics or dispensaries, and computer and Internet are rarely available Nutritionists thus have limited access to shared information about nutrition status of the population and climate. Patient information as well as medical supplies data are reported to higher level nutrition officers in hard copy on a monthly basis. Based on two sets of data from the end facility level, RUTF stock control data and OTP registrar data, the SNO or the CNO forecast and arrange the supplies to end facilities on a monthly basis.

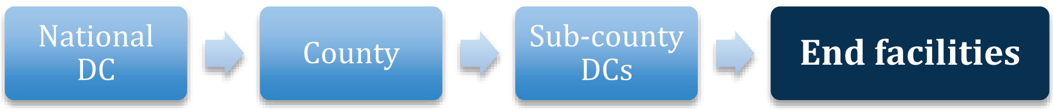


Figure 18: The layer of end facility within the RUTF supply chain.

As pointed out by many humanitarian logisticians and researchers, due to insufficient infrastructure, human resources and training, the adopted forecasting method at this level should be straight forward to understand and easy to implement. Ideally, it should be free of cost and instantaneous. Replenishment lead-time from the sub-county DCs to the end facilities should be short and the existing official replenishment policy is once a month. In this thesis, we thus have set the forecasting horizon of this level to one month in order to represent the current inventory management policy.

Current forecasting method

The current practice at the end facilities we visited is a naive time series method, which follows random walk of data series:

$$F_t = D_{t-1},$$

where F_t is the RUTF demand forecast of month t and D_t is the observed demand during month t, which consist of sachets distributed to OTPs.

Proposed forecasting method

By observing Table 3 and Figure 19 showing information of RUTF distribution records collected from three end facilities (Doldol dispensary and Segera missionary in Laikipia, and Kwavonza dispensary in Kitui), we notice that records are sometimes discontinuous due to stockouts and that missing orders (unsatisfied demand) are not recorded. We registered two types of shortages at the end facility level: 1) "real shortage", where both end facilities and sub-county DCs are running out of stock; 2) "false shortage", where supply is available at sub-county DCs, but end facilities suffer from stockouts due to difficulties in delivering supplies from sub-county DCs to end facilities. As illustrated in Figure 19, at end facility level, the demand has no perceivable seasonality or trend, but fluctuates randomly from month to month due to various reasons.

Month	Doldol	Segera	Kwavonza	Month	Doldol	Segera	Kwavonza
Jan-12	-	-	483	Jan-13	2100	18	-
Feb-12	-	2276	273	Feb-13	1735		-
Mar-12	940	654	-	Mar-13	690	283	-
Apr-12	966	1392	-	Apr-13	-	332	257
May-12	1784	477	-	May-13	-	225	469
Jun-12	2064	1238	574	Jun-13	-	323	207
Jul-12	561	86	42	Jul-13	-	3190	267
Aug-12	1725	63	144	Aug-13	-		-
Sep-12	1375	235	66	Sep-13	-	1425	-
Oct-12	-	308	-	Oct-13	-	1800	-
Nov-12	-	287	-	Nov-13	-	-	-
Dec-12	-	-	-	Dec-13	-	-	-

Table 3: RUTF distribution record (in sachet) at Doldol, Segera and Kwazonza end facilities, processed from Stock Control Card, where "-" represents that no record is registered.

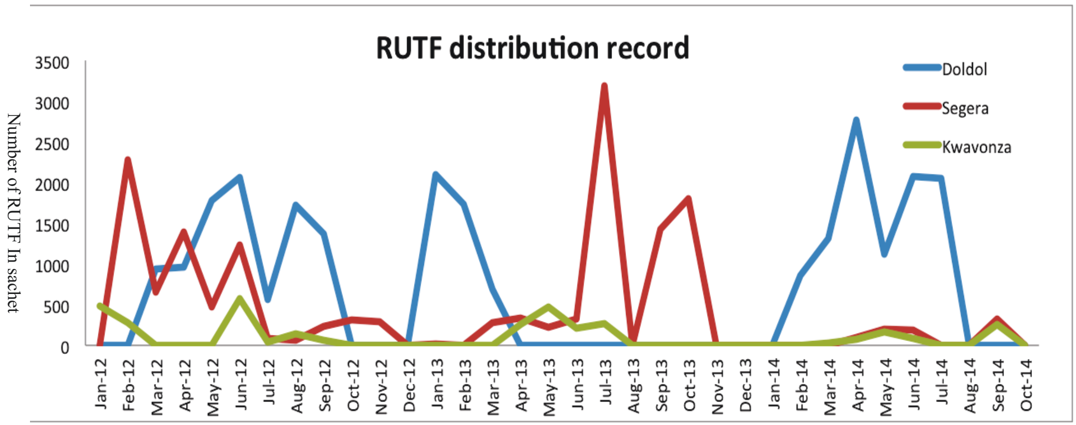


Figure 19: RUTF distribution record (number of sachets) from Doldol, Segera and Kwazonza end facilities (line chart), processed from Stock Control Card.

Taking into consideration our criteria for selecting the appropriate forecasting method (see Section 4.2) and characteristics of available data at this level, we suggest the following simple time series 3-month MA:

$$\boldsymbol{F_t = (D_{t-1} + D_{t-2} + D_{t-3})/3}$$

In the case that a stockout occurs within the three months previous to the forecasted period, which is not uncommon in our data set, forecasting based on historical RUTF demand is unfeasible or it would lead to great errors. Therefore, we have developed a time series model of 3-month MA based on SAM caseloads, which consists of the number of children affected by SAM and registered in the IMAM program (Community-Based Management of Acute Malnutrition), or the OTP. The SAM caseload data at this level is required to be documented locally by nutritionists. For a given end facility, the 3-month forecast MA based on SAM caseload is:

$$\boldsymbol{F_{i\,t} = d_i(SC_{i\,t-1} + SC_{i\,t-2} + SC_{i\,t-3})/3,}$$

where $F_{i\,t}$ is the RUTF demand forecast of facility i during month t, d_i is the consumption pattern, $SC_{i\,t}$ is the number of SAM caseloads at facility i for month t. Depending on availability of continuous data, d_i can be calculated as follow:

$$d_i = \frac{\left(\frac{D_{i1}}{SC_{i1}} + \frac{D_{i2}}{SC_{i2}} + \cdots \frac{D_{i\,t-1}}{SC_{i\,t-1}}\right)}{t-1},$$

where $D_{i\,t}$ is the RUTF observed demand at facility i during month t. d_i is calculated based on records from a single facility i, we cannot generalize such index to sub-county or county level.

To confirm the effectiveness of 3-month MA, we have also tested the Naïve, Exponential Smoothing (ES), and the two-month MA with available data from Doldol and Kwavonza dispensaries (Kwavonza has not been considered because there was not enough consecutive data available at that facility), using the Root Mean Square Error (RMSE) as the measurement of quality. The RMSE is the square root of the MSE, which is the arithmetic mean of the sum of the squares of the prediction errors.

2-month MA model:

$$\boldsymbol{F_t = (D_{t-1} + D_{t-2})/2.}$$

ES model:

$$\boldsymbol{F_t = \alpha D_{t-1} + (1 - \alpha) F_{t-1}.}$$

In these two models, F_t is the forecasted demand for period t, D_t is the observed demand at period t, and α is the demand smoothing parameter comprised between 0 and 1. α determines the level at which previous observations influence the forecast, the closer it is to one, the more weight is given to the real observed demand. MS Excel Solver has been used to optimized α.

Results are shown in Table 4. The 3-month MA has the smallest RMSE (213) in Kwavonza case and the second smallest RMSE (681) is observed for the Doldol case. However, in terms of simplicity, the ES method requires more professional skills and tools (e.g., using the MS Excel Solver to find the optimal α), which may be unfeasible for a nutritionist at rural clinic where computers are not available. In order to have the forecasting model easily implemented, we suggest using 3-month MA despite the fact that it has a slightly larger RMSE that that of the ES in some cases (e.g., at Doldol the RMSE of the 3-month MA is 681 and RMSE of the ES is 659).

Doldol	Demand	Naïve	MA *K*=2	MA *K*=3	ES	RMSE (Naïve)	RMSE (MA *K*=2)	RMSE (MA *K*=3)	RMSE (ES)
1	940					977	**799**	**681**	**659**
2	966	940							
3	1784	966	953		1784				
4	2064	1784	1375	1230	1784				
5	561	2064	1924	1605	1798				
6	1725	561	1313	1470	1736				
7	1375	1725	1143	1450	1735				

Kwavonza	Demand	Naïve	MA *K*=2	MA *K*=3	ES	RMSE (Naïve)	RMSE (MA *K*=2)	RMSE (MA *K*=3)	RMSE (ES)
1	600					**278**	**284**	**213**	**278**
2	150	600							
3	960	150	375		960				
4	540	960	555	570	960				
5	286	540	750	550	540				
6	464	286	413	595	286				
7	744	464	375	430	464				
8	483	744	604	498	744				
9	273	483	613.5	564	483				

Table 4: Performance of the ES and MA models at end facility level measured by RMSE, where "*K*" represents the number of observations (months) in the MA model.

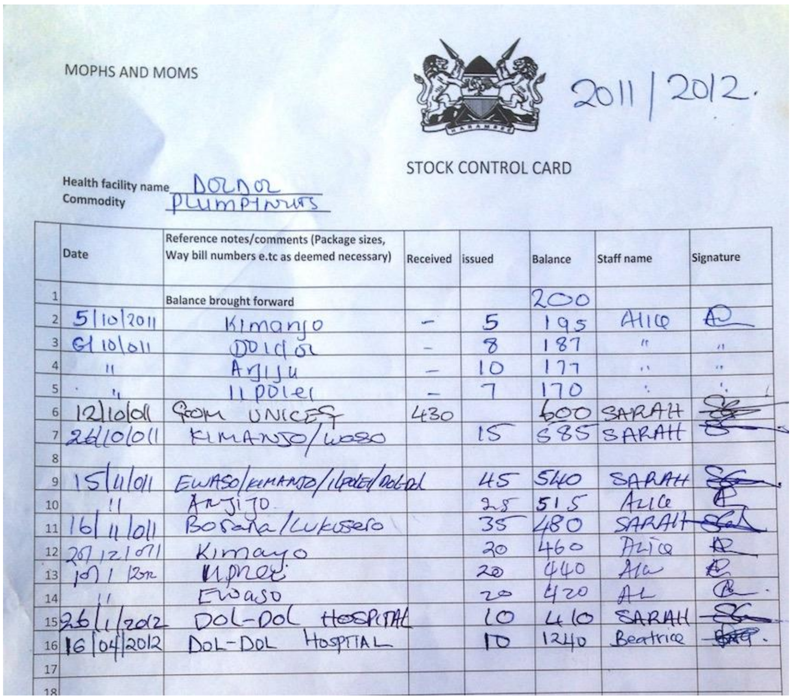
4.2.2 Forecasting Models at Sub-county Level

The position of Sub-county layer within the RUTF supply chain is illustrated in Figure 20. Distribution centers at sub-county level are mainly warehouses attached to the sub-county nutrition office, a district or a sub-county public hospital storehouse, or a backroom of a missionary. The SNOs are responsible for the management of the RUTF stocks at that level of the supply chain. The SNOs report to the CNOs about the nutrition status and the RUTF stock level, and make the RUTF supply requests on a monthly basis to the CNOs.

Figure 20: The layer of Sub-county DC within the RUTF supply chain.

At this level of the supply chain, we had access to a richer data set, including RUTF stock records, national warehouse outbound records (from Nairobi to sub-county warehouses), children nutrition status, and climate information, such as Standard Precipitation Index (SPI) and vegetation index. However, the data concerning RUTF supplies itself was still incomplete and discontinuous, and the nutrition status information was of weak quality due to poor reporting records. We have thus not made use of the causal methods since the geographical, demographic and socio-economic context is so different from one sub-county to another. In such a context, it would not be reasonable for an organization like UNICEF to build and maintain forecasting models for hundreds of sub-counties. Time series forecasting were therefore more appropriate in such a context.

Digitalized records of the past four year RUTF shipments to each sub-county were available from UNICEF's logistics service supplier (Kuehne+Nagel, K&N). However, as we observed shortages at both sub-county and end-facility levels, and back orders are not recorded, time series based on such shipment records would have lead to substantial underestimation of the real demand. Consequently, we have used data from local RUTF receipts and distribution records, which exist in hard copy only. An example of the Stock Control Card is shown in Figure 21.


MOPHS AND MOMS

2011 | 2012.

STOCK CONTROL CARD

Health facility name DOLDOL
Commodity PLUMPYNUTS

	Date	Reference notes/comments (Package sizes, Way bill numbers e.tc as deemed necessary)	Received	issued	Balance	Staff name	Signature
1		Balance brought forward			200		
2	5/10/2011	Kimanjo	–	5	195	Alice	
3	6/10/011	Doldol	–	8	187	"	"
4	"	Arjiju	–	10	177	"	"
5	"	Il poler	–	7	170	"	"
6	12/10/011	From UNICEF	430		600	SARAH	
7	26/10/011	KIMANJO/WASO		15	585	SARAH	
8							
9	15/11/011	EWASO/KIMANJO/ILPOLEI/DOLDOL		45	540	SARAH	
10	"	ARJIJO		25	515	ALICE	
11	16/11/011	Bosana/Lukusero		35	480	SARAH	
12	20/12/011	Kimanjo		20	460	Alice	
13	10/1/12	Ilpolei		20	440	Alice	
14	"	Ewaso		20	420	AL	
15	26/1/2012	DOL-DOL HOSPITAL		10	410	SARAH	
16	16/04/2012	DOL-DOL HOSPITAL		10	1240	Beatrice	
17							
18							

Figure 21: An example of a RUTF Stock Control Card of Doldol sub-county (2011-2012).

Current forecasting method

The RUTF orders from sub-county level are generated on a monthly basis by SNOs, it is then consolidated into quarterly orders by CNOs. According to the information collected from interviews with CNOs, the current forecasting method for each sub-county DC is based on naïve time series and a factor α:

$$\boldsymbol{F_q = D_{q-1} \times (1+\alpha)},$$

where F_q is the forecasted RUTF demand of quarter q and D_q is the observed demand of quarter q. In order to compute its level of safety stock or contingency stock, UNICEF sets α=10% if there is no apparent trend observed, α= 15% if there is a slight up-going trend observed, and α= 20% if a strong up-going trend is observed.

Proposed forecasting method

In this master thesis, we do not take into consideration arbitrary safety stock levels, but we concentrate on accurate demand forecasting. As shown in Table 5, the observations from sub-county DCs, aggregated quarterly (Q1, Q2, Q3 and Q4), are discontinuous and extremely limited in our data set.

Quarter	Kitui	Dol
2011		
Q4		170
2012		
Q1		50
Q2		10
Q3	259	
Q4	41	
2013		
Q1	297	35
Q2	177	179
Q3	206	199
Q4	57	
2014		
Q1	100	86
Q2	101	94
Q3	131	47

Table 5: Quarterly RUTF demand record (number of cartons) for Kitui Central and Doldol.

As previously, we have compare again the previously mentioned three forecasting techniques (2-month MA, 3-month MA and ES). Naïve method was excluded since we had no access to historic records and cannot determine the α. The results are listed in Table 6 and Table 7, where "K" represents the number of observations (quarterly) in the MA models. Note that any missing value, we have taken the average of the previous and following observations.

Demand	MA K=2	MA K=3	ES	RMSE (MA K=2)	RMSE (MA K=3)	RMSE (ES)
259			$\alpha = 0.8$	**71**	**90**	**96**
41						
297	150		297			
177	169	199	297			
206	237	172	201			
57	192	227	205			
100	132	147	86			
101	79	121	97			
131	101	86	100			

Table 6: Performance of ES and MA models at Kitui Central measured by RMSE.

Demand	MA K=2	MA K=3	ES	RMSE (MA K=2)	RMSE (MA K=3)	RMSE (ES)
35			$\alpha = 1.0$	**54**	**58**	**49**
179						
199	107		179			
142	189	138	195			
86	171	173	152			
94	114	142	99			
47	90	107	95			

Table 7: Performance of ES and MA models at Doldol measured by RMSE.

From the results shown in Tables 7 and 8, we can observe that the performance of the ES model is not stable, ranking from the lowest to the highest RMSE, and that the RMSE of the 3-quarter MA in both tests are bigger than that of 2-quarter MA. Based on the analysis of the available data, we thus suggest to use the simple 2-quarter MA at sub-county level:

$$\boldsymbol{F_q = \left(D_{q-1} + D_{q-2}\right)/\,2,}$$

where F_q is the forecasted RUTF demand of quarter q, and D_q is the observed demand of RUTF during quarter q.

As stated in Section 4.2.1, in the case that a shortage occurs in previous quarter(s) and that lost orders are not properly recorded, we should use a 3-quarter MA model considering the SAM caseloads and the consumption patterns:

$$\boldsymbol{F_{i\,q} = 3d_i\,(SC_{i\,q-1} + SC_{i\,q-2})/2,}$$

where F_{iq} is the forecast of quarter q at sub-county i, SC_{iq} is the SAM caseload of quarter q at sub-county i, d_i is the monthly demand of RUTF per caseload per quarter (consumption pattern) at sub-county i, with the same definition and computation as that of Section 4.2.1.

4.2.3 County & National Level

Figure 22 illustrates the position of National DC layer and the county layer within the Kenya RUTF supply chain. In this section, we develop a national and county level forecasting models at the same time for two reasons. First, from a material flow perspective, the "county level" is a virtual echelon in the current RUTF distribution network in Kenya. No physical facilities are in operation and no materials flow go through this level. However, the county level facilitates information and finance flows. Since 2010, the constitution of Kenya states that each county government should take major responsibilities of local development and welfare issues. Thus, the rich information concerning nutrition status should be elaborated and available at county level, and should be shared in electronic form. Second, once forecasting models for the 22 involved counties are developed, we can determine the national forecast by summing them up. Meanwhile, some adjustment on forecasting can also be done based on certain national level factors, such as national political stability. In this project, due to limited time and resources, we have considered a sample of three counties (Turkana, Laikipia and Kitui), and the national network in future discussion will be composed of these three counties only, but the idea would remain the same if the 22 counties would be considered.

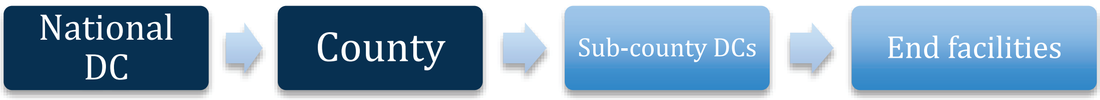


Figure 22: The layers of National DC and County on the RUTF supply chain.

Turkana is an arid county in the north of Kenya close to Sudan border, where food security has been constantly threatened. It is one of the biggest counties in terms of RUTF consumption rates and a sample county of IMAM. The program has been well implemented with relatively well-developed capacity and sufficient RUTF supplies. For this county, historic data is also better documented. The ASAL counties of Laikipia and Kitui have been included in our research because the implementation of IMAM program there needs to be improved based on a better understanding of the demand.

4.2.3.1 RUTF Demand Forecasting Models for Turkana County

Figure 23 shows the shipments of RUTF to Turkana, extracted from warehouse inbound and outbound records of K&N, and the RUTF demand calculated using historical supply shipments and recorded SAM caseload from DHIS2.

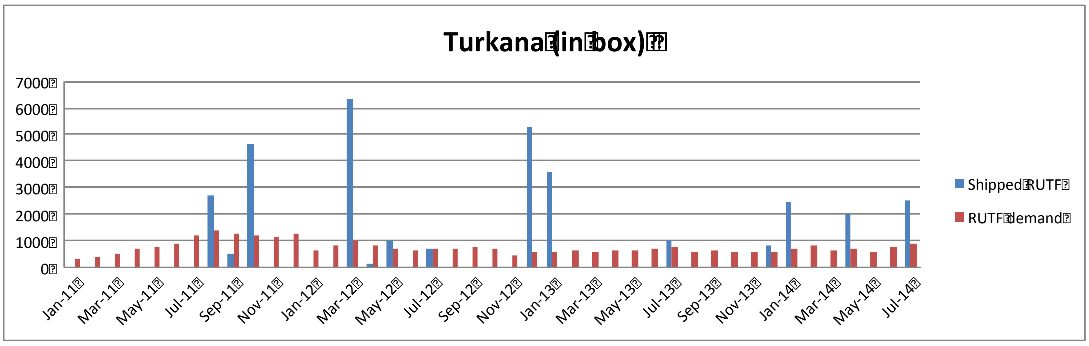


Figure 23: RUTF shipment record and RUTF demand of Turkana (2011-2014).

From Figure 23, we can observe that there is no evidence that the shipped quantities to Turkana and the number of recorded SAM caseloads in the county are correlated, which logically should be. According to our data analysis and interviews with the concerned nutrition officers, the shipped quantity of RUTF depends mainly on two factors: the quantity required (orders) and the inventory level at national DC. If the inventory level is high, like it was the case at the beginning of 2012, the nutrition officer at KCO may decide to "push" the supply down in the distribution network. Moreover, the replenishment interval is supposed to be fixed to three months, but it is adjusted due to various reasons in practice. For example, from August to October 2011 there were replenishments every month due to the crisis of 2011, and from August to November 2012, there were no shipment at all. The correlation between supply and demand is weak also because the demand is calculated based on historical supply. Since shortages are observed and supply is not sufficient, the demand is therefore under-estimated.

Consequently, in the rest of our thesis, instead of forecasting RUTF demand directly, we will apply causal methods to forecast the number of SAM caseloads. Once we have an estimation of the predicted SAM caseloads, the demand of RUTF can be computed by multiplying the SAM caseloads with the consumption pattern, as it is done in Section 4.2.1.

Causal methods to forecast SAM caseloads

We have extracted the SAM caseload data from January 2009 to July 2014 from the DHIS2, as illustrated in Figure 23. Due to various reasons, including the capacity development of IMAM program, we can observe a slight increasing trend from 2009 to 2014, even if this trend was interrupted by a spike in 2011 caused by a severe drought in East Africa. With limited observations, time series methods could not efficiently forecast the spikes like the one of 2011. Therefore, we try to include some relevant indicators in our model.

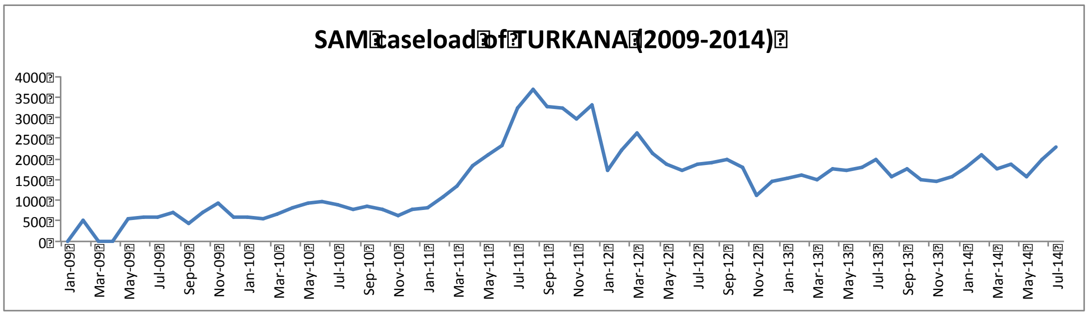


Figure 24: SAM caseloads for Turkana (2009-2014) (DHIS2, 2015).

Based on accessibility, updating frequencies and possible relevance, we haved investigated the following indicators:

- **%MUAC**: percentage of children under the age of five whose MUAC is less than 13,5cm (recently adjusted to 12,5cm). This index demonstrates the nutrition status of children at a given region and it is updated in the Drought Monthly Bulletin (DMB) by the National Drought Management Authority (NDMA) on monthly basis;
- **Monthly rainfall**: the average monthly rainfall of a given county, which is updated in the DMB by the NDMA on monthly basis;
- **Standardized Precipitation Index (SPI)**: a probabilistic meteorological indicator for the estimation of intensity and duration of drought events (Livada & Assimakopoulos, 2007). Table 8 shows the wet and drought period classification according to the SPI, which is available in the African Flood and Drough Monitor (AFDM) database;

Index value	Class
SPI ≥ 2.00	Extremely wet
1.50 ≤ SPI ≤ 2.00	Very wet
1.00 ≤ SPI ≤ 1.50	Moderately wet
-1.00 ≤ SPI ≤ 1.00	Near normal
-1.50 ≤ SPI ≤ -1.00	Moderate drought
-2.00 ≤ SPI ≤ -1.50	Severe drought
SPI < -2.00	Extreme drought

Table 8: Wet and drought period classification according to the SPI index (Livada & Assimakopoulos, 2007).

- **Three-month SPI**: It is the SPI that "provides a comparison of the precipitation over a specific three-month period with the precipitation totals from the same three-month period for all the years included in the historical record. It reflects short/medium-term moisture conditions and provides a seasonal estimation of precipitation" (NDMC, 2014). Figure 25 shows the three-month SPI of Loima in the past four years, which were extracted from AFDM database;

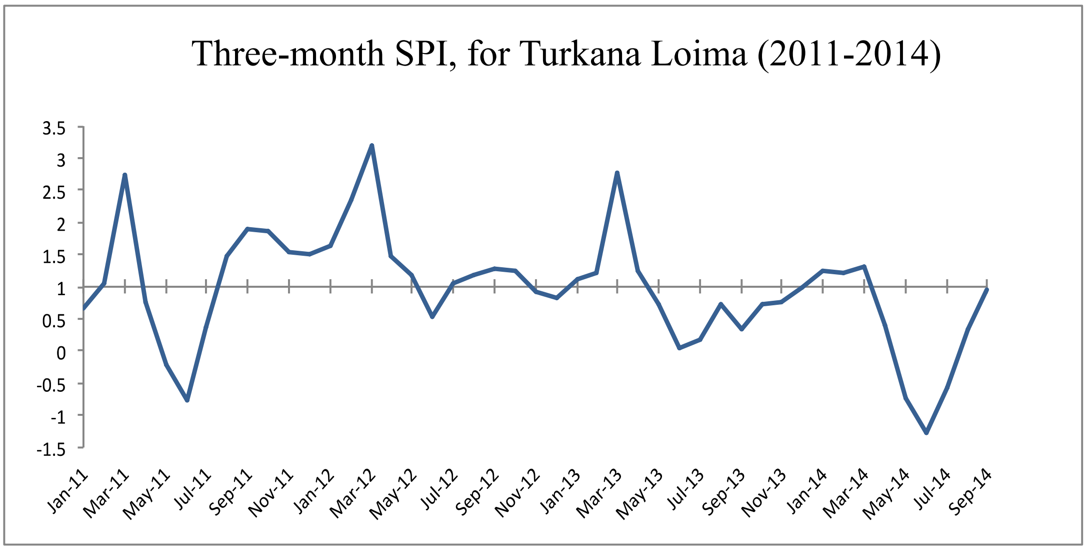


Figure 25: Three-month SPI, for Turkana Loima (2011-2014) (AFDM, 2014)

- **Normalized Difference Vegetation Index (NDVI)**: a satellite-based vegetation index that correlates strongly with aboveground net primary productivity (Pettorelli et al., 2005). Available on African Flood and Drough Monitor (AFDM, 2014);

- **Prices**: cattle price, goat price, maize price, etc., which is updated in the DMB by the NDMA on a monthly basis;
- **Term of Trade (ToT, cereal-meat price ratio)**: a ratio that indicates the pastoralist's purchasing power, which is updated in the DMB by the NDMA on monthly basis.

Due to resources constraints, it is difficult for the KCO and CNOs to do the RUTF supply planning and arrange replenishment on a monthly basis. As stated in previous sections, the planning at KCO and replenishment from Nairobi DC to counties (physically to sub-county DCs) are executed quarterly. Therefore, in this thesis, we have forecasted the county and national level demand on a quarterly basis. We have first screen these indicators to see which one(s) can predict the SAM caseload with lags of one, two, three or more months ($k \geq 1$, where k is the number of month lagged).

Indicator	***r***	*Number of observations*
% MUAC (k=1)	+0.278	28
% MUAC (k=2)	+0.146	28
% MUAC (k=3)	+0.372	28
% MUAC (k=4)	+0.622	27
% MUAC (k=5)	0.485	26
Rainfall (k=3)	+0.099	28
3-Mon SPI[6] (k=1)	0.046	28
3-Mon SPI (k=2)	-0.117	28
3-Mon SPI (k=3)	-0.194	28
3-Mon SPI (k=4)	-0.112	28
3-Mon SPI (k=5)	-0.079	28
NDVI (k=3)	-0.0749	28
Maize price (k=3)	-0.1239	23
ToT	-0.211	22

Table 9: Correlation analyses of different indicators, Turkana.

The correlation analysis has been run with MS EXCEL. In this thesis, we have considered a Pearson's coefficient $| r | > 0.3$ as statistically significant. The results of the correlation analysis are summarized in Table 9.

[6] We take the SPI point data from the town of Loima, the proximate center point of Turkana county, characterized by typical arid climate of the county.

According to the results in Table 9, only % MUAC with three to five months lag has a significant correlation with the SAM caseloads. A possible explanation could be that, before 2014, the NDMA considered MUAC<13.5cm as the threshold for SAM, and we have considered MUAC<12.5cm a determinant of SAM in this thesis as it is done by the UNICEF. Without medical interfere, i.e. treating patients with RUTF, the affected children's MUAC reading will be reduced from 13.5cm to 12.5cm within three to five months. However, there are not similar studies to support such assumption yet.

After testing, %MUAC has relatively better auto correlation and reasonable correlation with SAM caseloads with three, four and five-month lags. We developed the forecasting model using the %MUAC as follows:

$$\boldsymbol{F_q = \beta_3 M_{q-3} + \beta_4 M_{q-4} + \beta_5 M_{q-5}} \ ,$$

where F_q is the forecasted SAM caseload of quarter q, β_n is the coefficient of %MUAC for a n months lag, $M_{q\text{-n}}$ is the observation of %MUAC during the first month of quarter q-n. For instance, if we are at end of March 2015 and we have to forecast the demand of coming quarter (April, May and June). We use the %MUAC updated until January, multiply them with their respective SAM caseload coefficient (β_n), and sum them up to achieve the total SAM caseload of the coming quarter.

We ran the model and validated the results with the existing data (nine observations), and got a RMSE of 410. The results are shown in Table 10, where the annual quarters are denoted Q1, Q2, Q3 and Q4. We will compare these results with those of other models in following sections.

Quarter	Actual SC	Forecast SC	S.E	RMSE
2012-Q2	5699	5386	98078	410
2012-Q3	5744	5195	301797	
2012-Q4	4375	5181	648870	
2013-Q1	4654	5172	267851	
2013-Q2	5272	5110	26259	
2013-Q3	5285	5261	559	
2013-Q4	4510	4651	19766	
2014-Q1	5665	5315	122322	
2014-Q2	5422	5585	26475	

Table 10: RMSE of forecasting model with %MUAC.

Time series methods to forecast SAM caseload

Besides causal methods using the %MUAC indicator, we have also explored and compared different time series methods using solely historical data on SAM caseloads. The performances of the different methods measured with their resulting RMSE are summarized in Table 11.

Methods	Monthly forecast	Quarterly forecast
MA 2 months/quarter	364	1907
MA 3 months/quarter	395	2202
Exponential Smoothing	338	1393
Auto Regression 1 month/quarter	334	1442
Aggregation of Autoregressive Monthly forecast into quarterly one*	-	534

* Using autoregressive method to compute three monthly forecast, then sum the three months up to achieve the quarterly forecast.

Table 11: RMSE of SAM caseload time series methods.

Summary

- Among time series forecasting methods, forecasting on a monthly basis then sum up the monthly forecasts to obtain the quarterly forecast (Monthly Aggregation of Autoregressive) is more accurate than directly forecasting quarter demand. As shown in Table 11, the RMSE is reduced from 1393 (Exponential Smooth by quarter) to 534;

- For casual methods, the literature review and similar research papers have suggested numerous indicators, among them the most mentioned are %MUAC and SPIs. However, according to the available data collected for our research, only %MUAC is statistically significant. By using it into the forecasting model, we can further reduce the RMSE from 534 to 410.

4.2.3.2 RUTF Demand Forecasting Models for Laikipia County

For the county of Laikipia, since it covers agricultural favorable, semi-arid and arid regions, it is not possible for us to adopt the SPI data from any given location as it is not adequate. We focus on two set of data: %MUAC and SAM caseloads. According to records extracted from DHIS2 and Early Warning Monthly Bulletin, there is a rapid decrease of both %MUAC and SAM caseloads in Laikipia, as shown in Figure 26 and Figure 27. The observations of both tables suggest that the malnutrition among young children is decreasing very fast.

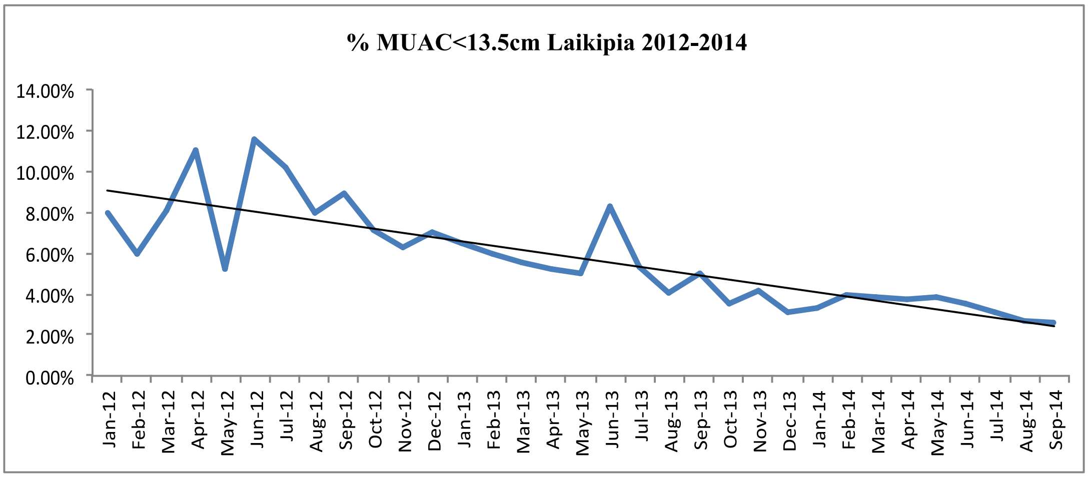


Figure 26: Laikipia rate of children under 5 MUAC <13.5cm (2012-2014) (NDMA, 2014).

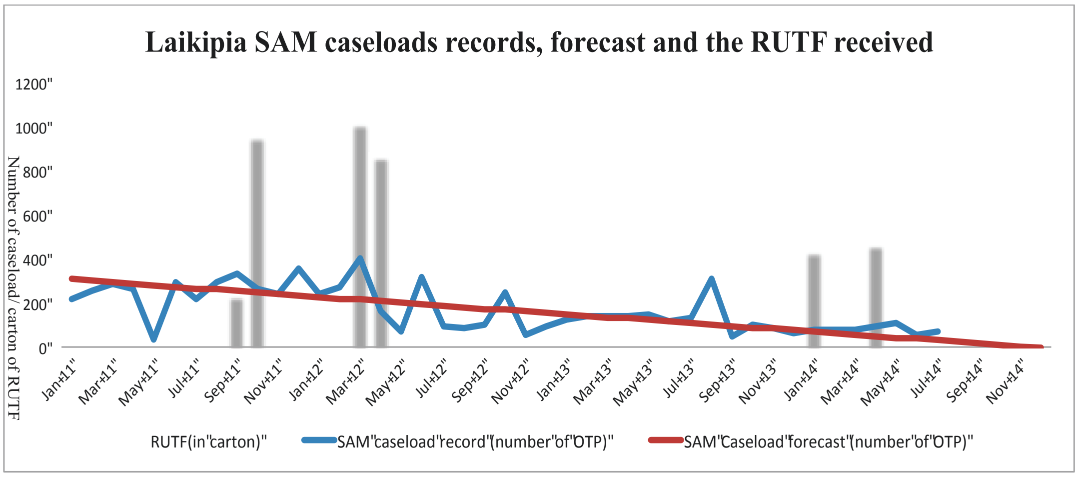


Figure 27: Laikipia SAM caseloads record, forecast & RUTF received (DHIS2, 2015; K&N, 2014).

However, it is unlikely that malnutrition among young children will completely disappear soon. Since the county is located across arid and semi-arid regions, and is less vulnerable compared with other arid and north boarder counties, Laikipia does not receive much attention in IMAM programs. With limited support, it suffers from humanitarian aid capacity bottlenecks. As shown in Figure 26, the replenishments to this county are highly irregular (e.g., no supply has been received in 2013). Also due to a decrease in capacity and resources, especially for outreach activities, the recorded SAM caseload decreased continuously. If we apply regular forecasting methods (as those for Turkana), the SAM caseload would tend to zero, and RUTF will no longer be needed, which does not represent what would really happen in practice. Moreover, fewer data were available for this county, the only available nutrition survey was conducted in August 2012. This survey was co-founded by UNICEF and partners such as the International Medical Corps (IMC), but the latter partner gradually withdrew its activities from Laikipia after 2012.

In this case, we could only improve the current forecasting mechanism by using data in the 2012 Nutrition Survey and in the last national population census conducted in 2009, which includes growth rate of population, percentage of children and percentage of children affected by SAM. The developed forecasting method is a three-step approach. These three steps are explained in the following.

Step 1. Computation of annual SAM caseload

In the first step, we need to estimate the annual SAM caseload among children by first calculating the total population, then use percentage of young children to calculate the total number of children, and finally multiply the number of children by the SAM rate to obtain the total number of SAM caseload among children.

Annual SC=Total Population× % children under 5 × Annual SAM rate

- Population in 2009: 399,227
- % Children under 5: 17.7%
- Population growth: 2.7%
- SAM rate: 2.30%

SAM caseload (2012) = 399,277 × $(1+2.7\%)^3$ × 17.7% × 2.3% =1,761

SAM caseload (2014) = 399,227 × $(1+2.7\%)^5$ × 17.7% × 2.3% = 1,857

Step 2. Computation of quarterly SAM caseload

It is worth noting that seasonality of %MUAC and SAM caseload is observable in Laikipia, as shown in Figure 28. The third quarter has much higher number of SAM caseloads than other quarters, whereas the second quarter has the lowest number of caseloads.

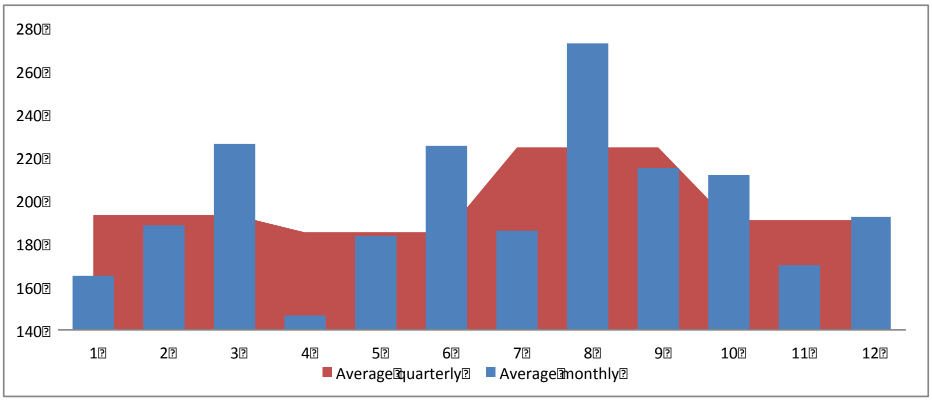


Figure 28: Distribution of the number of SAM caseloads in Laikipia (DHIS2, 2015; UNICEF, 2015; K&N, 2015).

We can further determine the quarterly demand (or seasonal demand) as follows:

$$F_{SC\,q} = F_{SC\,a} \times S_q$$

Where $F_{SC\,q}$ is the forecast of the number of SAM caseloads of quarter q, F_{SCa} is the forecast of SAM caseload of the year a, and S_q is the average proportion of SAM caseloads of quarter q of a year.

Month/year	2010	2011	2012	2013	2014	Monthly average	Quarterly average	Proportion
Jan		218	242	122	79	165		
Feb		258	273	141	82	189	193	24.3%
Mar		290	401	138	75	226		
Apr	73	262	166	138	92	146		
May	555	34	69	148	112	184	185	23.3%
Jun	345	292	319	120	52	226		
Jul	408	220	94	134	72	186		
Aug	398	297	86	311		273	225	28.3%
Sep	375	332	102	51		215		
Oct	233	267	246	101		212		
Nov	294	241	56	87		170	191	24.1%
Dec	252	360	93	63		192		

Table 12: Calculation of quarterly proportion of SAM caseload in Laikipia (DHIS2, 2015; UNICEF, 2015; K&N, 2015).

Table 12 shows how the quarterly share of SAM caseload is computed. We first calculate the average SAM caseload of every month in the column “monthly average”, aggregate them into quarterly value in the column “quarterly average”. Then the quarterly share is achieved through dividing quarterly average value by annually average value, as listed in the column “proportion”.

Using the total number of SAM caseloads for 2014 and the quarterly proportion, we can calculate the quarterly number of SAM caseloads for 2014 as follows:

F_{SC1}=1857 x 24.3% = 451

F_{SC2}=1857 x 23.3% = 427

F_{SC3}=1857 x 28.3% = 526

F_{SC4}=1857 x 24.1% = 448

Step 3. Computation of quarterly RUTF demand

Once we have the quarterly estimation of the number of SAM caseloads, we can calculate the RUTF demand based on the consumption patterns of RUTF:

$$\boldsymbol{F_q = 3dF_{SC\,q}},$$

where F_q is the forecast of RUTF demand for quarter q, d is the average demand of RUTF per caseload per month, $F_{sc\,q}$ is the forecasted number of SAM caseloads for quarter q.

Limitations and recommendations

First, since we only had SAM caseload data for the past five years, the quarterly calculated portion may not be reliable, and it should be updated continuously. Second, the SAM rate among children is not necessarily stable along the years. More nutrition surveys should be carried out in the future to update SAM rates as frequently as possible to achieve more accurate forecasting. Third, since the recorded SAM caseload is much lower than the actual one, and we obtained different value from other statistics institute, it is difficult to validate such model.

4.2.3.3 RUTF Demand Forecasting Models for Kitui County

Kitui is a large county that covers both arid and semi-arid areas. The RUTF demand forecasting is more challenging in this region due to the fact that this county has recently been merged to the district of Mwingi (a district that become a part of Kitui county after 2012), a district that has often been excluded from past county level surveys and reports. Moreover, according to available records as shown in Figure 29, both the monthly number of SAM caseloads and the aggregated quarterly numbers are random, no obvious seasonality or trend appears in the data. There is even no apparent spike in 2011, when serious famine affected the East Africa. According to our field studies, the previous supplies (RUTF shipments) have been too much adjusted, i.e. being arranged according to the stock level of RUTF at National DC instead of the actual reported demand of the county. Therefore, the quantity of RUTF shipped does not follow the number of SAM caseloads correctly.

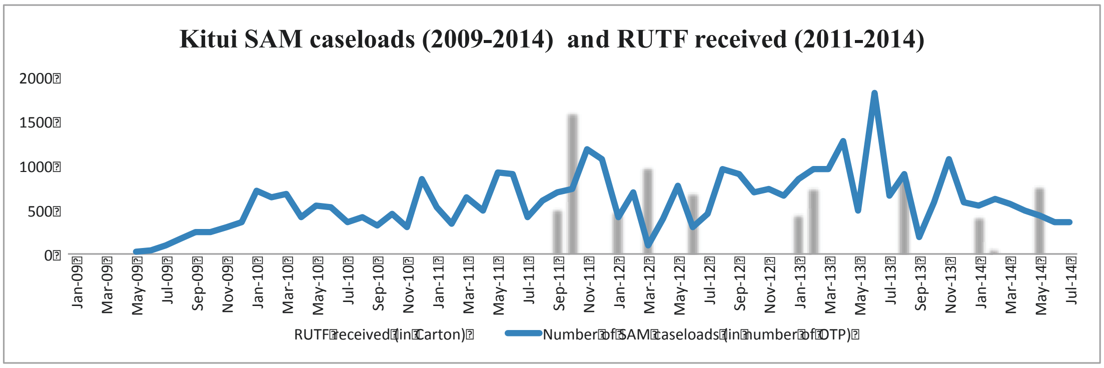


Figure 29: Kitui number of SAM caseloads and RUTF received (DHIS2, 2015; UNICEF, 2015; K&N, 2014).

We have also extracted nutrition status and metrological data from DMB by NDMA on monthly basis, and we have conducted a correlation analysis. The results are shown in Table 13. Most indicators do not show a correlation with the number of SAM caseloads and some coefficients are counter-intuitive. For example, the SPI, which intuitively should be in negative relation with the number of SAM caseloads, is positive in the case of Kitui.

Indicators	*r*	*Number of Observations*
% MUAC (*k*=3)	+0.123	26
% MUAC (*k*=4)	+0.100	26
% MUAC (*k*=5)	+0.233	26
SPI	+0.311	30
NDVI (*k*=3)	+0.146	27

Table 13: Correlation analyses of different indicators in Kitui.

To predict the number of SAM caseloads in Kitui, neither time series method nor causal method is applicable. We had to apply the same three-step forecasting model that has been used in Laikipia, which is based on the Nutrition Survey of Kitui executed in 2013 and the last national population census in 2009. The following parameters have been considered:

- Population in 2009: 1,012,709;
- % of children under 5: N/A (estimated at 17.7% as Laikipia, since two counties have similar geographic, economic and social conditions);
- Population growth: 2.1% (Nitration Survey, 2013);
- Estimated population distributions: 70% mixed farming zone and 30% marginal mixed (Nitration Survey, 2013);
- SAM rates: 0.3% for Mixed farming zone and 0.9% for marginal mixed farming zone (Nitration Survey, 2013).

The three steps of the RUTF demand forecasting model for Kitui are as follows:

Step 1. Computation of annual SAM caseload

Annual SC = Total Population× % children under 5 × Annual SAM rate

$$\text{SAM caseload (2012)} = 1{,}012{,}709 \times 70\% \times (1+2.1\%)^3 \times 17.7\% \times 0.3\% + 1{,}012{,}709 \times 30\% \times (1+2.1\%)^3 \times 17.7\% \times 0.9\% = 915$$ [7]

Step 2: Computation of quarterly SAM caseload

Quarter	2009	2010	2011	2012	2013	2014	Proportion
Q1		2022	1524	1219	2753	1738	25.3%
Q2		1488	2308	1461	3585	1284	27.7%
Q3	513	1100	1719	2330	1735		20.2%
Q4	916	1601	2973	2091	2233		26.8%

Table 14: Calculation of quarterly proportion of SAM caseload in Kitui (DHIS2, 2015; UNICEF, 2015).

Using data from Table 14, we can obtain the quarterly forecast on number of SAM caseloads.

Step 3: Computation of quarterly RUTF demand

We have calculated the RUTF demand based on the consumption patterns of RUTF, as stated in the Laikipia case. Let us mention that such method also suffers from the limitations listed in Sec.4.2.3.2.

4.3 Conclusion on Demand Forecasting Models

After studying different layers of the RUTF supply chain in Kenya and the characteristics of a sample of three counties, as well as experimenting with different forecasting methods, we have a few insights to share.

At end facility and sub-county levels, due to poor access to up-to-date metrological and nutrition status data, and the limited resources such as computers and professional logisticians, the sophisticated causal methods are not feasible in such a context. We thus suggest adopting the simple two-month or three-month moving average methods, which have better RMSE than the current naïve method. At county level, we have to utilize different methods depending on the feature of the given county.

[7] The number is 948 according to *Outpatient morbidity in patients below 5 years of age in 2012*, KNSB.

In counties where nutrition status data (e.g. number of SAM caseloads) and RUTF records are well documented and reliable, such as Turkana, causal methods that include indicators (e.g., SPI and %MUAC) should be taken into consideration. However, each indicator should be carefully qualified since not all indicators are applicable in all counties. The SPI might be an efficient indicator in some counties. Nevertheless, in our experiment with the data from the county of Turkana, the correlation between SPI and the number of SAM caseloads is very weak. For the counties with capacity bottleneck in IMAM program (such as Laikipia), and where the nutrition status data may be misleading or the counties where the quality of concerning data are questionable (such as Kitui), we suggest to use qualitative measures based on previous nutrition survey and census.

Based on the lessons drawn from our research, in order to enhance the information flow on the supply chain and facilitate the future attempts on demand forecasting, we suggest that UNICEF and the other stakeholders put more efforts in collecting, documenting and sharing of data, especially the data about RUTF stock level and SAM caseloads. Funds and budgets should be made available to invest in IT infrastructure. Regarding the DHIS2, all the RUTF commodity distribution and consumption data should be shared on this platform. Some important data (e.g. number of SAM caseloads) should be updated with shorter delay. The current three months' delay for updating information of SAM caseloads in the DHIS2 greatly increases the difficulties of forecast modeling and reduces the robustness of forecast results.

CHAPTER V

INVENTORY MANAGEMENT MODELS

"Inventory planning and control are crucial in most organizations… … relying on emergency orders and having stock-outs could detrimental and extremely costly."(Malakooti, 2013)

In this chapter, we will focus on the RUTF inventory management (IM) at the national level. In Section 5.1, we review the basic concepts in IM and the inventory control systems; in Section 5.2, simulations will be used to identify the best IM model to manage the RUTF inventory at a national level.

5.1 Overview of Inventory Management

To facilitate the simulation development and discussion in the following sections, in this section, we will introduce some basic concepts in IM. These include different inventory control systems, such as the EOQ model, the (*s, Q*) model, the (*R, S*) model and the (*R, s, S*) model.

5.1.1 Basic Concepts

Before introducing inventory management systems, we have to clarify some basic concept, based on Malakooti (2013), Axsäter (2007), Chopra and Meindl (2007) and APICS Dictionary (2013):

- *Safety stock:* the extra inventory kept beyond the projected demand to protect against fluctuations due to the uncertainty of demand or failure of production or transportation systems;
- *Ordering cost:* all costs that do not vary with the size of the order but are incurred each time an order is placed;
- *Acquisition cost:* the average unit price of material purchased, which can be subject quantity discounts;
- *Holding cost:* the cost of carrying one unit in inventory for a specified period of time (usually one year);

- *Shortage cost (Stock-out cost):* the cost for not fulfilling the demand for one unit of product for one period;
- *Backorder:* an unfilled customer order or commitment, an immediate (or past due) demand against an item whose inventory is insufficient to satisfy the demand;
- *Reorder point (ROP):* preset inventory level where, if the total stock on hand plus on order falls to or below that point, action is taken to replenish the stock;
- *Order-up-to-level:* the quantity up to which the inventory position is raised by placing a replenishment order.

5.1.2 Inventory Control Systems

The Inventory control systems can be classified differently from different perspectives:

- Number of products: Single product & multiple products. We are dealing with a single product –RUTF;
- Number of echelons: Single echelon & multiple echelons. We focus only on the national echelon;
- Number of periods: Single order lot size (newsboy problem) & multi period. Since the RUTF is ordered regularly in the long run, its inventory control system should be a multi period one;
- Nature of demand:
  - ➢ Deterministic: demand is known in advance with certainty
  - ➢ Stochastic: demand is not known in advance with certainty
  - ➢ Static: demand is stable over time
  - ➢ Dynamic: demand varies from one period to the next

  The assume demand of RUTF is stochastic.
- Type of replenishment:
  - ➢ Continuous review system: Replenishment with variable interval and fixed order quantity, e.g., the EOQ model and the (*s, Q*) model;
  - ➢ Periodic review system: Replenishment with fixed intervals and a variable order quantity, e.g., the (*R, S*) model, the (*R, s, S*) model.

To find the best replenishment system is one of the goals of this thesis.

The essential advantages and disadvantages of two replenishment policies are summarized by Mc Guire (2011) in Table 15.

	Advantages	**Disadvantages**
Continuous Review system	•Time and resourcing consuming. •Lower stock levels. •Quick reaction to shortages and stock-outs. •Shorter forecasting horizon and more accurate forecast.	•Larger number or orders. •Higher transportation costs.
Periodic Review system	•Can be operated manually. •Allows planning of reviews. Reduced workload. •Less frequent orders. •Lower transportation costs. •Updated stock on hand.	•Higher stock levels and cost. •Higher probability of stock outs. •Delay in reaction to shortages and stockouts. • Longer forecasting horizon and larger forecasting errors.

Table 15: Advantages and disadvantages of two inventory control policies, adapted from Mc Guire (2011).

In our research, since the data is incomplete and their quality is highly questionable, we use the simulation to test the performance of different models.

5.1.3 EOQ Model

The most well known and widely used inventory control model is the classic Economic Order Quantity (EOQ) model, which was originally published by Harris in 1913 (Harris, 1913). The model is based on following fundamental assumptions:

- Demand is constant and continuous;
- Ordering and holding cost are constant over time;
- The ordered quantity is delivered at the same time;
- No shortages are allowed.

In the EOQ model, the decision variable is the order quantity Q. The objective is to find the optimal Q, denoted by Q^*, which achieves the minimum total cost of the inventory system (ordering and holding cost). The necessary inputs are:

- D = annual demand of the product;
- C_o= ordering cost;
- C_a= unit acquisition cost;
- C_h=holding cost for one unit per year (sometimes expressed as a fraction of the product price);
- Annual ordering cost $= \frac{D}{Q} \times C_o$;
- Annual holding cost $= \frac{Q}{2} \times C_h$;
- Annual material cost= $D \times C_a$;
- Total annual cost $= \frac{D}{Q} \times C_o + \frac{Q}{2} \times C_h + \mathrm{D} \times C_a$.

As the product price is fixed and the demand is constant, the annual acquisition cost does not depend on Q. The fundamental tradeoff is between the ordering cost and the holding cost, as illustrated in Figure 30:

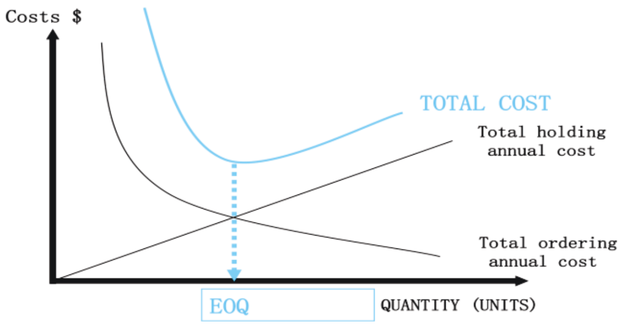


Figure 30: Effect of order quantity in EOQ model.

Then Q^*, is given by:

$$Q^* = \sqrt{\frac{2 \times D \times C_0}{C_h}}$$

The optimal ordering frequency n^* is:

$$n^* = \frac{D}{Q^*} = \sqrt{\frac{DC_h}{2C_0}}$$

The reorder point (ROP) is:

$$ROP = D \ x \ LT$$

where LT is the expected replenishment lead time.

One noteworthy point of the EOQ model is that total inventory cost is not very sensitive to the EOQ solution. “The cost goes up as the square root of the ratio of the actual order quantity to that of the optimal order quantity” (Dobson, 1988). This leaves management the flexibility to order a convenient lot size close to the EOQ rather than the precise EOQ.

5.1.4 (*s, Q*) Model, (*R, S*) Model and (*R, s, S*) Model

As stated in Section 2.1, the demand is normally uncertain in the humanitarian sector, and advanced information system and professional logisticians are often absent. In this context, continuous review system are not appropriate, especially those assuming stable demand, such as the EOQ model. The suggested IM models are periodic ones, e.g., the (*R, S*) periodic-review order-up-to-level model (Mc Guire, 2011), which is easy to understand and implement. In our research, we impose a service level and test the (*R, S*) models and the (*R, s, S*) model using cost as a performance measure. We then further compare these periodic review models with the (*s, Q*) model, which belongs to the continuous review system.

In the (*s, Q*) model, we continuously check the inventory position (stock on hand plus the stock on order). Whenever it drops to or below the preset reorder level *s*, a fixed order quantity *Q* will be ordered. In our model, we will approximate the optimal order quantity with the *EOQ*. This system is also called the two-bin system as it can be implemented with two bins. When the supply in the first bin is exhausted, the items in the second bin that is of size *s* will be used and an order is placed. Because of its simplicity, low cost and efficiency, the two-bin system is widely used in medical and humanitarian logistics (Battista et al., 2009).

The (*R*, *S*) model belongs to the periodic-review system. Every fixed interval *R*, the inventory position is reviewed. At the time of review, if the inventory position is below the preset order-up-to- level *S*, an order will be made bringing it back to t *S*.

The (*R, s, S*) model is also widely used in organizations without advanced information (Williams & Tokar, 2008). In order to avoid orders of small quantity, the reorder level *s* is preset. Every *R* units of time the inventory position is checked. If it is above *s*, then no action will be taken until the next review; otherwise, an order will be made, whose quantity will be the difference between the observed inventory position and the S.

5.2 Simulation of RUTF Inventory Management System in Kenya

In this thesis, we use a simulation model-based approach as an analytical tool to capture the stochastic behavior of different IM systems in Kenyan's RUTF distribution network. In order to compare the performance of the different inventory models in terms of service level and cost, we will allow the airlifting as an emergency shipment to cover the foreseeable shortage in the immediate three following months, and compare the results by evaluating metrics of inventory level, costs, cycle service level, and then give our insights of best practice.

The simulation of the complex RUTF supply chain is challenging, and its robustness is highly dependent on the correctness of the input data. Since the demand data at a sub-county and end facility levels are incomplete, we will focus on the IM system at the national level and identify the good inventory control policies for UNICEF Kenya.

For confidentiality purposes, certain unpublished data used in our simulations, i.e. the costs information extracted from commercial quotes and contracts between UNICEF and its LSPs, have been manipulated.

In the remainder of this section, we will explain in more detail the problems we simulate, introduce the parameters and variables, present the development of simulation models and scenarios, discuss the results of simulations and provide our suggestions on IM.

5.2.1 Problem Statement

In this chapter, we consider the three counties of Turkana, Laikipia and Kitui, and consider using emergency shipment by air to cover certain shortages. The aim of our simulation analysis is to answer the following questions:

- Which of the following IM system is more competitive in terms of cost-effectiveness and service quality?

- Continuous Review system, such as the (*S, Q*) model
- Periodic Review system, such as (*R, S*) and (*R, s, S)* models

- If the periodic review system is better than the continuous one, which review interval *R* will be the best: 3 months, 6 months or 12 months? As explained in previous sections, due to capacity and resources constraints, it is difficult for KCO to arrange inventory review and replenishment every month. Therefore, we propose the reviews on a quarterly, semi-annual and annual basis, which may be more compatible with the existing review system (quarterly review at national level).

5.2.2 Parameters and Variables

Before listing the IM systems we want to analyze, we first have to identify the available products. There are two origins of products:

- "Plumpy' Nut" from the manufacturer Nutriset in France;
- "INSTA" from the local manufacturer INSTA in Kenya.

However, since there are two modes of transportation from France to Kenya, by sea and by air, and the different transport modes will have a substantial impact on the landing cost (product cost plus transport and handling cost), we have classified the products into three categories: Nutriset by sea, Nutriset by air and INSTA Kenya (by truck).

5.2.2.1 Acquisition, Holding and Ordering Cost

Since the French producer quotes in EURO and the Kenyan one in USD, we first need to convert all quoting prices into USD. Then international transport (shipping from Le Havre port in France to Mombasa port in Kenya) and inland transport (trucking from Mombasa port to National DC at Nairobi) are charged in USD. However, since the historic shipping invoices are documented at UNICEF SD, and we don't have access to them, the international transport costs used in our simulations are estimations we extracted from the web-based quoting systems, such as the World Freight Rates, and are confirmed by logistics officers at the Logistics section KCO. The approach that the officers mainly used to calculate the approximate shipping cost is to look at the difference between the final payable amount and product ex-work costs. Handling fees such as port handling and costumes clearance are in Kenyan Shilling (KES). We also need to convert all these costs into USD. Exchange rates EUR to USD and KES to USD are referred to those published by the World Bank in January 2015. The total C_a, which is also called the landing cost, includes product cost, transport cost and handing cost. Nutriset by air has the highest C_a due to very high airlifting cost, Nutriset by sea has the lowest C_a. The detailed cost conversions are compiled in Table 16.

Cost (per carton)	Nutriset by sea	Nutriset by air	INSTA Kenya
Price (FCA)	€ 55.20	€ 55.20	$80.04
Ex.Rate (EUR:USD)	1.136	1.136	1
Price (USD)	$62.70	$62.70	$80.04
Int'l Trans' cost	$3.36	$74.45	0
Inland trans.	$2	$2	0
Handling fee in kenya (KES)	33	34.5	21
Ex' rate (KES:USD)	0.01091	0.01091	0.01091
Total (USD)	**$67.92**	**$139.04**	**$80.27**

Table 16: Calculation of acquisition costs (UNICEF SD, 2014; K&N, 2012).

The C_o of RUTF for KCO is composed of buyer's remuneration and administration costs, the processing fee charged by K&N for handling international shipmen and the minimum transport charges. Nutriset by sea has the highest C_o and INSTA Kenya has the lowest one. The C_o calculations are compiled in Table 16. The UNICEF buyer's labor and administration cost per order is estimated at 7.5 USD. K&N charges document processing fee (e.g. import customs clearance) of 18000 KES per shipment by sea and 6375 KES per shipment by air, regardless of the quantity of RUTF shipped. A shipment handling fee of 75 USD is also charged per shipment by air. There is also minimum transport charge of 120000 KES for each shipment from Mombasa port to Nairobi warehouse, and minimum charge of KES 9000 per shipment from Nairobi airport to the warehouse. Since these charges are not dependent on the order quantity, we categorize them as ordering cost. INSTA Kenya is responsible for the delivery from their facility to K&N Nairobi warehouse, so no more process fee or transport charge will occur.

Cost (per carton)	Nutriset by sea	Nutriset by air	INSTA Kenya
Buyer time & administration	$7.50	$7.50	$7.50
K&N process fee (KES)	18000	6375	
Minimum Transport (KES)	120000	9000	
Minimum Handling (USD)	-	$75	
Exchange rate (KES:USD)	0.01091	0.01091	
Total (USD)	**$1,513.08**	**$250.25**	**$7.50**

Table 17: Calculation of ordering costs (K&N, 2012).

The storage of RUTF at the national level is at Nairobi DC (K&N Nairobi warehouse). The warehousing cost is quoted at KES 241.05 per carton per year by K&N and obsolescence cost is estimated to be 0.25% of C_a per year. Nutriset by sea ranks the highest and Nutriset by air the lowest. The C_h calculations are compiled in Table 18. The warehousing cost includes the warehouse storage charge, which is quoted at per MT or CBM per day and we convert it into per carton per year by volume. The inbound outbound handling fee that charged per MT or CBM, we also convert it into per carton per year by volume. (We estimate the volume of RUTF per carton is 0.022 CBM). The obsolescence rate is the rate of damage and loss of products, which is estimate to be 0.25%.

Cost (per carton)	Nutriset by sea	Nutriset by air	INSTA Kenya
Warehousing cost(KES)	241.05	241.05	241.05
Exchange rate (KES:USD)	0.01091	0.01091	0.01091
Warehousing cost(USD)	$2.63	$2.63	$2.63
Acquisition cost(USD)	$67.93	$139.03	$80.27
obsolescence rate %	0.25%	0.25%	0.25%
obsolescence cost(USD)	$0.17	$0.35	$0.20
Total(USD)	**$2.80**	**$2.98**	**$2.83**

Table 18: Calculation of holding costs (K&N, 2012).

5.2.2.2 Demand and Lead-time

As explained in Sec.4.2, we can calculate the demand using SAM caseload and consumption pattern as following:

Demand = SAM caseload x Consumption pattern

We aggregated the monthly SAM caseload of three counties (2010-2014) into a total value, and used ARENA Input Analyzer to determine the distribution of the 43 observations. The analysis gave the triangle distribution of (1560, 2350, 4720)，where 1560 is the minimum value, 2350 is the most likely value and 4720 is the maximum value, as shown in Figure 31 :

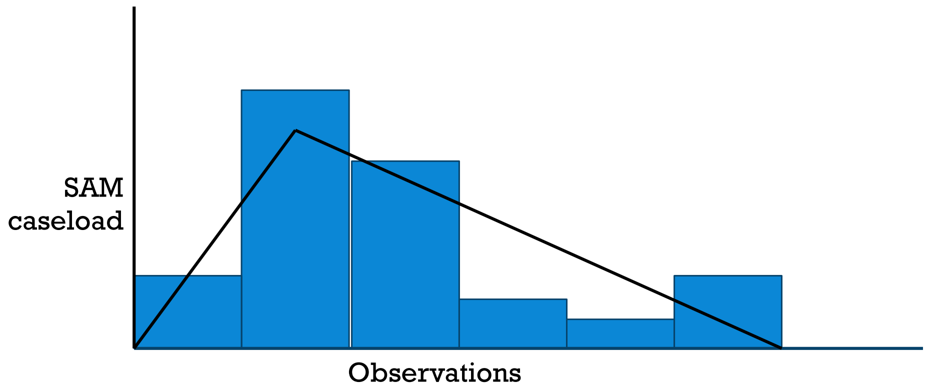


Figure 31: Distribution of SAM caseload provided by ARENA Input Analyzer.

We have the SAM caseload multiplied with the estimated consumption pattern (demand per affected child per month) suggested in the *National Guideline for Integrated Management of Accurate Malnutrition* (2009): "In general each child will require 112 sachets of RUTF a month, and we round this up to 120 sachets".

However, according to field observations and calculations, in certain regions and during certain periods, the consumption per caseload per month can be as low as 44 sachets or as high as 140 sachets. We assume that the consumption pattern follows a triangle distribution as well with (44, 120, 140). This sachet consumption converted into cartons become (0.293, 0.8, 0.933).

We multiply the two triangle distributed variables using @risk. The resulting probability distribution is depicted in Figure 32, the mean is 1943 and the mode is 1688.

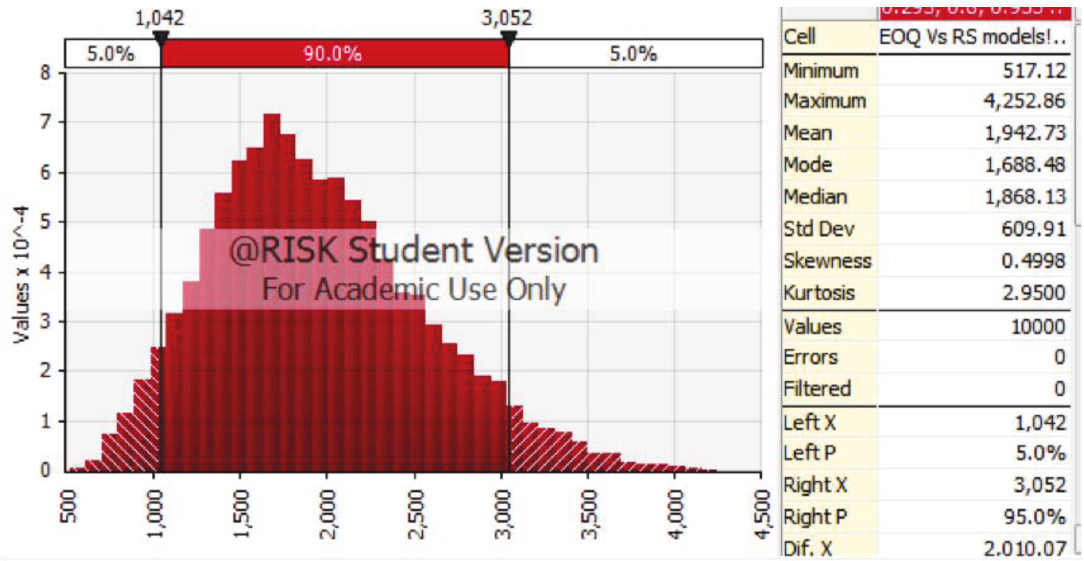


Figure 32: Distribution of RUTF monthly demand.

Regarding the lead-time, since we have only very limited observations (about 40 observations for Nutriset by sea, six by air and four for INSTA Kenya), we take the mean and round it up. The rounding up can facilitate the construction and solving of simulation models, leave the models more buffer against uncertainty, and have been confirmed by officers of UNICEF Kenya as reasonable.

- Nutriset by sea: 2.7 months, round up to 3 months;
- Nutriset by air: 0.9 month, round up to 1 month;
- INSTA Kenya: 3.6 months round up to 4 months.

The lead-time of INSTA Kenya is longer than Nutriset by sea. In theory, it should be slightly more expensive than those shipped from France by sea, but much faster to supply. In reality, probably due to the fact that most raw materials are imported and that local manufacturing capacity is still under development, INSTA Kenya has no advantage neither in lead-time nor in acquisition cost.

Since the “INSTA Kenya” is dominated by “Nutriset by sea” in terms of both cost and lead-time, it will never be a choice in our model. Therefore, the probability to buy from INSTA Kenya will be excluded.

5.2.2.3 Order-up-to Level *S*, Order quantity *Q*, Reorder level *s*

For simplicity purpose, in this thesis, we assume that, in the *(R, s, S)* system the *S* is similar to that of the (*R*, *S*) system, and that the *s* is similar to that of (*s*, *Q*) system (Mc Guire, 2011).

Reorder level *s*

We introduce the *s* for periodic review models in order to avoid placing orders for small quantities, which is not economical. Also the fixed order quantity system requires the (*s*). As the demand is dynamic in our simulation, safety stock (*SS*) should be considered to hedge against such uncertainty.

The calculation of *s* takes into consideration the uncertainty of the demand during the expected lead time as following (Mc Guire, 2011):

$$s = \overline{D} \times LT + SS$$

where $\overline{D}$ is average demand, LT is lead-time and SS is the safety stock.

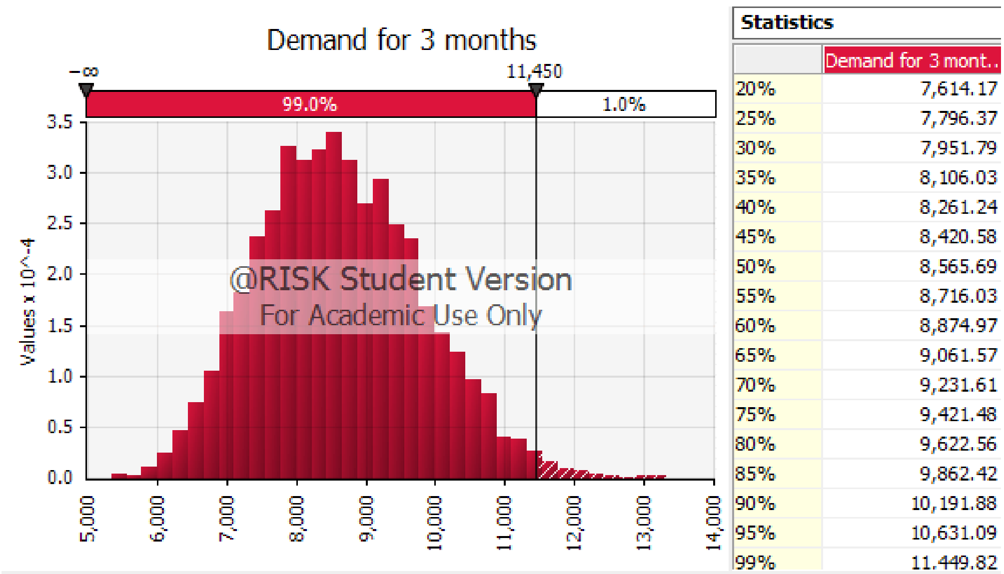


Figure 33: Distribution of RUTF demand for three months ($P = 99\%$).

We simulate the demand for three months also using @risk. We set the distribution of three months demand independently following the results in Figure 33, and then sum them up. We get the stock level required to cover the $\overline{D}$ during LT as well as the safety stock required to achieve the 99% service level, as shown in Figure 32. Such stock level is the Reorder level *s* for Nutriset by sea, and the *SS* can be reversely calculated as $s - \overline{D} \times LT$.

$s = 11450$

$SS = s - \overline{D} \times LT = 11450 - 8565 = 2885$

Order quantity *Q*

The order quantity Q of (s, Q) model can be calculated following the EOQ formula:

$$Q=\sqrt{\frac{2D\times C_o}{C_h}}\ .$$

We summarize the parameters and results in Table 19. TD here is the average total annual demand, achieved using @risk by summing up demands of 12 months. C_o and C_h are taken from Section 5.2.2.1

	TD (yearly, in carton)	C_o *(per caarton)*	C_h *(per carton)*	*Q (in carton)*
Nutriset by sea	26300	\$1,513.08	\$2.80	5332
Nutriset by air	26300	\$250.25	\$2.98	2103

Table 19: Calculation of order quantity Q.

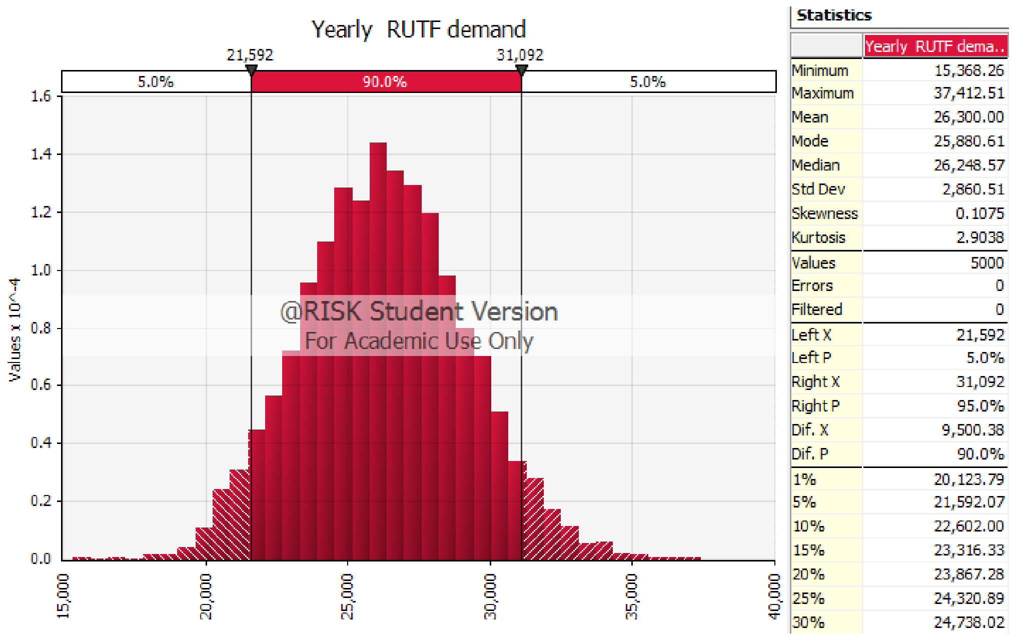


Figure 34: Distribution of yearly RUTF demand

Order-up-to level (*S*)

The formula of S is the following (Mc Guire, 2011):

$$S = \overline{D}\ \times\ (R + LT) + SS$$

where $\overline{D}$ is the average monthly demand, R is the review interval, LT is the lead-time and SS is the safety stock.

Following the same principal in calculation of Reorder level s, SS can be described as the difference between D_{max} (D_{max} for service level 99%) and $\bar{D}$ (the average demand, or the D for service level 50%) for the period of (R+LT). Then we can rewrite the formula as following:

$$S = \bar{D} \times (R + LT) + (D_{max} - \bar{D}) \times (R + LT)$$

$$= D_{max} \times (R + LT)$$

The sea transport will be prioritized in our decision making process since it is much less costly, the S should follow that of “Nutriset by sea”.

Since we will test the policies of R=3, 6 and 12 months, there will be three S accordingly. We simulate the demand of three durations, adjust the P to 99% in @risk, and achieve the results in Figure 35. We summarize the results in Table 20.

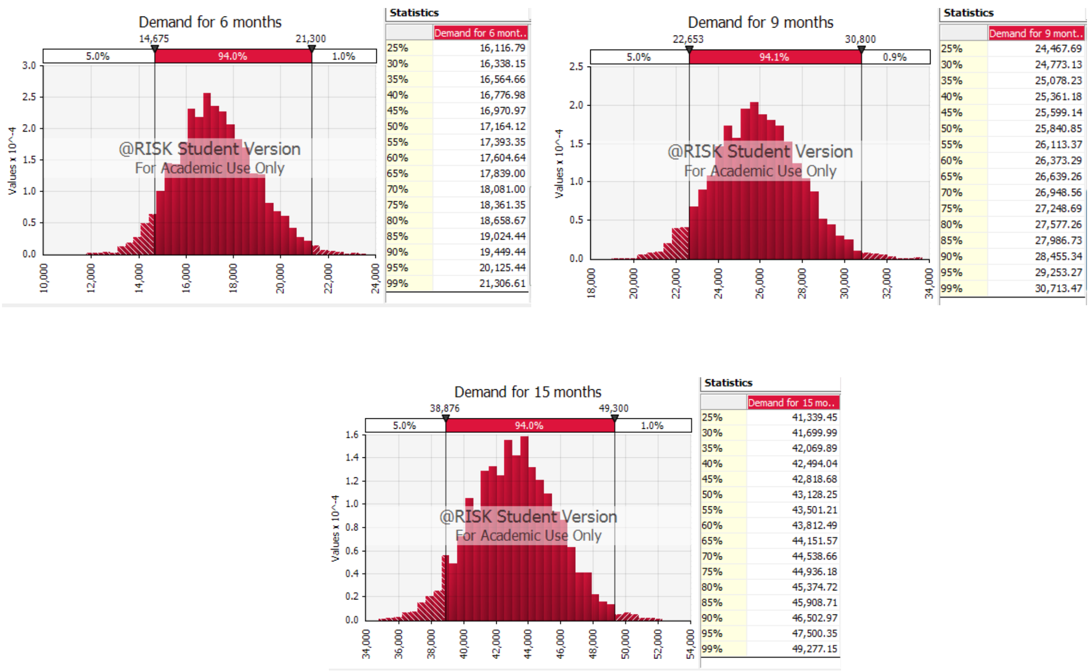


Figure 35 Distribution of RUTF demand for six, nine and fifteen months (P = 99%)

	LT(m)	*R(m)*	*Total Duration (m)*	*S (in carton)*
R(3)	3	3	6	21300
R(6)	3	6	9	30713
R(12)	3	12	15	49277

Table 20: Order-up-to level S for R is 3, 6 and 12 months.

As the LT for Nutriset by sea is fixed at 3 months, when the R ranges from 3 to 12 months, the total durations of interval become 6, 9 or 15 months. To cover 99% of the probability (P= 99%), the demands are 21300, 30713 and 49277 respectively, as shown in Figure 35.

5.2.3 Simulation Modeling and Programming

In this section, we focus on the construction of the simulation. We first introduce the generation of the random variable representing the demand of RUTF, then present the general assumptions and specific rules of the models.

5.2.3.1 Generating Demand

Since the lead-time is assumed to be fixed in our simulation, the only random variable is the demand D, which should be set according to the following rules:

For each replication, we generate demands of 60 consecutive months (five years).

The triangular distribution is used in each replication. Referring to the results presented in Section 5.2.2.2 and Figure 32, for the monthly RUTF demand, we used triangle (457, 1688, 4430). From Figure 32 we observe that the triangle distribution of monthly demand should be (517, 1688, 4252). However, since only the average and mode values in @risk Monte Carlo simulations are stable and robust, and the minimum and maximum varies randomly in different simulations, we only take the mode value of 1688 from @risk simulations. To calculate the D_{min} and D_{max}, we use the available data for SAM caseloads and the consumption patterns. Given that the monthly distribution of SAM caseload is (1560, 2350, 4720), and the monthly consumption of RUTF per SAM caseload is (0.293, 0.8 0.933), obviously, the D_{min} should be 456 (1560 SAM caseloads x 0.293 cases per SAM caseload = 457 cases), and the D_{max} should be 4430 (4720 SAM caseloads 0.933 cases per SAM caseload = 4430 cases).

MS Excel IF statement is used to generate the random numbers of such distribution, using following formula (Altiok & Melamed, 2010):

=IF (RN < ((Mode – Min)/ (Max – Min)), LS formula, RS formula),

note that *RN (*Random Number*)* refers to a cell containing a random number between 0 and 1.

LS formula (if expr. is true) = Min +SQRT (RN) (Mode − Min) (Max − Min)

RS formula (if expr. is false) = Max − SQRT (1 − RN) (Max − Mode) (Max − Min)

For each model, we simulate with 150 replications, belonging to three sets of scenarios. There are 50 replications for each scenarios.

- **Scenarios with seasonality**: Demand varies with a certain trend in a given period. In reality, the seasonality is not robust due to limited records. For simplicity, we assume that the upward and downward trends each takes six consecutive months, i.e., the demand increases in the first six month of each year, and it decreases in the latter half of the year. To capture such trends, as shown in Figure 36, we perform the following steps

   i. For the first six months of each year, we set six intervals between zero and one evenly (0 to 1/6, 1/6 to 1/3, 1/3 to 1/2, 1/2 to 2/3, 2/3 to 5/6 and 5/6 to 1) in ascending order;

   ii. We generate one RN within each interval;

   iii. We convert the RN into demand using the above mentioned Excel IF statement.

   iv. For the last six months of each year we set six intervals between one and zero evenly in descending order;

   v. We generate the RN and the demand as per the process described in step two and three. As a result, the demand we generate follows both certain trend (upward or downward) and the triangle distribution.

	Zone	RN	Demand
Month 1	0 – 0.166	0.099	1139
Month 2	0.167–0.333	0.267	1624
Month 3	0.334–0.500	0.478	1831
Month 4	0.500–0.667	0.630	2464
Month 5	0.668–0.833	0.791	2535
Month 6	0.834–1.000	0.920	3488
Month 7	0.834–1.000	0.951	3245
Month 8	0.668–0.833	0.762	2677
Month 9	0.500–0.667	0.613	2192
Month 10	0.334–0.500	0.380	1834
Month 11	0.167–0.333	0.271	1476
Month 12	0 – 0.166	0.166	1220

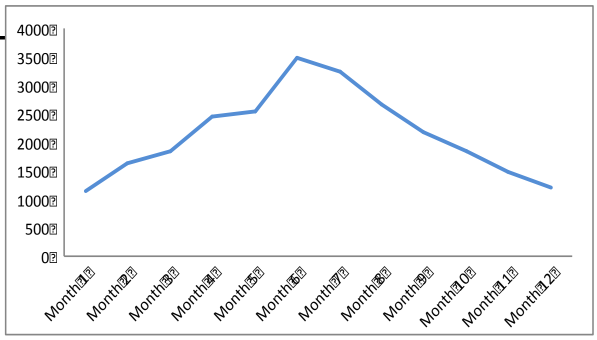


Figure 36: Construction of Scenarios with seasonality.

- **Scenarios with spike**: in the historical record, we have observed an abnormal rise of demand during certain years, such as the year of 2011. To further test how the different models respond to such unpredicted spikes of demand, we designed another round of simulation (five years x 50 replications) assuming that the demand of the second year doubled due to various reasons, as briefly illustrated in Figure 37. To generate the demands, we mostly repeat the five steps for scenarios with seasonality, only multiple the demands of the first six months of the second year by ratio ranging from 1.1 to 1.9, the multiple the demands of the last six months of the second year by ratio ranging from 1.9 to 1.1.

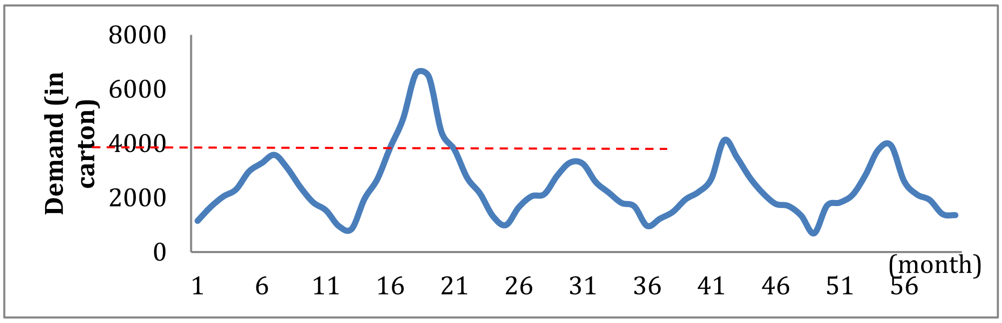


Figure 37: Demand variation scenarios with spike in the 2nd year.

- **Scenarios without seasonality**: We assume demand is stochastic, i.e. it is generated from an adequate probability distribution. Such a scenario simulates the variation of monthly demands we observed in certain counties, especially where the IMAM program is not well implemented and the RUTF inventory data is not properly documented, such as the county of Laikipia. As shown in Figure 38, the generation of demand follows two steps, generating RN ranging from zero to one, and converting them into demand using Excel IF statement as mentioned above.

	RN	Demand
Month 1	0.062	2747
Month 2	0.480	2600
Month 3	0.243	637
Month 4	0.712	2111
Month 5	0.507	1019
Month 6	0.130	3373
Month 7	0.972	2584
Month 8	0.929	2409
Month 9	0.958	1760
Month 10	0.239	1472
Month 11	0.666	2690
Month 12	0.586	1398

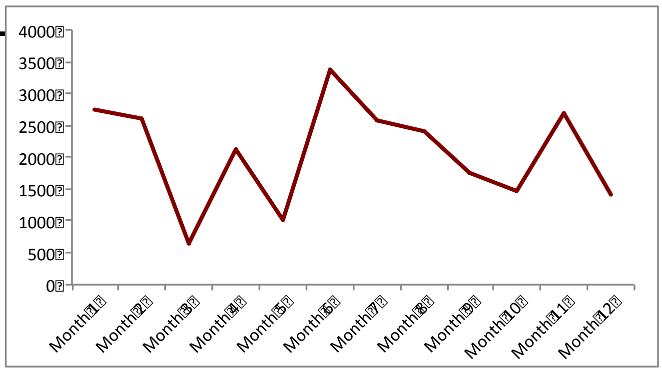


Figure 38: Construction of scenarios without seasonality.

To better visualize the difference between scenarios with and without seasonality, we illustrate them in the same graphic, in Figure 39.

Figure 39: Two scenarios of demand variation.

5.2.3.2 General Assumptions

Before describing the specific rules for the different models, we firstly list the general assumptions for all our models:

- The inventory level indicated will be that of the end of each month;
- The Stock Keeping Unit (SKU) in our simulation is a carton; If not specified otherwise, the basic time unit in our simulation is one month;
- To avoid the decrease of service level due to insufficient initial stock level, which is set manually, we let it be initially the order-up-to level *S*s. For the *(s, Q)* model, we adopt the *S* of (*R, S*) model with *R*=3 as the initial stock level.
- Lead-time by sea is preset to three months, and the one by air is one month;
- The prioritized transport method will be “by sea”; products lifted by air will only be ordered when a stock out is observed in the following three months, i.e., the total demand in the following three months is more than the on hand inventory at the time of review. Three months is the lead-time for transport by sea and we are able to forecast the demand of the following three month, as explained in Chapter IV.
- When the inventory level of a given month *t* is lower than the demand of the

immediate following month t +1, ordering by air cannot avoid the shortage since the lead-time for supply by air is one month. In such a case, cycle $t + 1$ will be marked as a "stock out" cycle, and the difference between demand of month t +1 and inventory of month t will be the "shortage", which is lost demand.

5.2.3.3 Specific Rules

(*s, Q*) model

In the (*s,Q*) model the ordering process will be triggered whenever the inventory is below preset reordering level *s*, which is 11450 for "Nutriset by sea", as calculated in Section 5.2.2.3. The order quantity (by sea) is to the EOQ, which should be 5332 cartons. No order quantity is prefixed for orders by air.

(*R, S*) models

The (*R, S*) models periodically review the inventory level with 3-months, 6-month or 12-month intervals. The ordering process will be triggered if the inventory level upon review is below a preset order-up-to-level *S*. The order quantity is the difference between *S* and the reviewed inventory position (inventory on hand + inventory on order).

(*R, s, S*) models

The (*R, s, S*) models also periodically review the inventory level with intervals of three months, six months or twelve months. The ordering process will be triggered if, after reviewing, the inventory level is below preset reordering level *s*, which is the same as that for (*s, Q*) model, orders should be placed. The order quantity is also the difference between Order-up-to level (*S*) and reviewed inventory position (inventory on hand plus inventory on order).

5.2.4 Results and Analysis

We use MS VBA to run the simulations on the models. To measure and compare the performance of different models, we have developed following metrics or performance indicators:

- Total demand, which should be approximately at the same level for all the models to ensure the comparability;
- Mean inventory level, which is highly relevant to the inventory holding cost;
- Number of orders by sea per year;
- Number of orders by air per year;
- Total cost per year, which includes the ordering cost and holding cost of orders shipped by sea, and extra ordering and transport cost caused by airlifting. The transport cost by sea is excluded as we integrated it into the acquisition cost, which is also excluded;
- Number of replenishment cycle with shortage (after airlifting is allowed to minimize foreseeable shortage in immediate following three months);
- Shortage quantity (after airlifting is allowed to minimize foreseeable shortage in immediate following three months);
- Cycle service level (CSL), defined as "the probability of not having a stockout in a replenishment cycle" (Chopra & Meindl, 2001):

$$CSL = 1 - \frac{\text{Number of unfulfilled cycles with a shortage}}{\text{Total number of replenishment cycle}}$$

- Fill rate (FR), which is "the long run average fraction of demand satisfied immediately using on-hand stocks" (Zhang & Zhang, 2007). In this thesis, we adapt the traditional approximation approach and calculate the FR as follows (Babiloni et al., 2012):

$$FR = 1 - \frac{\text{Unfulfilled demand from stock per replenishment cycle}}{\text{Total demand per replenishment cycle}}$$

5.2.4.1 Scenario with Seasonality

As depicted in Table 21, when the demand follows certain seasonality and does not fluctuate randomly, both continuous and periodic systems can cope with it efficiently, except the (*R, s, S*) model with *R*=12. The frequency of inventory review is essential for the control of cost. The (*s, Q*) model and all (*R, S*) models have CSL of 100% without any supply to be airlifted. Among (*R, s, S*) models, the ones with *R*=3 and *R*=6 can maintain the CSL at 100%, but extra shipping cost will occur due to airlifting.

When the review interval is fixed to three months, the (*R, s, S*) model requires approximately about 50% more budget than the (*R, S*) model. In the case that the review interval is fixed to six months, the (*R, s, S*) model and the (*R, S*) model have almost the same cost.

The (*R, s, S*) model with *R*=12 fails to maintain the CSL at 100% even though large quantity of supply need to be airlifted.

Scenario with seasonality	*s, Q*	*R,S (R=3)*	*R,S (R=6)*	*R,S (R=12)*	*R,s,S (R=3)*	*R,s,S (R=6)*	*R,s,S (R=12)*
Total demand (60 months, in carton)	131562	131421	131297	131566	131534	131212	131419
Mean inventory level (in carton)	8167	12689	19118	31549	9780	13035	21768
Number of orders by SEA per year	4.6	3.8	1.8	0.8	1.8	0.8	0.4
Number of orders by AIR per year	0.0	0.0	0.0	0.0	0.7	0.4	0.4
Total cost (in USD)	29858	41278	56254	89549	67581	54801	283319
Number of Ordering cycle with shortage	0.0	0.0	0.0	0.0	0.0	0.0	2.0
Cycle Service level (CSL)	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	60.0%
Shortage quantity	0	0	0	0	0	0	12822
Fill rate (FR)	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	90.24%

Table 21: Performance of models under scenarios with seasonality.

5.2.4.2 Scenario with Spike

The performances of the models under such a scenario are listed in Table 22. Due to the abnormally high demand of the second year, the systems with preset *s* are not agile enough to cope in the case. With the preset *s*, replenishment can only be done once the inventory level reaches the level assumed to cover the demand at CSL of 99% for the lead-time. However, the unexpected huge demand during the lead-time under this scenario exhausts the safety stock and cause stockouts.

Airlift is required with the total cost rising significantly for all models. However, the three (*R, S*) models and (*R, s, S*) model *R*=6 could maintain the CSL of 100%, whereas the CSL dropped to approximately 95% for the (*s, Q*) model and (*R, s, S*) model *R*=3. The (*R, s, S*) model with *R*=12 is always the least cost-effective and the least efficient, mainly due to the fact that the review interval is too long, replenishment cannot be done in time when the spike occurs.

Under this type of scenarios, the (*R, S*) model with *R*=12 performs very well, maintaining the CSL of 100% without triggering any airlifting.

Scenario with spike of demand	*s, Q*	*R,S (R=3)*	*R,S (R=6)*	*R,S (R=12)*	*R,s,S (R=3)*	*R,s,S (R=6)*	*R,s,S (R=12)*
Total demand (60 months, in carton)	147770	147700	148683	147791	148046	147831	148276
Mean inventory level (in carton)	7169	11956	17772	29159	9185	13081	21143
Number of orders by SEA per year	5.2	3.8	1.8	0.8	1.8	1.0	0.4
Number of orders by AIR per year	1.0	0.4	0.2	0.0	0.9	0.6	0.4
Total cost (in USD)	152670	188179	149066	82895	356344	158493	524433
Number of Ordering cycle with shortage	3.0	0.0	0.0	0.0	1.0	0.0	2.0
Cycle Service level (CSL)	95.0%	100.0%	100.0%	100.0%	95.2%	100.0%	60.0%
Shortage quantity	7652	0	0	0	1241	0	27382
Fill rate (FR)	94.84%	100.00%	100.00%	100.00%	99.16%	100.00%	81.53%

Table 22: Performance of models under scenarios with spike of demand.

5.2.4.3 Scenario without Seasonality

As shown in Table 23, when the demand fluctuates randomly, the (*s, Q*) model can ensure the service level at 100% at the lowest cost without any airlifting. The (*R, S*) models can also maintain a CSL of 100%, but with higher cost due to higher levels of stock.

Among the (*R, s, S*) models, the one with *R*=3 can keep the CSL at 100% with large quantity of supply shipped by air; the ones with *R*=6 and *R*=12 fail to maintain the CSL at 100% even though large quantity of supply has to be airlifted.

Scenario without seasonality	*s, Q*	*R,S (R=3)*	*R,S (R=6)*	*R,S (R=12)*	*R,s,S (R=3)*	*R,s,S (R=6)*	*R,s,S (R=12)*
Total demand (60 months, in carton)	132369	131235	130845	130676	131475	131937	133424
Mean inventory level (in carton)	8141	12757	19241	31567	9719	13168	21493
Number of orders by SEA per year	4.6	3.8	1.8	0.8	1.8	0.8	0.4
Number of orders by AIR per year	0.0	0.0	0.0	0.0	0.5	0.6	0.4
Total cost (in USD)	29748	41469	56599	89598	85432	207260	364778
Number of Ordering cycle with shortage	0.0	0.0	0.0	0.0	0.0	0.3	2.0
Cycle Service level (CSL)	100.0%	100.0%	100.0%	100.0%	100.0%	97.0%	60.0%
Shortage quantity	0	0	0	0	0	352	11232
Fill rate (FR)	100.00%	100.00%	100.00%	100.00%	100.00%	99.73%	91.58%

Table 23: Performance of models under scenarios without seasonality.

5.2.4.4 Simulation with Historical Data

In order to better understand the performance of different models, we further test the models with the real demand data, from August 2009 to July 2014 (60 months). As we can observe in Figure 40, the historical demand not only follows quasi-random fluctuation, but also has an obvious spike in summer 2011. This is the combination of scenarios without seasonality in Section 5.2.4.2 and those with spike demand in

Section 5.2.4.3.

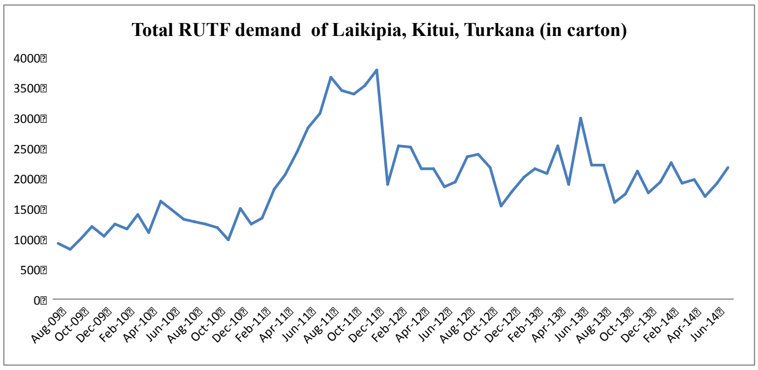


Figure 40: Total RUTF demand of Laikipia, Kitui and Turkana (08/2009 – 07/2014) (K&N, 2014; UNICEF, 2015).

The results of this simulation are summarized in Table 24. Since the demand fluctuates arbitrarily, the shorter review interval is the more responsive the model is. The continuous review system can handle the fluctuation very well, so do the (*R, S*) models.

Since there is an abnormal increase of demand, the periodic review models with *s* and long review intervals (*R=6,* 12) lead to a huge shortage and substantial decrease of CSL, exactly the same as under the scenarios in Section 5.2.4.2.

Historic record	*s, Q*	*R,S (R=3)*	*R,S (R=6)*	*R,S (R=12)*	*R,s,S (R=3)*	*R,s,S (R=6)*	*R,s,S (R=12)*
Total demand (60 months, in carton)	117469	117469	117469	117469	117469	117469	117469
Mean inventory level (in carton)	9049	13651	20351	33602	10775	14694	21732
Number of orders by SEA per year	4.0	3.8	1.8	0.8	1.8	0.8	0.2
Number of orders by AIR per year	0.0	0.0	0.0	0.0	0.4	0.6	0.2
Total cost (in USD)	31389	43972	59707	95296	86509	209667	426946
Number of Ordering cycle with shortage	0.0	0.0	0.0	0.0	0.0	1.0	2.0
Cycle Service level (CSL)	100.0%	100.0%	100.0%	100.0%	100.0%	90.0%	60.0%
Shortage quantity	0	0	0	0	0	5680	21007
Fill rate (FR)	100.00%	100.00%	100.00%	100.00%	100.00%	95.16%	82.12%

Table 24: Performance of models with real demand data (Aug 2009 – Jul 2014).

5.3 Analysis and Recommendations

To better analyze the results of our simulations and facilitate the comparison of tested IM models, we summarize their key performance indices under different scenarios in Table 26, Figures 41 and 42.

		s, Q	*R,S (R=3)*	*R,S (R=6)*	*R,S (R=12)*	*R,s,S (R=3)*	*R,s,S (R=6)*	*R,s,S (R=12)*
Scenario with seasonality	CSL	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	60.0%
	Total cost (in USD)	29858	41278	56254	89549	67581	54801	283319
Scenario with spike of demand	CSL	95.0%	100.0%	100.0%	100.0%	95.2%	100.0%	60.0%
	Total cost (in USD)	152670	188179	149066	82895	356344	158493	524433
Scenario without seasonality	CSL	100.0%	100.0%	100.0%	100.0%	100.0%	97.0%	60.0%
	Total cost (in USD)	29748	41469	56599	89598	85432	207260	364778
Historic record	CSL	100.0%	100.0%	100.0%	100.0%	100.0%	90.0%	60.0%
	Total cost (in USD)	31389	43972	59707	95296	86509	209667	426946

Table 26: Key performance indices of inventory management models.

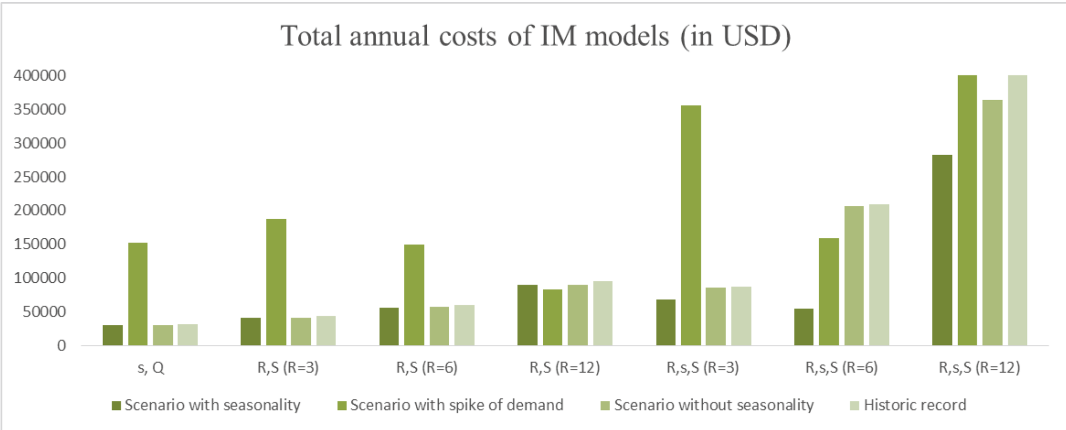


Figure 41: Total annual costs of inventory management models.

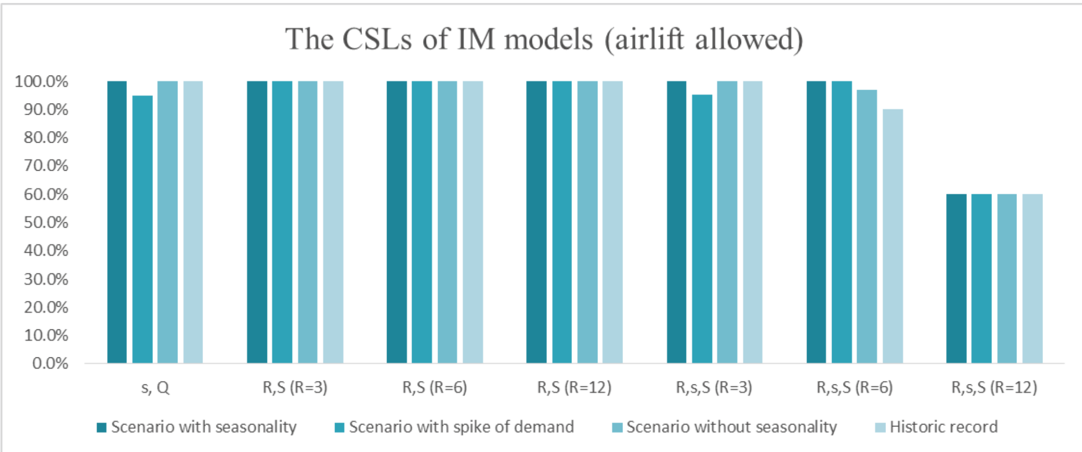


Figure 42: The CSLs of inventory management models

Generally speaking, the choice of inventory management model is to balance the tradeoff between resources and time consumed to review inventory level and the holding cost. In the case of RUTF in Kenya, since we have stochastic demand, it is easier for an inventory control system with frequent review and replenishment to maintain the high level of service (CSL), as shown in Figure 41. However, for the case of an unexpected spike of demand, the continuous review model with *s* fails to maintain the CSL at 100%.

For maneuverability in field operations, where advanced information and communication infrastructure are not available, and the administrative procedures of procurement take considerable time, even if the (s, Q) model is proved to be efficient under most scenarios, we have to choose among periodic review models. We try to identify the best review interval out of three, six and twelve months.

The (R, S) model with $R=3$ has the best performance under most of the scenarios, except those with spike of demand, with 100% CSL and the lowest cost among all periodic review models. If the demand of RUTF can be stabilized without spikes for a long period of time (e.g. five years), and UNICEF Kenya can increase the frequency of ordering to once a quarter without huge a increase of cost, this model should be selected. Moreover, in Chapter IV we have shown that the demand of future three months is predictable. Such a forecasting horizon can make the (R, S) model with R=3 very efficient because any potential stockout within three months would be foreseeable and airlifting orders can be placed on time.

For the scenarios with spike of demand, the best solution is the (R, S) model with $R=12$. It can maintain the CSL of 100% without any substantial rise of cost. The current practice of UNICEF KCO is to place orders of RUTF once a year. In the case that the spikes of demand are inevitable and UNICEF Kenya have to keep the current ordering frequency, the (R, S) model with R= 12 is recommended since it can cope with all tested scenarios efficiently with slight higher cost than that of R=3 and avoid large extra airlifting costs when the spike of demand occurs. However, the perishability of RUTF should be taken into consideration if this model is chosen. Orders are to be shipped in carefully planned batches. Otherwise, expiration at lower echelons of the supply chain would be highly possible.

The periodic review models with s are not recommended under any scenario due to their unstable service levels and high costs.

CHAPETR VI

CONCLUSIONS

Severe accurate malnutrition has been a life threatening issue for young children in sub-Saharan Africa. To fight against it, UNICEF has launched a community-based program (Integrated Management of Accurate Malnutrition) in the most vulnerable regions by distributing RUTF to families in need. One measure of the IMAM's success is the efficiency and effectiveness of the RUTF distribution network. This is normally composed of several echelons across national borders and includes various participants such as local authorities, commercial partners and NGOs. In recent years, the program has faced many challenges and occasional malfunctions of the RUTF supply chain, mainly related to demand forecasting and inventory management issues. In this research, we study these issues in the country of Kenya and three of its counties.

We have segmented the RUTF supply chain into three levels and have developed demand forecasting models for each level, using mathematical and statistical methods. At the end facility and sub-county level, the Moving Average method has been shown to be the most effective approach to forecast RUTF demand. At the national level, since more information about different causal factors and more complete data on RUTF are available, more sophisticated time series and causal techniques are tested on the three sample counties, with a forecasting horizon fixed to three month (the lead-time for supply by sea). For the county of Turkana, the autoregressive method with the indicator %MUAC has been shown to be efficient to forecast the number of SAM caseloads. For counties like Laikipia and Kitui, where the collected data are very misleading, only the naïve forecasting method accompanied by qualitative approaches are chosen.

For the inventory management system, due to availability of data, we have focused on the national level inventory control policies, and we have develop a simulation framework to compare and analyze the different inventory management models. The (s, Q) model from the continuous review systems, the (R, S) and (R, s, S) models from the periodic review systems have been chosen. Three scenarios of stochastic demand were tested, with and without seasonality, and with a spike in demand in a year. It would be ideal to use the output of our forecasting models as input to further test our IM models. Nevertheless, since we have no means to validate the naïve models of Laikipia and Kitui yet, the test results on the IM models might be misleading. Instead, we have tested the IM models by using real historic data of the three sample counties.

The outputs of the simulations suggest that, under most scenarios, the (*s, Q*) model of has the best service level of 100% and the least cost. The (*R, S*) models can also maintain the service level of 100% with higher cost, since most of the time supply by airlift is required. The (*R, S*) model with *R*=3 has the lowest cost among all (*R, S*) models tested under most of the scenarios, but when an unexpected spike of demand occurs, this model requires large quantity of supply by airlift with high cost. The (*R, S*) model with *R*=12 operates with higher cost under most scenarios, but it does not require extra budget for airlifting when a spike of demand occurs, The (*R, s, S*) models can hardly maintain the service level at 100%, especially the one with *R*=12, that can only keep the CSL at 60% even though large quantity of supply has to be shipped by air at high cost. Both the (*R, S*) models with *R*=3 or 12 would be recommendable, the selection of *R* depends on the feasible frequency of ordering in practice and the attitude towards unexpected rise of demand.

To conclude, regarding RUTF demand forecasting, we would suggest that the UNICEF Kenya adapt the causal forecasting methods using the qualified indicators at a county level and sum the results up for the national demand forecasting. In case no causal forecasting method is suitable and time series methods are misleading, the naïve forecasting method should be used. Regarding the inventory management model, the (*R, S*) models with *R*=3 or 12 are recommended. The interval *R* can be determined by UNICEF Kenya to best fit the field situation and practice.

In this research project, due to the resources and time constraints, and the lack of complete data sets, we have limited most of our research and analysis at the county and national level, and have studied a limited number of methods and models. Regarding the inventory management, much further research could also be carried out at lower echelons, i.e. sub-county and end facility levels. This could focus on inventory control policies, shipment schedules, transshipment practice, etc. Moreover, at a national level, future study could take into consideration more factors such as budgetary constraints, aggregation of orders across countries, borrowing mechanisms between countries, etc. For demand forecasting, observations for several years is definitely not enough, longer historical data should be collected and analyzed in the future studies; more climatic and geo-hydraulic data should be processed and explored with support from specialists.

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