# Food4All: Supply Chain Network Design Optimization For Food Bank Operations

by

Erin Elizabeth Bahm
B.S. in Applied Engineering Sciences, Michigan State University, 2020

and

Jesse Quinn Brouillette
B.S. in Business Management and Operations & Supply Chain Management, California State University, Long Beach, 2020

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Signature of Author: ______________________________________________

Erin Elizabeth Bahm
Department of Supply Chain Management
May 9, 2025

Signature of Author: ______________________________________________

Jesse Quinn Brouillette
Department of Supply Chain Management
May 9, 2025

Certified by: ______________________________________________

Christopher Mejía Argueta
Founder & Director, MIT Emerging Market Economies Logistics Lab
Capstone Advisor

Accepted by: ______________________________________________

Prof. Yossi Sheffi
Director, Center for Transportation and Logistics
Elisha Gray II Professor of Engineering Systems
Professor, Civil and Environmental Engineering

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ABSTRACT

Food banks across the globe share a common goal of alleviating hunger and, in a broader scope, making the world a more humanitarian and equitable place for all. They also face a common challenge: balancing their ability to serve society and the environment while maintaining the economic stability required to perform their intended purpose. This capstone investigates the food banking sector and common tactical challenges, using South Africa's largest food banking network, FoodForward SA (FFSA), as the primary case study and sponsoring organization to apply real-world data and context to the proposed supply chain solutions. The main research goal is to optimize FoodForward SA's supply chain network with models that separately address cost, emissions, and social impact, then evaluate tradeoffs across those criteria, deriving insights that may be applicable beyond FFSA. Data from FFSA and Stellenbosch University informed criteria aligned with three objective functions: economic (minimizing transport and handling costs), environmental (reducing emissions and food waste), and social (improving equitable access using multidimensional poverty indices). Using three optimization models built with Python and Gurobi to optimize each objective function separately, we analyzed FFSA's distribution network to identify tradeoffs across these solutions across the models. The proposed methodology supports decision-making by evaluating network performance under baseline and scenario analyses. Scenarios include opening and closing warehouses, adjusting demand among beneficiary organization clusters, and changing lower bounds in the social model to assess cost, equity, and efficiency impacts. Results of modeling showed that there are clear tradeoffs for food banks in prioritizing each objective. While opportunity for improvement in each measure is apparent, optimizing for one criterion will affect the performance measures of the other two objectives within each model. Each food bank is responsible for assessing its needs, goals, capabilities, and risk tolerance when toggling its network and service strategies. Still, leaders in the food banking industry may use this approach as a practical framework and applied methodology. By inputting their own food bank data, organizations can evaluate operational performance, assess tradeoffs, and generate insights to drive informed business decisions.

Capstone Advisor: Dr. Christopher Mejía Argueta
Title: Founder & Director, MIT Emerging Market Economies Logistics Lab (EMeL)

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Erin Bahm & Jesse Brouillette

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# 1 INTRODUCTION

## 1.1 Motivation

Hunger and food insecurity are significant global challenges. According to *The State and Food Security Nutrition in the World 2024* report, between 713 and 757 million people worldwide experienced hunger in 2023, equating to one in every 11 people globally and one in five people in Africa. The prevalence of moderate or severe food insecurity has also remained high, with 2.3 billion people facing some level of food insecurity in 2021 (UN Report, 2024). Food insecurity has far-reaching consequences, including poor health outcomes and increased healthcare costs, especially for developing countries and vulnerable communities[1] (Rancourt et al., 2015).

While food insecurity affects over 2 billion people, up to 40% of food is wasted across supply chains (Food and Agriculture Organization of the United Nations [FAO], 2022). One avenue to help alleviate food insecurity is through food banks. Food banks operate in fragmented, donation-based networks that often struggle to match supply with need (Rivera et al., 2023). This leads to inequities and waste, especially in rural areas (Sengul Orgut & Lodree, 2023). Optimizing logistics through network design[2] may improve access, reduce waste, and support a food bank's economic viability required to serve. FoodForward SA, founded in 2009, is the largest food distribution organization in South Africa, focused on recovering surplus food from the consumer goods supply chain and distributing it to vulnerable communities. Through a network of 2,500 beneficiary organizations (BOs),[3] they provide largely nutritious meals to those in need, helping alleviate hunger and reduce food waste[4] (*FoodForward SA*, 2024).

Through this capstone, we support the FoodForward SA mission statement: "To reduce hunger in South Africa by safely and cost-effectively securing quality food and making it available to those who need it." Via support from donors, partners, and volunteers, FoodForward SA has achieved a cost per

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[1] When this capstone refers to "vulnerable communities," the term is used in a social context, as it relates to the population segments in specific geographical locations that show a low value in the South African Multidimensional Poverty Index (SAMPI).
[2] Network design refers to the locations, connections, and flows that exist within a supply chain.
[3] Beneficiary organizations (BOs) are customers of the food bank. In the FoodForward SA network, beneficiary organizations collect food from FoodForward SA locations, transport it back to their organization, and then distribute it to people in need.
[4] Food waste refers to safe and edible food that is ultimately not consumed at any point along the supply chain or by the end consumer.

meal of R0.50,[5] equivalent to $0.03 (*FoodForward SA*, 2024).[6] Their cost-effective food banking model combats food insecurity and the environmental impact of food loss and waste across all nine provinces in South Africa.

The current state of FoodForward SA's distribution channels presents opportunities for capitalizing on processes. FoodForward SA distributes food through three main distribution channels: a warehouse-based distribution channel called “Warehouse Foodbanking”,[7] a virtual food banking platform called “FoodShare” that connects donors[8] with their nearest food retail partner store, and a fleet of trucks known as “Mobile Rural Depots” to serve rural areas. The traditional food banking model is the warehouse-based distribution channel that focuses on sourcing, collecting, and storing food from farmers, manufacturers, and retailers, then redistributing it to its network of BOs.

## 1.2 Problem Statement and Key Questions

Given the demand and supply planning and capacity complexities of a donation-drive supply chain, the project's key objective is to assess FoodForward SA's warehouse-based distribution network and propose potential strategies to improve food recovery and distribution to vulnerable communities by effectively and efficiently connecting suppliers and donations to beneficiary organizations.

This project uses optimization modeling to evaluate the food bank’s supply chain network design to minimize food inaccessibility and maximize coverage. This approach ensures that food reaches underserved communities more efficiently and cost-effectively.

The research questions to be answered in this capstone are:

1. What strategies can FFSA use to better serve BOs based on varying network scenarios?
2. What improvements in costs, $CO_2$ emissions, food accessibility and coverage can be achieved through an optimized supply chain network?
3. What are the tradeoffs under diverse distribution strategies?

These questions frame the foundation of the project goals and expected outcomes that will be presented as conclusions of this capstone project.

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[5] “R” is the symbol for the South African Rand (ZAR), the official currency of South Africa, like “$” for USD.
[6] As of April 22, 2025, the exchange rate is 1 USD, equal to 18.61 South African Rand (*USD to Sa Rand Exchange Rate - Google Search*, 2025).
[7] Warehouse foodbanking refers to a food bank network design that links donors to warehouses, and warehouses to beneficiaries without using digital channels.
[8] Donors are the organizations or companies that donate surplus food to FoodForward SA for redistribution to beneficiaries.

## 1.3 Project Goals and Expected Outcomes

The project assesses FoodForward SA's supply chain network and proposes potential strategies to improve food recovery and distribution to beneficiary organizations and vulnerable communities by optimizing the flows throughout the logistics network. The goal is to maximize coverage to prioritize vulnerable communities while reducing costs and $CO_2$ emissions. While the deliverables are focused on the case study of FoodForward in South Africa, the project's overall findings are designed to apply to other food banks and supply chains across other emerging markets and underserved population segments.

Cost savings and improved operational performance are expected as an outcome of this project, and environmental and social gains are measured to evaluate the long-term impact of the enhanced logistics network. To best achieve this goal, the project plan includes optimizing a network design that integrates FoodForward SA's primary distribution channel and includes criteria[9] that quantifies and assesses the value and tradeoffs. This project builds upon previous research on food banks and network analysis. Relevant literature is reviewed in Section 2, State of the Practice, to explore the intricacies of donation-based supply chains and identify methods to integrate social and environmental impacts into optimization modeling. Before this capstone assignment, Stellenbosch University and FoodForward SA partnered on several projects, including a warehouse network analysis using agent-based modeling. Primary data is collected from Stellenbosch University and Food Forward SA partners through semi-structured interviews at different organizational levels to understand context, strategies, behaviors, business models, and data.

The learning outcomes for the sponsor include:

1. A network analysis of FoodForward SA's “Warehouse Foodbanking” distribution channel.
2. Three optimization models, one per objective function (i.e., economic, environmental and social impacts) with tradeoff analyses.
3. Scenario analysis and validation to provide actionable recommendations to improve the supply chain network.

Distinguishing our capstone from the current state of the practice, this paper takes a different approach by imposing three separate optimization models on a food bank’s distribution network. These

[9] In this paper, “criteria” refers to a set of criterion that are specific measurable factors included within an objective function to evaluate the performance across economic, environmental, or social goals.

combinatorial optimization models[10] optimize the network for economic, environmental, and social objectives separately. This methodology allows us to isolate and analyze tradeoffs across these criteria rather than combining them into a single, weighted function. By doing so, we can minimize costs to strengthen economic sustainability, reduce emissions and waste to improve environmental performance, and better prioritize social impact through equitable food distribution. Our approach offers food banks a practical framework for making insights and evaluating different strategies based on their specific goals.

The following chapters of this capstone include a review of literature on current food banking[11] operational and academic practices, our methodology and modeling approach, mathematical formulation for our models, and a breakdown of results and scenarios followed by conclusions.

[10] A combinatorial optimization model is a mathematical method used to find the best solution from a set of possible choices, such as routes, schedules, or resource allocations. In this capstone the models are used to redesign the food bank distribution network. The use of “combinatorial optimization models” refers to the three optimization models collectively.

[11] Food banking (also written as “foodbanking”) refers to the operational activities of food banks.

# 2 STATE OF THE PRACTICE

Our capstone centers on developing a comprehensive food bank supply chain network design that evaluates tradeoffs across various criteria and distribution channels to effectively serve vulnerable communities in emerging market economies. We reviewed relevant (scientific and non-scientific) literature to tackle this challenge across several key areas. First, we examined the vital role of food banks in addressing food insecurity and mitigating food waste. Next, we analyzed the structure of food bank supply chains to understand the operational complexities. We then identified and examined various metrics for measuring the impact of food bank supply chain network decisions. Finally, we evaluated different methods to optimize network design.

## 2.1 Role of Food Banks

Vulnerable communities, as defined by the UN Office for Disaster Risk Reduction (UNDRR, 2022), are groups of people who face heightened risks or disadvantages due to their physical, socio-economic, political, or environmental circumstances. Food insecurity in these communities is often a result of intersecting adverse conditions, including economic poverty, social exclusion, and geographic isolation. For example, low-income households face difficulties in purchasing sufficient and nutritious food. In many developing countries, food insecurity is also driven by income inequality and lack of access to economic opportunities (FAO, 2022). Rural populations dependent on agriculture for their livelihood are also at risk, especially those facing limited access to land, markets, and credit (Friel et al., 2011). Marginalized groups of people, such as women, indigenous people, and ethnic minorities, are often more vulnerable due to discrimination and unequal access to resources and decision-making processes (Quisumbing, A. R., & Maluccio, 2003).

Emerging market economies, defined as rapid economic growth, industrialization, improving infrastructure, and increasing integration into global markets, often have large segments of their population facing economic, environmental, and social vulnerability. These communities more acutely experience the effects of economic change and are disproportionally affected by the risks and challenges posed by rapid development, political instability, and social inequality. In a 2022 study by the U.S. National Library of Medicine, findings classified 20.6% of adults in South Africa as socially vulnerable (measured by socio-economic status, household composition, and housing and transportation), with the risk of food insecurity almost threefold higher in the social vulnerability group.

Non-profit organizations (NPOs) play a vital role in addressing societal challenges, such as food insecurity, for vulnerable communities in emerging market economies. They are often essential for filling service gaps not covered by the state or private sector.

For example, in sub-Saharan Africa, where healthcare systems are often underfunded, NPOs are crucial in providing essential health services, especially in rural and underserved areas (Koch & Thaut, 2017). Similarly, in Latin America and the Caribbean, NPOs frequently address issues related to education and housing, providing services to marginalized populations (López & Weitzman, 2010).

Unfortunately, food insecurity is also accompanied by food waste and food loss. One-third of all food produced for humans is either wasted or lost (WFP USA, 2022). Food loss,[12] more prevalent in low-income countries, happens when food is damaged or destroyed before the consumer can eat it. Food destruction often comes early in the food supply chain, when farmers face challenges in growing, harvesting, and storing food. Alternatively, food waste, more prominent in high-income countries, happens when edible food is discarded prematurely or unnecessarily. This trend occurs when excess food is thrown away in restaurants, hotels, homes, and grocery stores, when food expires before sale, or when farms discard "imperfect" or surplus produce (WFP USA, 2022).

Food banks play a critical role in fighting food insecurity and food waste. These non-profit, humanitarian organizations serve as key hubs that recover, store, and distribute food donations to local communities in need (Valerie et al., 2020). They are integral to building sustainable food systems; food banks recover safe, surplus food from all stages of the food system and connect it with community organizations and people facing hunger (Global FoodBanking Network, 2024). Improving the operational efficiency of food banks can significantly amplify their impact and reach.

## 2.2 Structure of Food Bank Supply Chains

Food banks operate much differently from commercial food supply chains. While commercial supply chains rely on predictable, planned inventory, food banks face significant uncertainty regarding incoming donations. Rather than sourcing goods through fixed suppliers, food banks collaborate with a diverse range of donors across the food system (farmers, manufacturers, distributors, retailers, and consumers) to source surplus food. This reliance on donations means food banks have limited control over the quantity, variety, and nutritional composition of the items they receive. As a result, they often struggle to match their supply with the specific needs of the communities they serve.

Food banks redistribute donations to beneficiary organizations, including schools, food pantries,

[12] Food loss is similar to food waste in that both involve food not being consumed but differ by cause. Food loss happens earlier in the supply chain due to production, storage, or transport problems. In contrast, food waste occurs along the supply chain through discard or spoilage, particularly in the downstream supply chain.

community kitchens, and shelters. (Global FoodBanking Network, 2024). As non-profit entities, their primary objective is to distribute food equitably based on need, rather than focusing on profit maximization (Rivera et al., 2023). This equity/coverage-driven emphasis often necessitates tradeoffs in operational efficiency. Moreover, the heavy reliance on volunteers, donors, and their equipment can limit the speed and scale of operations, constraining overall operational throughput. Effective delivery systems are crucial to ensure that food reaches the most vulnerable populations, especially in underserved or rural areas.

The length and complexity of food bank supply chains significantly influence the efficiency, cost, and sustainability of operations. Networks can vary widely in terms of the number and types of partner organizations involved, the geographic reach, and the type of distribution channel.

Shorter supply chains, characterized by fewer intermediaries and a more localized scope, are often more cost-efficient, flexible, and favorable to freshness. Food donations move quickly and directly from donors to food banks to BOs, reducing transportation costs and logistics overhead. This is particularly important for food banks with limited budgets or relying heavily on volunteer labor. Short supply chains also allow food banks to adapt more readily to changes in food availability or emergency situations. For example, in the event of a disruption, such as a local disaster or crisis, food banks with short supply chains may be able to mobilize more quickly and secure necessary food supplies from nearby donors or producers (Feeding America, 2022). Reliance on local sources may increase vulnerability to supply disruptions and difficulties maintaining a consistent variety of donations (Webster et al., 2018).

Longer or more complex supply chains have a broader scope; they often include regional or central hubs and source larger quantities of food from distant or international suppliers. The complexity and length of the supply chain increases the number of intermediaries involved, each adding costs related to storage, transportation, and distribution (Gunderson et al., 2018). This added complexity can also increase the risk of inefficiencies and delays and requires advanced logistics systems to track food across multiple stages and locations. For example, food banks might face challenges in synchronizing inventory and distribution schedules across multiple regions or organizations, particularly if they rely on third-party logistics providers (Gunderson et al., 2018). However, a significant advantage of more sophisticated supply chains is the potential for greater access to various food types. Food banks can source food from national or international suppliers, allowing them to secure more diverse and nutritious food options, especially when challenged with insufficient local donations (Nguyen et al., 2023).

The volume and types of food donations that food banks receive can vary greatly depending on factors such as seasonal trends, donor priorities, and public awareness. For example, many food banks experience an uptick in donations during the holidays but face shortages in the following months (Bazerghi et al., 2016). Additionally, food banks may struggle to secure donations of perishable or nutritious foods like fresh produce, dairy, and proteins, which are less readily available than processed or non-perishable foods.

Food banks also face unique challenges with perishability. Unlike commercial supply chains, where products are often managed well before expiration dates, food banks receive donations that are typically closer to or past their peak freshness, creating a more time-sensitive distribution process (Rivera et al., 2023). Approximately 35% of food that food banks distribute, such as produce and perishable refrigerated items, require careful management to ensure safety and quality (Sengul, Orgut & Lodree, 2023). The diverse nature of donations complicates storage and transportation, requiring proper temperature control and strategies to minimize spoilage and waste.

Food banks play a critical role in addressing food insecurity, but their supply chains are complex and face a range of challenges related to economic fluctuations, supply uncertainty, operational constraints, and food waste. Food banks must carefully consider the tradeoffs and strategies that best align with their operational capacities, financial resources, and the needs of the communities they serve. In the next section, we will discuss the criteria and metrics that affect these types of non-profit organizations.

## 2.3 Food Bank Metrics

Non-profits face challenges in identifying performance measurements because of the intangibility of the services offered, immeasurability of the missions, unknowable outcomes, variability in the donations, and the variety, interests, and standards of stakeholders (Beamon & Balcik, 2008). In the context of broader humanitarian relief efforts, performance metrics must account for a range of multidimensional objectives. Holguín-Veras et al. (2013) propose the use of deprivation cost, which represents the economic valuation of the human suffering associated with a lack of access to essential goods or services. This metric helps ensure delivery strategies maximize benefits for the greatest number of people. Similarly, Huang et al. (2024) introduced the concept of delay cost to quantify the human suffering resulting from delays in humanitarian aid. To effectively assess and improve relief chains, Beamon & Balcik (2008) recommend building a comprehensive performance measurement system that includes at least one metric from each of three categories: Resources, Output, and

Flexibility.

Traditionally, the success of food banks has been measured by metrics such as the volume of food distributed, the number of individuals served, or the number of meals provided. However, researchers increasingly acknowledge that these metrics fail to capture the full complexity of food bank operations and their broader economic, environmental, and social impacts. This insight is particularly relevant to our capstone, where we aim to select and incorporate a range of metrics into our food bank supply chain network design. The objective functions we develop must evaluate various operational tradeoffs from economic, environmental, and social dimensions that food banks face in food distribution.

While profit is not the primary objective of food banks, "they must efficiently use their existing resources to maximize operational effectiveness and best serve their communities" (Davis et al., 2014). Financial metrics are included in nearly all assessments of food bank operational success. Martins et al. (2019) incorporated fixed costs for supporting agencies and costs for operating storage areas and handling products in their economic objective function. Similarly, Islam and Ivy (2021) calculated the total operations cost of receiving and distributing food, considering factors such as the quantity of distributed food, the distance traveled, and the per-mile transportation cost.

Standard environmental objective criteria include minimizing food waste and carbon emissions. For instance, Stauffer et al. (2022) incorporated a penalty for the amount of undistributed food in their objective function. Martins et al. (2019) selected environmental metrics under standards developed by the Global Reporting Initiative, including the cost of disposing of one unit of food product per period and the cost of $CO_2$ emissions generated from transporting one ton of food product over a given period. Additional metrics related to transportation emissions include the carbon intensity per mile and the carbon footprint per unit of food distributed (Bastien et al., 2020). Additional environmental criteria identified for food banks included resource conservation and packaging waste reduction. For example, kilowatt-hours per ton of food distributed can help identify energy efficiencies (Chung et al., 2021).

Most of the reviewed literature on food bank operations identifies equity in food distribution as the primary social objective. Equity is generally defined as "distributing goods in proportion to the needs, often estimated as the population living in poverty in an area" (Rivera et al., 2023). Various methods have been used to quantify this metric, such as minimizing the upper and lower values, the variance, the coefficient of variation, the sum of absolute deviations, or the mean absolute deviation (Fianu and Davis, 2018). Martins et al. (2019) incorporated equity into their social objective function by measuring the proportion of charities awaiting support that eventually receive food assistance and the monetary value of volunteer work. Sengul Orgut & Lodree (2016) integrated equity in their model by imposing a user-specified upper bound on the absolute deviation of each agency from a perfectly equitable distribution, where the total food donations allocated to each BO corresponds to the fraction of the total poverty population assigned to that BO.

Rautenbach (2025) introduced a comprehensive framework to accurately evaluate non-financial performance in food banks, ensuring consistency and relevance. The study follows a structured, iterative process to maintain academic rigor and practical applicability based on a design research methodology. The resulting framework is divided into two parts: the non-financial performance evaluation, which proposes standardized indicators and evaluation methods, and the non-financial performance reporting, which offers a structured reporting format inspired by environmental, social, and governance practices. The framework was applied to the sponsor organization and presented interesting tools to measure diverse criteria.

Nutrition is another key social factor in measuring the impact of food banks. Sourcing food with high nutritional quality is a challenge for food banks due to the inconsistency of donations, the high cost of healthier foods, and limited storage capacity (Bazerghi et al., 2016). To account for uncertainty in examining nutritional value and freshness, a multi-objective robust fuzzy model was used for modeling a food bank network (Ghahremani-Nahr et al., 2023). In a 2012 study conducted with the University of Minnesota's School of Public Health, Feeding America calculated the nutrient composition of food items using the Nutrition Data System for Research (NDRS), a dietary analysis software application (Snelling et al., 2014). Another key tool for assessing nutritional quality is the Healthy Eating Index (HEI), a scoring system used to evaluate diet quality by measuring how well a set of foods aligns with key dietary guidelines and recommendations (Food and Nutrition Service, 2024). A summary of the food bank metrics used in the reviewed literature is presented in Figure 1 below.

*Figure 1. Food Bank Metrics Used in Reviewed Literature*

| | Social | | | | | Environmental | | Economic | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Authors (Year)** | Equitable Distribution | Unsatisfied Demand | Nutritional Value | Product Freshness | Value of Social Work | $CO_2$ Emissions | Food Waste | Distribution/Transportation Costs | Storage and Handling Costs | Cost of Unused Capacity | Operating Cost of Mobile Visits | Value of Donated Product |
| *C.I. Martins, M.T. Melo, M.V. Pato (2022)* | ☑ | ☑ | | | ☑ | ☑ | ☑ | ☑ | ☑ | ☑ | | |
| *Irem Sengul Orgut, Emmett J. Lodree* | ☑ | | | | | | ☑ | | | | | ☑ |
| *Islam, M., Ivy, J.S. (2022)* | ☑ | | | | | | | ☑ | ☑ | | | |
| *Stauffer, J. M., Vanajakumari, M., Kumar, S., & Mangapora, T. (2022)* | | | | | | | ☑ | ☑ | ☑ | | ☑ | |
| *Fianu, A & Davis, L. (2018)* | ☑ | ☑ | | | | | | | | | | ☑ |
| *Ghahremani-Nahr, Ghaderi, Kian (2023)* | | | ☑ | ☑ | | | | ☑ | ☑ | | | |
| *Snelling, A., Maroto, M., Jacknowitz, A., & Waxman, E. (2014)* | | | ☑ | | | | | | | | | |

## 2.4 Supply Chain Network Design Optimization

We incorporate optimization modeling to create and assess the food bank supply chain network across various criteria and evaluate tradeoffs. Optimization models help food banks maximize storage, transport, handling, and distribution efficiency, addressing resource constraints like limited budgets, capacities, routes, and tradeoffs. Food bank operations can benefit significantly from tailored optimization models that address their unique challenges. However, complexity in food bank supply chains make the optimization processes difficult.

These challenges include high uncertainty in donations that subsequently cause variable storage and handling capacities, traveling flows across the logistics network, and tradeoff evaluations that require advanced modeling to ensure equitable food distribution while minimizing food waste and food loss and aiming to fulfill demand (Sengul Orgut & Lodree, 2023). Optimization methods and supply chain network design modeling include linear programming, mixed integer linear programming, and multi-objective optimization.

Linear programming is an optimization method that focuses on maximizing or minimizing a linear objective function subject to linear constraints, making it ideal for efficiently solving non-discrete resource allocation problems. Combinatorial optimization, such as mixed integer linear programming combines integer and linear variables to provide optimal solutions for facility location, routing, and inventory allocation (Rivera et al., 2023). It is a common practice for complex supply chain problems, although computation power may be a limitation based on the application size (Reusken et al., 2023). Multi-objective optimization (MOO) uses weighting functions to balance costs, efficiency, and equity to enable solutions for limited resources, as well as the specific needs of each region and their unique requirements (Sengul Orgut & Lodree, 2023). Pareto optimization and epsilon-constraint methods for MOO are both approaches used in multi-objective optimization but differ in handling multiple objectives. The Pareto optimization method evaluates tradeoffs between conflicting objectives, providing decision-makers with a set of optimal solutions rather than a single result (Rivera et al., 2023). The epsilon-constraint approach converts multi-objective problems into single-objective problems by simplifying the solution process and keeping the design flexible (Rivera et al., 2023). Islam and Ivy (2021) used sensitivity analyses to explore the tradeoffs between efficiency and effectiveness as a function of the cost of shipping, truck capacity, and inequity cap.

Recent applications of optimization models in food bank supply chain design highlight their effectiveness in addressing tactical challenges. In food bank supply chains, for example, linear programming (LP) can optimize the distribution of donations and transportation resources to meet demand while minimizing costs. Mixed-integer linear Programming (MILP) is widely used, such as in the Dutch food bank supply chain, where it optimizes investments in storage and transportation to improve efficiency and increase beneficiary reach by 32% (Reusken et al., 2023). Pareto optimization has been employed to evaluate tradeoffs between conflicting objectives like efficiency and equity, providing decision-makers with a range of optimal solutions tailored to specific constraints (Rivera et al., 2023). Additionally, epsilon-constraint methods have been applied to convert multi-objective problems into simpler single-objective frameworks, enabling flexible designs that balance cost, efficiency, and resource allocation across regions (Rivera et al., 2023). These approaches showcase the versatility of optimization models in overcoming the complexities inherent in food bank operations.

Combinatorial optimization methods, such as Mixed-Integer Linear Programming (MILP), are potentially well-suited for strategic decision-making in food bank supply chains by offering precise solutions for facility location, inventory allocation, and equitable distribution. However, the computational intensity and extensive data requirements of exact methods can be limiting, especially for real-time, large-scale applications where fast-changing landscapes must adapt quickly to uncertainties like fluctuating donations or demand. As an alternate to exact optimization modeling, heuristics offer advantages to support strategic decision-making in food bank supply chains.

Heuristic methods may be more practical for operational decision-making in food banks due to their speed and flexibility. While they provide approximate solutions, their reduced computational demands make them suitable for dynamic settings such as vehicle routing and scheduling deliveries for perishable items quickly, given a set of constraints or reallocating resources during emergencies (Davis et al., 2014). This practicality addresses the historical challenges of food banks, where constraints such as costs, volunteer reliance, fluctuating donation quantities, and other supply chain uncertainties require agile responses. Exact optimization models and heuristics are critical in food bank supply chain strategies. While both methods are valuable, there are tradeoffs in choosing one tool over another, just as in balancing criteria within optimization models.

Our capstone addresses several key gaps identified in the existing state of the practice. First, there is a lack of tradeoff analysis between economic, environmental, and social optimization models, which our approach directly evaluates by running separate models for each objective. Second, most studies combine multiple goals into a single weighted model, while our capstone separates them into distinct optimization models to better isolate and understand the impact of each objective. Third, few food bank optimization efforts use comprehensive indices like the multidimensional poverty index (SAMPI) to guide social prioritization, which our capstone integrates into the social model to target areas of greatest need.

Building on these insights, our methodology uses optimization modeling to evaluate and address the complex tradeoffs and operational challenges inherent in food bank supply chain strategies. The methods covered include criteria selection, data handling, optimization network modeling, assumptions, and scenario analyses.

# 3 METHODOLOGY

This capstone project focuses on developing an applied approach that reconfigures a food bank's distribution network by optimizing three objective functions focused on social, environmental, and economic impacts separately. This methodology aims to support decision-makers in analyzing and evaluating tradeoffs for food banks serving vulnerable communities while also serving as an applied research initiative with conclusions that can be extended to other industries with similar challenges in supply chain optimization. Additionally, this capstone evaluates the supply chain network optimization and criteria for FoodForward SA's traditional warehouse food banking model.

This chapter describes the methodologies integrating the economic, environmental, and social criteria in FoodForward SA's supply chain network design over its distribution channels. The methodologies are designed to build upon our evaluation of the FFSA network and incorporate the literature reviewed in Section 2 to enhance tradeoff analysis and develop actionable insights for FoodForward SA and other food banks that may use the proposed approach.

To achieve these objectives, the methodologies and criteria for this study are informed by a combination of data analysis, in-depth conversations, and interviews with Stellenbosch University researchers and leaders at FoodForward SA. These practices provided critical insights into the operational challenges and opportunities within the food bank's supply chain, shaping the evaluation criteria and modeling traditional and emerging food banking distribution strategies.

## 3.1 Evaluation Criteria Selection

By reviewing the literature and analyzing trends and levels from food bank data, we developed criteria to implement in the network design for FoodForward SA using Python and Gurobi Optimization modeling. In measuring social and environmental criteria for this capstone, *Beyond Financial Impact: A Framework for Evaluating and Reporting the Non-Financial Performance of South African Food Banks*, a 2025 thesis by Daniel Rautenbach, offers a methodology for integrating non-financial performance for food banks in South Africa, as well as data analysis from FoodForward SA and the South African Medical Research Counsel. The economic and financial features of the model were mainly developed using data from FoodForward SA and an evaluation of literature. The economic criteria assess operational costs to identify cost-saving strategies and resource utilization opportunities. The environmental criteria are applied to optimize transportation and food waste-related emissions. Lastly, the social criteria ensure that warehousing operations prioritize service and coverage to vulnerable communities. Further details related to the criteria selection follow.

### 3.1.1 Economic Criteria Selection

Economic criteria focus on cost efficiency and resource utilization to evaluate economic performance. Key economic metrics include transportation costs, operational/tactical expenses, and resource allocation efficiency, and aim to quantify the financial impact of operational decisions and highlight cost optimization opportunities.

To select the optimal economic criteria for our model, we leveraged data from FFSA's operations budget, fleet master records, and fuel reports to analyze baseline operational costs and identify key areas for optimization. This analysis enabled us to identify two primary metrics: 1) transportation costs and 2) handling and storage costs. These cost drivers represent core components of FFSA's operations and were prioritized over other drivers due to their direct influence on overall financial performance by researchers and FFSA leaders.

Transportation costs are modeled based on the distance traveled between donors, warehouses, and beneficiary organizations. The evaluation uses an estimated unit cost of ZAR[13] 10.40 (USD 0.56) per kilometer, derived from FFSA's internal fuel expenditure reports and fleet master records. This rate incorporates the full transportation costs: fuel, maintenance, vehicle depreciation, and driver labor expenses.

We included a fixed cost of ZAR 0.113 (USD 0.006) per kilogram handled/stored to represent warehouse-level expenses, based on FFSA's operational budgeting data. This value reflects labor, energy, inventory handling, insurance, and space-related costs incurred at warehouse facilities.

Integrating these metrics into our economic model enables FFSA to evaluate how inbound and outbound transportation decisions and warehouse utilization impact costs.

### 3.1.2 Environmental Criteria Selection

To assess the supply chain network's environmental impact, we evaluated criteria, including environmental impact indicators and sustainability metrics. This criteria focuses on minimizing the ecological footprint of the supply chain, with key metrics such as carbon emissions from transportation and logistics operations to identify areas for optimization, and food waste reduction, which tracks reductions in food spoilage and losses within the food bank supply chain. The environmental criteria we selected incorporate these two primary sources of emissions: carbon emissions from transportation and carbon emissions associated with food waste. These indicators were selected based on their relevance to FFSA's tactical structure and potential for significant improvement through network optimization.

[13] ZAR is the abbreviation for the South African Rand, the official currency of South Africa.

Other emissions from storage, handling, and other logistics activities were not included to maintain the suitable reliability of the model and due to the data unavailability.

Transportation-related emissions are calculated based on the distance traveled between donors, warehouses, and beneficiary organizations. We apply an emissions factor of 3.92 kg $CO_2e$ per kilometer traveled (du Plessis, 2023), aligning with emission intensities for medium-to-heavy duty freight vehicles commonly used in food distribution. Food waste emissions is calculated separately to reflect the losses occurring within the warehouse network. Based on operational insights from FFSA, we assume a 5% spoilage rate at the warehouse level. To translate food loss into environmental cost, we apply a conversion factor of 2.5 kg $CO_2e$ per kilogram of wasted food sourced from Daniel Rautenbach's thesis (2025).

By incorporating transportation and food waste emissions, our model reflects the dual environmental benefits of efficient routing and reducing food loss. However, due to the limitations of getting exact data regarding food losses, the food loss emissions act in the model as a fixed value. These insights provide FFSA with a strategic framework to minimize its carbon footprint and develop a journey to identify food loss determinants and enhance its modeling in the future.

### 3.1.3 Social Criteria Selection

To assess the social impact of the supply chain network, our evaluation focuses on two key dimensions: food accessibility and social value delivery. In this capstone, we integrate the South African Multidimensional Poverty Index (SAMPI)[14] into our analysis as a proxy for social vulnerability and need as a measurement for social impact in this capstone. Developed by the South African Medical Research Council using Census data from Statistics South Africa (StatsSA), SAMPI captures deprivation across multiple dimensional indicators (economic status, education, health, and living standards) and provides a composite measure of poverty at the community level. It is an index that ranges from 0 (no poverty) to 1 (maximum poverty) and is calculated by multiplying the headcount ratio (the portion of people who are multi-dimensionally poor) by the intensity (the average proportion of indicators in which poor people are deprived). This index enables us to evaluate how well the optimized FoodForward SA network aligns with areas of highest social need and to incorporate equity-driven features into our social objective function. By including SAMPI as a prioritization and coverage factor, we ensure that food distribution strategies are socially equitable.

[14] The South African Multidimensional Poverty Index (SAMPI) is a key component to this capstone because it captures multiple dimensions of poverty, allowing food distribution strategies to prioritize communities with the highest levels of need based on this index.

We determined an upper and lower bound for the social optimization model's objective function to maintain a minimum and maximum service level for each beneficiary organization. The number of meals was measured for the lower and upper bounds. A one-meal lower bound was set, which indicates that for any individual BO, the model attributes a flow of at least one meal per beneficiary[15] that is serviced by that BO. One meal equals 0.5 kg of food, which is multiplied by the number of beneficiaries served by a given BO in a day (as reported by the BO). The upper bound for the social model is 14 meals. These figures mean that each BO may have a different minimum and maximum meal count, though proportional to the number of beneficiaries allocated to each BO.

## 3.2 Data Gathering

Effective decision-making in food bank operations requires accurate and comprehensive data collection and processing. Given the complexity of FoodForward SA's distribution network, this capstone relies on many data sources, including operational records, geographic and demographic datasets, and dummy data, to fill in gaps where sufficient reliable data could not be gathered, all for factoring into optimization models. Gathered data serve as the foundation for understanding the business aspects that affect each food bank (FoodForward SA in this case) and developing each of the optimization models and their criteria.

This section details the sources from which data was obtained, the data incorporated into the models, and the process used to clean and prepare the data for analysis. First, we outline the primary datasets collected, including internal FFSA data, academic resources from Stellenbosch University, publicly available information gathered from literature and publicly available sources, and external research studies. Then, we describe the preprocessing steps conducted to ensure the data's accuracy, consistency, and usability in the optimization models.

### 3.2.1 Data Sources

Data for this capstone come mainly from four primary sources: FFSA internal operational data, academic contributions from Stellenbosch University, publicly available data, and external research and reports. These sources provide a robust data library necessary for analyzing FFSA's supply chain and informing the optimization models that can be applied to other food banking networks.

FFSA has provided critical operational data that serves as the backbone of this study. The data collected and shared by the sponsor organization played a significant role in the research and

[15] A beneficiary is a recipient of food from a beneficiary organization. Beneficiaries are considered the end-user in the food banking supply chain network.

development of this capstone project. We gathered and analyzed relevant datasets in collaboration with FoodForward SA's ICT Manager and researchers at Stellenbosch University. This review includes 10 files, totaling about 1.6GB of data, and most of the data provided is from March 2023 to February 2024. Significant data cleansing is outlined in the following sections. Data are made accessible, which we and our partners for this project can access. FFSA provided location data, including GPS coordinates for warehouses, rural provincial depots (RPDs)[16], mobile rural depots (MRDs), and beneficiary organizations. The datasets include location information, demand information from BOs, donor supply records, and transportation and logistics data. These data files detail the monthly food movement through FFSA's network, capturing supply flows from donors to warehouses and MRDs, and all other possible flows that ultimately reach the BOs. This information was sourced from representatives at FFSA, including their Chief Technology Officer and Warehouse Manager, and includes details such as source and destination locations, product types, volumes (in kilograms), and delivery dates. Cost-related metrics came from a wide variety of sources. The South African Reserve Bank (SARB) was the source of the official currency exchange rate between the SA Rand and the U.S. Dollar. A professor from Stellenbosch University, who was working with FFSA on multiple projects, provided the truck transportation rate per kilometer. Additionally, the National Operations Manager for FFSA provided data on warehousing and associated handling costs. These data were used to estimate the financial implications of various logistical activities, such as moving food through the warehouses and to other locations.

Publicly available datasets supplemented internal and academic data, offering broader demographic, economic, and food security insights. Census data from South Africa's National Statistics Agency provided information on poverty levels and population distribution, which was incorporated into modeling for social impact. Sustainability data, including carbon dioxide emissions per weight per time factors for transportation and food waste decomposition, were obtained from interviewing an expert from Stellenbosch University and referencing his research to ensure environmental impact assessments were aligned with industry standards.

Combining these data sources enables further analysis of FFSA's operations, allowing the optimization models to incorporate economic, environmental, and social considerations. Integrating these primary and secondary datasets ensures that the models not only reflect FFSA's real-world constraints (with stated assumptions) but may also serve other food bank logistics and humanitarian

[16] Rural provincial depots (RPDs) are facilities in the FoodForward SA distribution network. While similar to warehouses, they are much different. RPDs do not accept food directly from donors but only from FFSA’s warehouses. They also operate at a limited capacity—a few days at a time, every other week.

supply chain management efforts by using input data from other organizations. With this comprehensive dataset compiled, the next step was to ensure its quality and consistency through data cleansing.

### 3.2.2 Data Cleansing

This subsection explains the preprocessing steps taken to ensure data quality for the optimization models. These steps include format standardization, handling missing values, correcting inconsistencies, and verifying key variables.

The first step in the data cleansing process involved standardizing data formats. Since data were retrieved in multiple formats (Excel files, PDFs, reports, and interviews), all datasets were converted into a uniform structure using Microsoft Excel to ensure compatibility with the modeling framework. This process involved consolidating datasets and restructuring key fields with consistent date formats, location codes, location names, currency, weight measurements, and emission measurements.

Handling missing and incomplete data was another critical step in our analysis. Larger datasets (particularly in the non-profit sector) often contain missing values, especially in fields such as geographical coordinates from geographical positioning systems (GPS) and demand estimates. In our case, this issue was most prominent in the donor dataset, where nearly all entries lacked complete address information, preventing the identification of precise locations. Since geographic distance was key in our network design optimization approach, we developed a methodology to assign proxy (dummy) locations to donors.[17]

Recognizing that most donors were likely near major population centers, often manufacturers or large-scale retailers, we implemented a randomized GPS coordinate generation strategy by province. Specifically, 70% of donor locations were assigned within each province's most populous urban areas: 50% from the largest city and 20% from the second largest. The remaining 30% were distributed randomly across the province to simulate geographically dispersed or emerging donor sites. This approach allowed us to reasonably approximate donor locations while preserving the geographic dynamics needed for our optimization models. We use this method, given that it might be easily expanded to model new donor sites or groups and assess the potential performance of the whole logistics network under new or different circumstances. We ran sensitivity analyses to validate the

[17] The methodology developed for assigning dummy locations is explained in 3.2.2 but may be re-examined and re-configured by FFSA and other organizations depending on their understanding of their network.

donor locations' effect in the methodology, confirming that increased randomness and geographical dispersion of donor locations led to significantly higher costs and emissions.

We also encountered incomplete values within the BO dataset. Several BO records were missing key information, such as GPS coordinates, reported monthly food needs, or details on the beneficiary organization profile. To address these inconsistencies, we adopted a pragmatic approach: rows with missing critical data were removed from the dataset, and in some cases, the BO was excluded from the network entirely. However, the impact of this data removal was minimal, affecting only about 4% of the total BOs. Should updated or additional data become available in the future, the optimization models can be readily revised to integrate the new information into the network design.

Data inconsistencies also required identification and resolution before modeling. For instance, warehouse capacity was listed using two different metrics: "square meters under roof" and "pallet spaces," which are not directly proportional. Through discussions with FoodForward SA's National Operations Manager, we confirmed that "pallet spaces" were the most appropriate metric for storage capacity. However, he clarified that the valid constraint was not storage space but throughput capacity—driven by labor availability, equipment, and time. FFSA warehouses can process up to 60 tons per day across 20 working days per month, equating to a throughput capacity of 1,200,000 kg/month. This value was incorporated into our modeling as the warehouse or throughput capacity constraint. Other data inconsistencies were resolved through direct validation efforts with FFSA and Stellenbosch University contacts, including manual checks and cross-referencing records.

Qualitative insights from interviews with experts at Stellenbosch University highlighted operational inefficiencies in FFSA's supply chain, including concerns about the reliability of demand reported by BOs. To validate the reporting, we used headcount data from BO visits and a predefined average weight per plate of food to estimate the expected demand. Comparing this calculation with the reported demand showed that, assuming the headcount figures are accurate, reported demand is generally within a 10% margin of our calculated estimates.

These preprocessing steps ensured the data used in the models were accurate, consistent, and reliable. Once the core datasets were verified, assumptions (Section 3.3.2) and constraints (Section 4.4) were applied to align with FFSA's operational framework. The optimization models could effectively assess FFSA's food distribution network tradeoffs and support efficiency, sustainability, and social impact improvements with a clean dataset, constraints, and assumptions. Such optimization models are presented below.

## 3.3 The Optimization Models

### 3.3.1 Network Optimization Modeling

The proposed optimization model minimizes costs while maximizing coverage of beneficiary organizations, reducing food waste, and ensuring equitable distribution based on vulnerability indices. Constraints address warehouse throughput capacity limits, transportation fleet capacity, demand satisfaction, and compliance with regional regulations. The analysis includes a baseline scenario reflecting the current network, optimized configurations incorporating capacity and demand changes, warehouse activations, and distribution channel variations.

The optimization models aim to minimize cost and $CO_2$ emissions while maximizing BO coverage or food accessibility separately. This approach improves food recovery efficiency and ensures equitable distribution across different supply chain strategies. This study employs three optimization models for the logistics network design, which are built and executed using Visual Studio Code with Python and Gurobi Optimization Solver.

The mathematical framework that outlines the models in Section 4 ensure that supply chain decisions (e.g., food allocation, warehouse capacity, and transportation routes) are optimized to capture fluctuations in food donations, demand levels, perishability, and operational constraints. This enables FoodForward SA to adjust distribution strategies tactically based on their data.

### 3.3.2 Assumptions

Our methodology is based on simplifying assumptions to allow for practical and consistent modeling of FoodForward SA's supply chain and provide a framework that other food banks can adopt using their own data. These assumptions help us make appropriate guesses and translate real-world dynamic complexities into a workable framework while acknowledging the limitations and potential areas for future research.

All food products and each kilogram are treated equally in composition and nutritional value. The latter means our models do not distinguish between types of food (e.g., produce, dairy, grains) and assumes a uniform nutritional profile across all product flows. Unfortunately, the level of granularity in the data was insufficient to capture the composition of the orders or their nutritional value.

Product movement is aggregated monthly for all flows in the sponsor's network for this capstone. This means that all inflows and outflows are modeled using monthly periods. Most of the data gathered for this project was reported in monthly totals, and any exceptions were converted to maintain consistency. The timing of deliveries within each month is not factored into the models; therefore, we assume that data transactions occur on the first day of each month. For the six scenarios outlined in Section 3.3.3 Scenario Analysis, a monthly median in donations and flows is used from the year of data collected. We use the median value because it won't underestimate the monthly values of the data set. These assumptions simplify the models and reduce data complexity, which is necessary given the limiting scope and ability to assess real-world complexities.

The donor supply dataset used in this analysis spans from March 1, 2023, to February 28, 2024. While generally comprehensive, the dataset contains minor line-item inaccuracies, primarily related to returns or rejected donations that were not corrected on the same day. These discrepancies may have temporarily altered the reported supply quantities. However, given that our analysis was conducted on a monthly aggregate level, we assessed the impact of these inaccuracies to be minimal. The aggregation effectively smooths out short-term fluctuations, making the dataset reliable for this capstone's network modeling and comparisons.

In our modeling approach, we assume unlimited transportation capacity, meaning a sufficiently available fleet of trucks to fulfill the monthly flows dictated by the objective functions. Specifically, we assume that all product movement between supply and demand nodes within a given month can be executed using a single truck movement per route without the need to account for load balancing across multiple vehicles. Additionally, truckload capacity is treated as unconstrained. No upper bounds on the volume or weight can be delivered in a single trip. This simplification enables focus on optimizing network-level flows and transportation without introducing additional layers of complexity related to vehicle-level routing or load consolidation. However, fleet management and routing projects must be developed at an operational level to deploy the strategic/tactical solutions proposed in this capstone project.

In our comparative analysis of the three network optimization models and scenarios, transportation costs between warehouses and BOs are excluded from the economic criteria. This decision reflects a key operational characteristic of the FFSA Network: BOs are responsible for collecting food directly from the warehouses (WHs). As such, FFSA does not bear the cost of the last-mile distribution to BOs, and including these costs would not accurately represent the organization's actual financial obligations. However, the model structure is flexible and can be adapted to include WH-BO transportation costs, as well as other context-specific costs, for food banks that do provide last-mile delivery, enabling broader applicability across varying operational models.

Demand from each beneficiary organization is treated as static, known, and deterministic. Although, in practice, BOs report demand quarterly, our models hold this demand constant month-to-month throughout, using the verified demand estimates described in Section 3.2. This simplification helps isolate network design impacts without adding temporal variability in demand. However, further research must be conducted to address the future demand's stochasticity and reliability.

In our models, warehouse locations are fixed, meaning their geographic coordinates are predetermined and not subject to a facility location model. However, the models incorporate flexibility in facility utilization through warehouse activation decisions. Therefore, a warehouse can be designated as either “open” or “closed” in a given scenario, allowing the model to assess tradeoffs based on selective facility use.

Food waste, a complicated and critical issue in food banking, is simplified for the modeling in this capstone. We assume a percentage of food volume is lost in transit from the donor to the warehouse and then to the BO. Food waste occurs each day, hour, and second as products near expiration. This continuous, diminishing feature is too complex for our scope and is considered out of scope. Incorporating food waste in a model with a diminishing factor can be further explored in future work.

These assumptions allow the models to focus on high-level decisions such as linking supply to demand, managing product flow through warehouses, and optimizing distribution without being weighed down by the many operational details.

### 3.3.3 Scenario Analyses

As part of the optimization model analysis, six scenarios were developed to provide deeper insights into the combinatorial model’s potential applications. These scenarios are grouped into three categories based on possible network disruptions and decisions, using monthly median donor donations and BO distributed weights as the basis for simulation. The categories and scenarios are outlined below.

**Warehouse Activation Decision – Turn On/Off Warehouses**

We conduct warehouse activation scenarios to test how significant business decisions and infrastructure changes, such as closing or upgrading existing facilities, would affect network expenses, efficiency, and service levels. We address these effects by modeling the following scenarios:

**Scenario 1: Impact of Central Warehouse Closures**

- Close the two largest and centralized warehouses

**Scenario 2: Impact of Activating Rural Province Depots**

- Transform the 2 rural provincial depots (RPDs) into warehouses

**Demand Changes in Top 10 BOs Served by Each Warehouse**

Demand change scenarios are conducted to evaluate how the FFSA network would adapt to significant shifts among key beneficiary organizations, highlighting the flexibility of the food bank under unforeseen conditions and the potential transferability of the combinatorial model to other food bank networks. A factor of 12% is based on empirical evidence from real-word food bank cases that demonstrate that small, controlled deviations from strict equity (within 5-15%) provide necessary flexibility to better align with operational realities (Sengul Orgut & Lodree, 2023). The modeled scenarios follow:

**Scenario 3: Impact of Localized Demand Surge**

- Selective clusters of BOs that grow (most critical)

**Scenario 4: Impact of Localized Demand Reduction**

- Selective clusters of BOs that shrink (most critical)

**Change Lower Bound Flow to BOs for Social Model**

Lastly, we conduct lower bound flow scenarios to understand how adjusting minimum service guarantees impacts social equity across all BOs regarding resource allocation. We may inform decision-making for food bank leaders as they evaluate different service levels across their network. These scenarios are listed below:

**Scenario 5: Impact of Raising Baseline Service Per Beneficiary Organization**

- The lower bound is three meals per person per month at each BO

**Scenario 6: Stress-Testing Social Coverage Requirements**

- The lower bound is six meals per person per month at each BO

The following section provides a detailed explanation of the optimization model.

# 4 Mathematical Formulation: Mixed-Integer Linear Programming Models

The models are formulated to optimize food distribution from donors to warehouses and subsequently to beneficiary organizations (BOs) over the entire time horizon. The models account for supply availability, demand fulfillment, warehouse capacity, and flow conservation at warehouses.

The models are implemented in Visual Studio Code using Gurobi Optimizer, with data extracted from the donor, warehouse, and BO datasets to construct decision variables, arcs, and constraints. The mathematical notation below outlines the core structure of the optimization modeling.

## 4.1 Sets and Indices

This section defines the sets and indices used in the optimization models, specifying the donors, warehouses, beneficiary organizations, and the origin and destination nodes for the network flows.

$D$: Set of donors, indexed by $d$

$W$: Set of warehouses, indexed by $w$

$B$: Set of beneficiary organizations (BOs), indexed by $b$

$i \in \{D, W\}$: index for origin node

$j,k \in \{W,B\}$ : index for destination node

## 4.2 Parameters

This section defines the fixed parameters used to build and run the optimization models.

$S_d$: Food supply available at donor $d$

$N_b$: Minimum distributed food requirement at BO $b$

$F_b$ :Total food needed at BO $b$

$U_w$: Throughput capacity at warehouse $w$

$C_{ij}$: Transportation cost from origin $i$ to destination $j$

$h$: Handling cost per unit per warehouse

$e_{ij}$: $CO_2$ emissions transported from origin $i$ to destination $j$

$\beta$: percentage of total food that is wasted/lost in transport

F: $CO_2$ emissions factor per unit of food waste/loss

$M$ is a sufficiently large number

$A_b$: SAMPI (poverty index) score per BO $b$

## 4.3 Decision Variables

This section defines a model's decision variables for transportation flows, such as how much food to transport and which routes to use.

$x_{ij}$: Continuous flow variable representing the quantity of food transported from origin *i* to destination *j* (measured in kg).

$y_{ij}$: Binary decision variable indicating whether a transportation flow from origin *i* to destination *j* is inactive (0) or active (1).

## 4.4 Constraints

This section describes the constraints the models must follow to ensure output decisions stay realistic and feasible.

**Supply Capacity**: The amount shipped from each donor does not exceed its available supply.

$\sum_{j \in W} x_{ij} \le S_i \quad \forall i \in D$ (1)

**Demand Fulfillment**: The monthly amount distributed to each BO equals or exceeds its minimum volume requirements but does not exceed its total reported monthly need.

$\sum_{i \in W} x_{ij} \ge N_j \; \forall j \in B$ (2)

$\sum_{i \in W} x_{ij} \le \mathrm{F}_j \; \forall j \in B$ (3)

**Warehouse Throughput Capacity Constraint:** The inbound and outbound flows through the warehouse cannot exceed its throughput capacity.

$\sum_{i \in D} x_{ij} + \sum_{k \in B} x_{jk} \le U_j \quad \forall j \in W$ (4)

$\sum_{i \in D} x_{ij} \le \frac{U_j}{2} \quad \forall j \in W$ (5)

**Flow Conservation at Warehouses**: The total food a warehouse receives must equal the total food shipped from that warehouse, ensuring no accumulation or loss.

$\sum_{i \in D} x_{ij} = \sum_{k \in B} x_{jk} \quad \forall j \in W$ (6)

**Linking Constraint:** Ensures that flow between origin and destination only occurs if that specific route is actively used.

$x_{ij} \le M \cdot y_{ij} \quad \forall i \in D \cup W,\ j \in W \cup B,\ i \ne j$ (7)

**Domain Constraints:** These define the valid values for decision variables in the model.

$x_{ij} \in \mathbb{R} \; \forall\, i, j$ (8)

$y_{ij} \in \{0, 1\} \quad \forall\, i, j$ (9)

## 4.5 Objective Functions

We run the optimization models separately for each of the three objective functions. Each model uses the same sets, indices, parameters, decision variables, and constraints. Assumptions also remain constant across all models unless otherwise specified in scenario-specific analyses. This approach allows for a precise evaluation of tradeoffs across objectives.

**The Economic Objective Function** minimizes transportation costs and warehouse handling costs.

$$c1 = \sum_{i \in D \cup W} \sum_{j \in W \cup B} (c_{ij} + h) \cdot x_{ij} \quad (10)$$

**The Environmental Objective Function** minimizes $CO_2$ emissions from transportation and food waste

$$c2 = \sum_{i \in D \cup W} \sum_{j \in W \cup B} \left(e_{ij} \cdot y_{ij}^{t} + \beta \cdot F \cdot x_{ij}\right) \quad (11)$$

**The Social Objective Function** maximizes the reduction of the multidimensional poverty index, prioritization, and coverage of donations.

$$c3 = \sum_{i \in W} \sum_{j \in B} A_j \cdot x_{ij} \quad (12)$$

To solve the optimization models, we used the Gurobi Optimization Solver for mathematical programming, integrated within Python. Supporting packages included Pandas for data cleaning and manipulation, Geopy for geospatial calculation, and Folium for generating interactive maps to visualize network flows and facility locations. Development and execution of the code were done in Visual Studio Code. Our contribution lies not in developing a novel algorithm, but in applying proven optimization techniques to a real-world problem, showcasing how data-driven models can inform strategic decisions in food banking.

# 5 RESULTS AND RECOMMENDATIONS

## 5.1 Results

The results present a structured evaluation of FFSA’s network performance across optimization models and disruption scenarios. First, comparing the current baseline operational network and three optimized networks shows substantial opportunities for cost savings, emissions reductions, and improved social coverage. Next, we conduct a comparative analysis of three primary optimization models—economic, environmental, and social—highlighting the trade-offs between cost efficiency, environmental sustainability, and equitable service delivery. Then, scenario-based analyses explore the resilience and adaptability of the network under disruptions, including warehouse activation decisions, shifts in localized demand and raising minimum service thresholds for beneficiary organizations. These results collectively illustrate both the potential for operational improvements and the complexities of balancing economic efficiency, sustainability, and social impact within FFSA’s distribution system.

### 5.1.1 Comparative Analysis of Current vs. Optimized FFSA Network

To evaluate the performance of FFSA's current operational warehouse network, we first developed a baseline model to compare the existing system against optimized configurations across three dimensions: economic efficiency, environmental impact, and social equity. This comparison aimed to quantify the potential improvements in cost savings, emission reduction, and equitable service delivery achievable through a redesigned distribution network.

The model was run using monthly aggregate data from FFSA data, spanning March 2023 to February 2024. Three representative months (April 2023, August 2023, and January 2024) were selected for detailed evaluation. These months reflect varying levels of product flow across FFSA's network (i.e., low, median, and high flows) and serve as benchmarks to compare the current state against an unconstrained optimized scenario: the current state reflects actual observed flows and arc usage. In contrast, the optimized state allows for more efficient transportation, allocation, and flow across network nodes. Full monthly results are provided in Appendix A.

Under the economic model, the optimized network significantly reduced total operational costs across all observed months. Comparative results from Table 1 show that April 2023 total costs decreased by 10.9%, with similar trends in August 2023 (-11.3%) and in January 2024 (-11.2%). The most notable savings come from donor-to-warehouse transport, which dropped by 82.3% in April 2023, 73.0% in August 2023 and 89.3% in January 2024. This indicates a significant opportunity for more efficient and intentional donor transport allocation.

*Table 1. Current vs. Optimized Economic FFSA Network Comparison*

| | Current Network | Optimized Network | % Change |
|---|---|---|---|
| *April 2023* | | | |
| **Economic Total Cost (ZAR)** | **1,395,905** | **1,243,920** | **-10.9%** |
| Total Handling Cost (ZAR) | 51,991 | 51,991 | 0.0% |
| Transportation Cost: Donors to Warehouses (ZAR) | 45,772 | 8,124 | -82.3% |
| Transportation Cost: Warehouses to BOs (ZAR) | 1,298,143 | 1,183,805 | -8.8% |
| *August 2023* | | | |
| **Economic Total Cost (ZAR)** | **1,272,757** | **1,128,384** | **-11.3%** |
| Total Handling Cost (ZAR) | 43,818 | 43,818 | 0.0% |
| Transportation Cost: Donors to Warehouses (ZAR) | 77,952 | 21,017 | -73.0% |
| Transportation Cost: Warehouses to BOs (ZAR) | 1,150,986 | 1,063,549 | -7.6% |
| *January 2024* | | | |
| **Economic Total Cost (ZAR)** | **1,090,658** | **968,172** | **-11.2%** |
| Total Handling Cost (ZAR) | 26,056 | 26,056 | 0.0% |
| Transportation Cost: Donors to Warehouses (ZAR) | 63,962 | 6,843 | -89.3% |
| Transportation Cost: Warehouses to BOs (ZAR) | 1,000,640 | 935,273 | -6.5% |

In addition to total cost reduction, the economic optimization model revealed a shift in warehouse utilization across the network (illustrated in Figure 2). The April 2023 current vs. optimized network warehouse utilization is compared in Figure 3. Under the current configuration, GP-WH (Gauteng), an urban hub, was the most utilized warehouse at 24.55%. Another urban site, WC-WH (Western Cape) followed at 16.33% and KZN-WH (KwaZulu-Natal), located near a major port city, at 14.72%. After optimization, utilization decreased slightly at these major urban hubs, with GP-WH falling to 20.73% and WC-WH to 14.11%, while KZN-WH utilization increased to 15.84%, suggesting a shift toward better regional load balancing. More rural warehouses, such as LIM-WH (Limpopo) and NW-WH (North West), maintained similar low utilization levels, indicating that optimization did not place an excessive burden on less-connected nodes. FS-WH (Free State), a centrally located but rural warehouse, saw the most significant drop, decreasing from 8% to 3.8%**,** reflecting a strategic reduction in its role within the network.

*Figure 2. FFSA Warehouse Network*

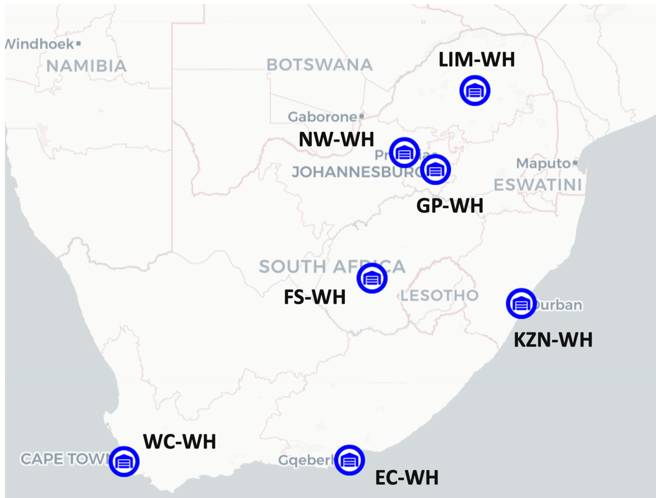
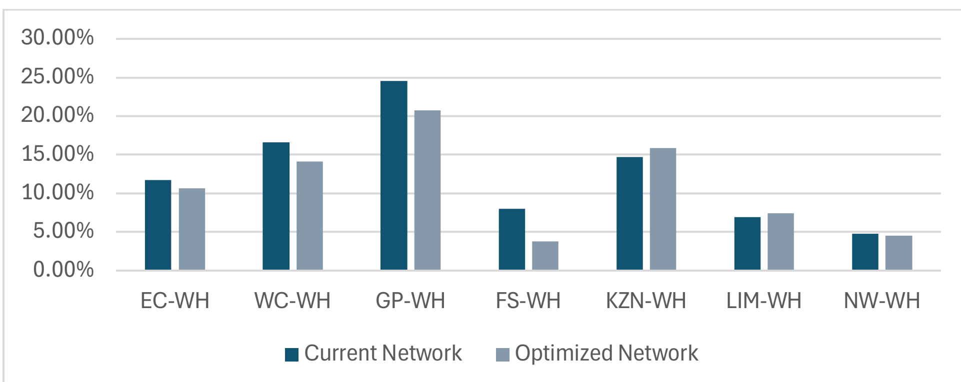



*Figure 3. Current vs. Optimized Network Capacity Utilization % by Warehouse (April 2023)*




The environmentally optimized network also demonstrated improved performance across all three periods. As shown in Table 2, total $CO_2$ emissions were reduced by approximately 14% overall, with emissions decreasing by 12.5% in April 2023, 13.2% in August 2023 and 16.7% in January 2024. Like the economic improvements, these environmental gains were primarily driven by more strategic transportation between donor and warehouse nodes, significantly reducing transportation distances and associated emissions. In addition to transport efficiencies, food waste emissions declined meaningfully under the optimized network. Food waste emissions dropped by 21.1% in April 2023, 23.9% in August 2023, and a substantial 51.6% in January 2024. These reductions suggest improved warehouse throughput, with the network minimizing excess goods stored in warehouses and optimizing the direct flow of goods from donors to BOs.

*Table 2. Current vs. Optimized Environmental FFSA Network Comparison*

| | Current Network | Optimized Network | % Change |
|---|---|---|---|
| *April 2023* | | | |
| **Environmental Total Emissions ($CO_2e$)** | **579,774** | **507,076** | **-12.5%** |
| Emissions: Donors to Warehouses ($CO_2e$) | 17,254 | 3,062 | -82.3% |
| Emissions: Warehouses to BOs ($CO_2e$) | 489,347 | 446,247 | -8.8% |
| Food Waste Emissions ($CO_2e$) | 73,172 | 57,767 | -21.2% |
| *August 2023* | | | |
| **Environmental Total Emissions ($CO_2e$)** | **527,269** | **457,524** | **-13.2%** |
| Emissions: Donors to Warehouses ($CO_2e$) | 29,385 | 7,922 | -73.0% |
| Emissions: Warehouses to BOs ($CO_2e$) | 433,875 | 400,915 | -7.6% |
| Food Waste Emissions ($CO_2e$) | 64,009 | 48,687 | -23.9% |
| *January 2024* | | | |
| **Environmental Total Emissions ($CO_2e$)** | **461,031** | **384,091** | **-16.7%** |
| Emissions: Donors to Warehouses ($CO_2e$) | 24,111 | 2,580 | -89.3% |
| Emissions: Warehouses to BOs ($CO_2e$) | 377,201 | 352,560 | -6.5% |
| Food Waste Emissions ($CO_2e$) | 59,720 | 28,952 | -51.5% |

Warehouse utilization under the environmental optimization model followed similar trends to those observed under the economic criteria. Major hubs such as GP-WH and WC-WH experienced modest decreases in utilization, while mid-sized nodes like KZN-WH saw slight increases. Smaller and underutilized warehouses maintained relatively low usage, indicating that environmental objectives aligned closely with cost-efficient routing patterns. This consistency suggests that environmentally optimized flows also support balanced and efficient network operations.

The social optimization model was explicitly designed to prioritize equitable food distribution, ensuring greater service to vulnerable communities as measured through a SAMPI-weighted social impact score. This score is calculated as the sum of each BO's SAMPI value multiplied by the volume of food received. For reference, the median monthly social impact score across the current network is 12,598, while the median for the optimized network state is 24,531. In all three months evaluated, the optimized network consistently outperformed the current network in terms of social impact. As shown in Table 3, April 2023 saw the score nearly double from 12,732 to 25,172. August 2023 increased from 10,595 to 21,659, and January 2024 rose from 6,536 to 20,633. These results demonstrate that when social outcomes are prioritized, the network can substantially expand its reach to the most vulnerable beneficiary organizations.

*Table 3. Current vs. Optimized Social FFSA Network Comparison*

| | Current Network | Optimized Network | % Change |
|---|---|---|---|
| *April 2023* | | | |
| **Social Total Impact Score (SAMPI x Volume)** | **12,732** | **25,172** | 97.7% |
| *August 2023* | | | |
| **Social Total Impact Score (SAMPI x Volume)** | **10,595** | **21,658** | 104.4% |
| *January 2024* | | | |
| **Social Total Impact Score (SAMPI x Volume)** | **6,536** | **20,633** | 215.7% |

Warehouse utilization differs significantly under social optimization. In the April 2023 scenario, EC-WH (Eastern Cape) was the sole warehouse activated, operating at 97.6% of its capacity, while all other warehouses remained unused. This outcome reflects both the geographic location of EC-WH and its proximity to high-SAMPI beneficiary organizations. The Eastern Cape province contains some of the highest concentrations of vulnerable communities in South Africa, and concentrating distribution through EC-WH allows the model to direct a greater share of volume toward areas with greatest need, thereby maximizing the SAMPI-weighted social impact score.

These findings demonstrate that data-driven network optimization can deliver significant operational improvements across economic, environmental, and social priorities. By reassigning donor flows and rebalancing warehouse throughput, FFSA can reduce operating costs, lower emissions, and increase service prioritization to vulnerable communities. However, achieving these improvements requires trade-offs across objectives. These trade-offs are further assessed in the following subsection.

### 5.1.2 Comparative Analysis of Three Network Optimization Models

This subsection presents a comparative analysis of the three distinct optimization models applied to the distribution network of FFSA, each structured around a different primary objective: minimizing economic cost, minimizing environmental impact, and maximizing social equity. The models were tested using a monthly average scenario, using median values for donor supply and BO need as representative input levels. This approach ensures that the findings reflect a typical operating month of FFSA. This analysis aims to highlight operational trade-offs and inform decision-making in a complex system where costs, emissions, and social equity do not always align. The findings underscore that while some trade-offs are severe, not all improvements require steep sacrifices. A comparison of the findings is shown in Table 4.

*Table 4. Comparative Results of the Three Network Optimization Models*

| | Economic Optimization | Environmental Optimization | Social Optimization |
|---|---|---|---|
| **Economic Total Cost (ZAR)** | **261,375** | **263,975** | **8,556,795** |
| Total Handling Cost (ZAR) | 99,394 | 99,394 | 99,394 |
| Transportation Cost: Donors to Warehouses (ZAR) | 161,981 | 164,581 | 8,457,401 |
| **Environmental Total Emissions ($CO_2e$)** | **4,480,982** | **653,860** | **7,727,573** |
| Emissions: Donors to Warehouses ($CO_2e$) | 61,060 | 62,041 | 3,188,096 |
| Emissions: Warehouses to BOs ($CO_2e$) | 4,309,484 | 481,382 | 4,429,040 |
| Food Waste Emissions ($CO_2e$) | 110,437 | 110,437 | 110,437 |
| **Social Total Impact Score (SAMPI x Volume)** | **24,875** | **23,497** | **37,388** |

The comparison of the economic, environmental, and social optimization models reveals distinct trade-offs between cost efficiency, emissions reduction, and equitable service delivery. The economic optimization model achieved the lowest total cost at ZAR 261,375, driven primarily by minimized donor-to-warehouse transport costs. However, this configuration relies heavily on cost-saving routes that do not account for emissions or equitable access. The environmental burden is substantial, over 4 million $CO_2e$, primarily from emissions between warehouses and BO routes. Likewise, the social coverage is limited, with a SAMPI impact score of 24,875.

The environmental model dramatically improves sustainability outcomes by reducing the total emissions footprint significantly to 653,856 $CO_2e$, representing an 85% reduction compared to the economic model. These gains are driven by re-routing supply chains to favor shorter and lower-emission paths, particularly for deliveries from warehouses to BOs. Notably, these environmental improvements do not come at a steep economic cost. The total costs rise modestly to ZAR 263,975, an increase of just 1%. This indicates that significant emissions reduction is possible with only marginal increases in total system cost, presenting a compelling case for integrating environmental considerations into standard planning without jeopardizing financial viability. However, the social outcome remains relatively low, meaning the most vulnerable communities are still underserved.

In contrast, optimizing for social equity yields the highest social impact score of 37,388, a 50.3% improvement over the economic model, but at the expense of dramatically higher transportation costs and total emissions. While this output indicates broad, prioritized service to vulnerable communities, this improvement also comes with steep economic and environmental trade-offs. The economic objective spikes to ZAR 8.56 million, more than 130 times higher than the cost minimization model. This surge is almost entirely driven by donor-to-warehouse transport costs (ZAR 8.46 million), reflecting long-distance routing to reach vulnerable areas. Overall, the findings illustrate that while economic and environmental efficiencies can be balanced with minimal cost penalty, achieving higher levels of social impact requires substantial increases in both cost and environmental footprint. Trade-offs along each dimension are shown in further detail in Appendix B.

Analyzing demand flows across the economic, environmental, and social optimization models reveals key differences in how BO needs were met. Results are shown in Table 5. While the total number of BOs served and mean volume per BO (534 kg) remained constant, volume distribution varied notably. The economic and environmental models showed higher variability (i.e., standard deviations of 2,413 kg and 1,976 kg, respectively) than the social model (1,160 kg), indicating that the social model achieved a more balanced distribution of goods. Maximum volumes per BO were also much lower under the social model (11,431 kg) compared to the economic (49,519 kg) and environmental (45,585 kg) models. Although the social model allocated a greater share of volume to the top 10% of BOs (57.22%) than the other models, it resulted in lower average monthly need coverage (22.92%) and fewer meals covered per BO (3.53 meals). These results highlight that the social optimization strategy redistributed supply more equitably but at the cost of lower per-BO service levels.

*Table 5. BO Demand Flow Under Each Network Optimization Model*

| | **Economic Optimization** | **Environmental Optimization** | **Social Optimization** |
|---|---|---|---|
| Total BOs Served | 1,658 | 1,658 | 1,658 |
| Mean Volume (kg) | 534 | 534 | 534 |
| Median Volume (kg) | 274 | 274 | 162 |
| Std Dev (kg) | 2,413 | 1,976 | 1,160 |
| Min Volume (kg) | 45.00 | 45.00 | 6.18 |
| Max Volume (kg) | 49,518.81 | 45,585.00 | 11,431.00 |
| Volume to Top 10% BOs (%) | 53.73% | 53.58% | 57.22% |
| Avg. % of Total BO Need (kg) Covered | 31.38% | 32.20% | 22.92% |
| Avg. Number of BO Meals Covered | 4.41 | 4.53 | 3.53 |

An analysis of warehouse utilization across economic, environmental, and social optimization models reveals distinct flow patterns and capacity use shifts. A summary of warehouse utilization is shown in Table 6. Under both the economic and environmental models, flows were relatively balanced across strategically located hubs: GP-WH in Gauteng (Johannesburg region), WC-WH in Western Cape (Cape Town), and KZN-WH in Kwa-Zulu (Durban). These sites, situated in urban centers with strong transit infrastructure, each operated between 24% and 44% of capacity. While flow patterns were broadly similar, a few noticeable differences emerged between economic and environmental models. GP-WH had the highest utilization under the economic model at 44.46%, but this dropped to 32.25% under the environmental model. Meanwhile, utilization at LIM-WH and NW-WH increased from 5.42% to 7.08%, and from 0.39% to 10.94%, respectively. These shifts suggest that while GP-WH remains a cost-efficient hub, it may not be the most emissions-efficient choice for all delivery routes. The environmental model appears to favor greater use of LIM-WH and NW-WH to serve demand in their surrounding rural regions, reducing long-haul transport emissions from Gauteng. This indicates that minimizing carbon footprint can lead to more decentralized flow patterns, prioritizing geographic proximity to demand over centralized consolidation. In contrast, the social optimization model concentrated nearly all flows into EC-WH (99.95% utilization), redirecting distribution toward regions with high SAMPI vulnerability scores. Utilization at GP-WH and WC-WH dropped below 2%, while rural or less central sites such as LIM-WH and NW-WH saw increased activity, indicating a deliberate shift to prioritize equitable access over logistical efficiency. These results suggest that while the economic and environmental strategies promoted the balanced use of central warehouses, the social model intentionally redistributed flows to maximize reach across more vulnerable regions, resulting in extreme concentration at select nodes and underutilization elsewhere.

*Table 6. Warehouse Utilization Under Each Network Optimization Model*

| Warehouse | Economic Optimization | | Environmental Optimization | | Social Optimization | |
|---|---|---|---|---|---|---|
| | Total Flow (kg) | Capacity Utilization | Total Flow (kg) | Capacity Utilization | Total Flow (kg) | Capacity Utilization |
| EC-WH | 317,086 | 26.42% | 317,086 | 26.42% | 1,199,428 | 99.95% |
| WC-WH | 325,833 | 27.15% | 325,833 | 27.15% | 1,996 | 0.17% |
| GP-WH | 533,515 | 44.46% | 387,033 | 32.25% | 22,791 | 1.90% |
| FS-WH | 221,033 | 18.42% | 221,033 | 18.42% | 2,312 | 0.19% |
| KZN-WH | 299,773 | 24.98% | 299,773 | 24.98% | 14,679 | 1.22% |
| LIM-WH | 65,028 | 5.42% | 84,954 | 7.08% | 327,652 | 27.30% |
| NW-WH | 4,732 | 0.39% | 131,288 | 10.94% | 198,141 | 16.51% |

The comparative analysis reveals that not all gains come at equal expense. Environmental improvements can be realized with minimal economic penalties, making enhancements to baseline operations viable. Social improvements, while essential for equity, require significant financial and environmental investment, particularly in last-mile transport logistics. These insights suggest opportunities for hybrid approaches that blend objectives, such as minimizing emissions while meeting a minimum threshold for SAMPI coverage or reducing cost while capping emissions within acceptable limits.

### 5.1.3 Scenario 1: Impact of Central Warehouse Closures

To test the resilience of each optimization model, we introduced a disruption scenario in which the two largest and most centrally located warehouses, GP-WH (Gauteng) and WC-WH (Western Cape), were removed from the network. These warehouses serve as major hubs in the baseline optimization model, so their closures simulate a realistic contingency such as a facility failure, natural disaster, or strategic exit.

The results in Table 7 show varying degrees of sensitivity across economic and environmental dimensions. Under the economic optimization model, total costs more than doubled, increasing by 102% compared to the baseline network. Transportation costs from donors to warehouses rose sharply by 165%, highlighting the network's heavy reliance on central nodes for efficient upstream logistics. Environmental performance also deteriorated substantially. Total $CO_2$ emissions rose by 157% and emissions associated with warehouse to BO flows nearly tripled.

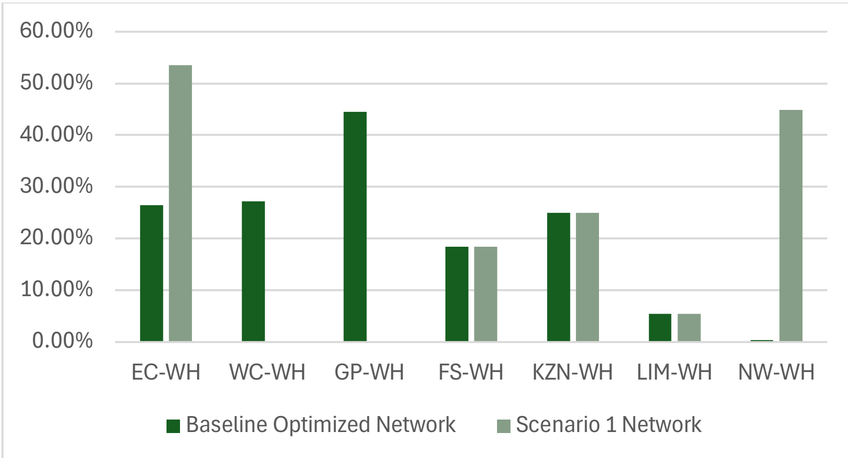
The social impact score remained stable at 37,388, indicating that despite significant operational and environmental challenges, the system maintained equitable service levels to beneficiary organizations. However, the cost and emissions penalties suggest that the network's resilience is highly sensitive to the centralized nodes, highlighting the network's cost-efficiency limitations under constrained infrastructure.

*Table 7 Comparative Results of Baseline Optimized Network vs. Scenario 1 Network*

| | Optimized Baseline Network | Scenario 1 Network | % Change |
|---|---|---|---|
| **Economic Total Cost (ZAR)** | **261,375** | **528,280** | **102%** |
| Total Handling Cost (ZAR) | 99,394 | 99,394 | 0.0% |
| Transportation Cost: Donors to Warehouses (ZAR) | 161,981 | 428,886 | 165% |
| **Environmental Total Emissions ($CO_2e$)** | **653,860** | **1,682,386** | **157%** |
| Emissions: Donors to Warehouses ($CO_2e$) | 62,041 | 162,179 | 161% |
| Emissions: Warehouses to BOs ($CO_2e$) | 481,382 | 1,409,770 | 193% |
| Food Waste Emissions ($CO_2e$) | 110,437 | 110,437 | 0.0% |
| **Social Total Impact Score (SAMPI x Volume)** | **37,388** | **37,388** | **0.0%** |

Warehouse utilization patterns shifted significantly following the removal of GP-WH and WC-WH. The comparison is visualized in Figure 4. GP-WH and WC-WH were the two most heavily utilized warehouses in the baseline economic optimized network, operating at 44.46% and 27.15% capacity, respectively. Their closure in Scenario 1 forced a significant redistribution of flows. EC-WH absorbed the largest share of displaced volume, with its utilization increasing from 26.42% to 53.58%**,** doubling its operational load. This shift can be attributed to EC-WH's relatively central geographic location among remaining active nodes and its proximity to beneficiary organizations. NW-WH, previously operating at near-zero utilization (0.39%)**,** was activated as a central node, reaching 44.85% utilization. This jump can be attributed to its adjacency to the now-closed GP-WH. As a neighboring province with lower baseline throughput, NW-WH was well positioned to absorb regional demand that would have otherwise been routed through GP-WH. Other warehouses such as FS-WH, KZN-WH, and LIM-WH, maintained relatively stable utilization levels, indicating that network adjustments were concentrated primarily on EC-WH and NW-WH. These results underscore the network's flexibility and highlight critical reliance on specific nodes for surge absorption, reinforcing the value of maintaining underutilized capacity as a resilience strategy.

*Figure 4. Baseline Optimized vs. Scenario 1 Network Capacity Utilization % by Warehouse*




### 5.1.4 Scenario 2: Impact of Activating Rural Province Depots

FFSA's two rural provincial deports (RPDs) were introduced into the network as additional warehouses in the following scenario. These nodes operate as cross-docking nodes that only receive food from other warehouses to stage and distribute. For this scenario, the RPDs were modeled with full warehouse functionality and capacity (1.2 million kg). This scenario aimed to test the impact of network expansion on distribution efficiency, emissions and equity outcomes.

For the sake of space, scenario results are shown in the Appendix C. Modeling the RPDs as two additional warehouse nodes, MP-WH and NC-WH, had a minimal impact on operational measures or warehouse utilization, indicating a limited need for this transformation in the network under current circumstances.

### 5.1.5 Scenario 3: Impact of Localized Demand Surge

In Scenario 3, we introduced a targeted demand increase of 12% for a select cluster of the most critical beneficiary organizations (BOs). These BOs were selected based on the warehouse's most significant historical volume throughput, representing high-priority service points in the network. The objective of this scenario was to evaluate the system's ability to absorb localized surges in need without compromising overall cost efficiency, environmental sustainability, or equitable distribution.

Economic costs increased modestly from ZAR 65,173 to ZAR 66,612 (a ~2.2% rise), indicating strong cost resilience to the localized demand increase. Transportation from donors to warehouses rose by ~7.2%, but emissions remained controlled. Warehouse handling costs also slightly increased in line with greater flow volumes.

Economic model warehouse utilization results, shown in Table 8, indicate that Scenario 3 led to a moderate shift in flow concentration across the network. GP-WH increased utilization from 44.5% to 48.3%, reinforcing its role as a key hub to serve inland regions. LIM-WH, in the more remote Limpopo region, saw an increase in use, from 5.4% to 8.5%, highlighting its strategic position to reach BOs in the northern parts of South Africa.

*Table 8. Baseline Optimization vs. Scenario 3 Network Capacity Utilization % by Warehouse*

| | Baseline Optimization | | Scenario 3 | |
|---|---|---|---|---|
| **Warehouse** | **Total Flow (kg)** | **Capacity Utilization** | **Total Flow (kg)** | **Capacity Utilization** |
| EC-WH | 317,086 | 26.42% | 317,560.75 | 26.46% |
| WC-WH | 325,833 | 27.15% | 303,310.10 | 25.28% |
| GP-WH | 533,515 | 44.46% | 579,293.69 | 48.27% |
| FS-WH | 221,033 | 18.42% | 153,611.06 | 12.80% |
| KZN-WH | 299,773 | 24.98% | 369,225.78 | 30.77% |
| LIM-WH | 65,028 | 5.42% | 102,510.40 | 8.54% |
| NW-WH | 4,732 | 0.39% | - | 0.00% |

The demand flow analysis in Table 9, shows that distribution became slightly more concentrated. The standard deviation of volumes increased from 2,413 kg to 3,443 kg**,** and the maximum volume delivered to a single BO rose sharply from 49,519 kg to 86,849 kg. The top 10% of BOs received 54.65% of the total volume compared to 53.73% under the baseline. Nonetheless, average monthly need coverage across BOs improved from 31.38% to 32.85%**,** and average meals covered increased from 4.41 to 5.03. These results indicate that the network absorbed the targeted surge effectively, improving service levels at critical sites.

*Table 9. BO Demand Flow Under Each Network Optimization Model*

| | Baseline Optimized Network | Scenario 3 Network |
|---|---|---|
| Total BOs Served | 1,657 | 1,657 |
| Mean Volume (kg) | 533.84 | 530.95 |
| Median Volume (kg) | 273.62 | 269.54 |
| Standard Deviation (kg) | 2,412.67 | 3,442.65 |
| Min Volume (kg) | 45.00 | 45.00 |
| Max Volume (kg) | 49,518.81 | 86,849.40 |
| Volume to Top 10% BOs (%) | 53.73% | 54.65% |
| Avg. % of Total BO Monthly Need (kg) Covered | 31.38% | 32.85% |
| Avg. Number of BO Meals Covered | 4.41 | 5.03 |

### 5.1.6 Scenario 4: Impact of Localized Demand Reduction

Scenario 4 explores the network's behavior when demand from the same selected cluster of high-priority BOs is reduced by 12%, simulating stabilization or temporary relief periods. The objective was to evaluate how reduced pressure impacts network performance. For the sake of space, scenario results are shown in Appendix C. While a 12% demand reduction improved flow equity and balance across the network, it led to slightly lower service levels per BO and limited efficiency gains.

### 5.1.7 Scenario 5: Impact of Raising Baseline Service Per Beneficiary Organization

In Scenario 5, the social optimization model was modified by increasing the minimum meals served constraint from one to three meals per beneficiary organization. This adjustment raised the baseline service requirement across the network and tested the system's ability to meet more stringent social equity thresholds.

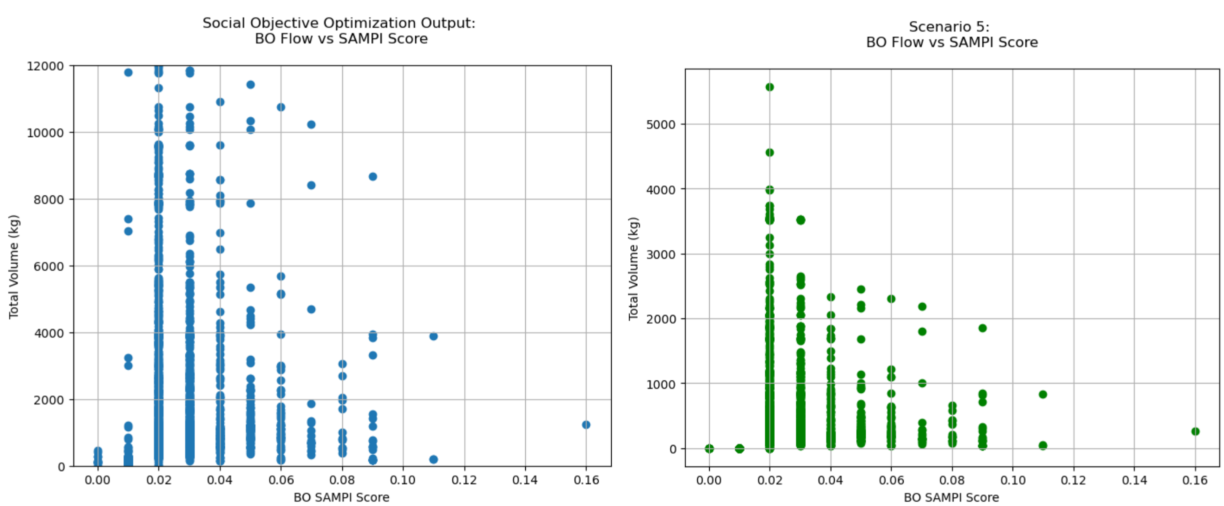
The results are presented in Table 10. The number of BOs capable of being served decreased from 1,657 to 1,531, and unmet demand totaled 133,335 kg. Although mean and median volumes per BO increased, volume distribution became more equitable (with the top 10% of BOs receiving only 39.87% of total volume compared to 53.73% in the baseline). These results highlight that raising minimum service levels strengthens support depth but at the cost of reaching fewer BOs and increasing unmet need.

*Table 10. Baseline Social Optimized Network vs. Scenario 6 BO Demand Flow*

| | Baseline Optimized Network | Scenario 5 Network |
|---|---|---|
| Total BOs Served | 1,657 | 1,531 |
| Mean Volume (kg) | 533.84 | 577.83 |
| Median Volume (kg) | 273.62 | 295.50 |
| Standard Deviation (kg) | 2,412.67 | 687.11 |
| Min Volume (kg) | 45.00 | 0.00 |
| Max Volume (kg) | 49,518.81 | 5,575.50 |
| Volume to Top 10% BOs (%) | 53.73% | 39.87% |
| Avg. % of Total BO Monthly Need (kg) Covered | 31.38% | 19.53% |
| Avg. Number of BO Meals Covered | 4.41 | 3.00 |

The results also showed meaningful shifts in distribution patterns based on BO SAMPI scores. The BO Flow vs. SAMPI Score plots in Figure 5 show that raising the minimum meals served requirement from 1 to 3 meals led to lower maximum flow volumes and a more compressed distribution across BOs. Compared to the baseline, where many BOs received flows above 8,000 kg, scenario 5 capped flows below 6,000 kg and reduced extreme allocations. While the spread across SAMPI scores remained, flows became more equitable and consistent, prioritizing broader baseline coverage over high-volume distribution.

*Figure 5. Social Objective Optimization vs. Scenario 5: BO Volume Flow (kg) vs. SAMPI Score*



### 5.1.8 Scenario 6: Stress-Testing Social Coverage Requirements

In Scenario 6, the social optimization model was stress-tested even more by significantly increasing the minimum service threshold from one to six meals per BO. This change represents a substantial policy shift, aiming to guarantee deeper support across all BOs, especially those serving the most vulnerable populations. For the sake of space, scenario 6 results are shown in Appendix C. The results demonstrated that enforcing a higher minimum service level per BO significantly increased support depth and equity, it also halved the number of BOs served and generated substantial unmet demand.

## 5.2 Managerial Insights

The optimization modeling and scenario analysis provide several important managerial insights for FFSA and offer a transferable framework for other food banks seeking to adopt a similar methodology. The section expands on warehouse utilization patterns, the influence of facility location, and the inherent trade-offs across economic, environmental, and social objectives.

A prominent finding is the distinct shift in utilization across the network when comparing the current state to optimized scenarios. Urban hubs, GP-WH (Gauteng), WC-WH (Western Cape), and KZN-WH (KwaZulu-Natal), currently serve as the primary distribution facilities due to their proximity to donor volumes and their strategic positioning. However, under optimized models, utilization at these hubs decreases moderately (e.g., GP-WH from 24.55% to 20.73%; WC-WH from 16.63% to 14.11%), with corresponding increases in rural warehouses such as LIM-WH (Limpopo) and NW-WH (North West). When situated near high-need communities, more rural warehouses can absorb more flow in equity-focused models. EC-WH (Eastern Cape), for instance, saw increased utilization in the social model due to its proximity to beneficiary organizations with high SAMPI vulnerability scores. This redistribution suggests that, while large urban hubs are cost-efficient under current operations, integrating rural warehouses more actively can enhance environmental and social outcomes without significantly increasing overall cost.

Warehouse location is also a critical driver of performance across different objectives. The economic model favors centrally located warehouses to reduce long-haul donor to warehouse transportation costs. The environmental model minimizes emissions by shifting flows toward more decentralized routing, reducing the distance to beneficiary organizations. The social model prioritizes service coverage in high-need areas, leading to increased reliance on warehouses situated near vulnerable communities. The closure of a centrally located warehouse, such as FS-WH (Free State), further demonstrates the network's sensitivity to facility configuration: utilization shifts sharply to adjacent rural nodes (e.g., NW-WH), reinforcing the value of geographic redundancy and balanced distribution.

More broadly, the results highlight meaningful trade-offs across the three objectives. Economic optimization yields the greatest cost reductions but often at the expense of equitable service coverage and higher emissions. Environmental optimization reduces emissions by up to 25% through shorter distribution paths but introduces modest cost increases. Social optimization, while delivering the greatest improvements in equitable access, comes with the highest operational cost and emissions burden. These trade-offs emphasize that no single configuration simultaneously optimizes all goals; rather, decision-makers must weigh competing priorities depending on strategic intent and resource constraints.

The effectiveness of this model is highly dependent on the accuracy and completeness of input data. For FFSA, limitations in donor location data, such as missing GPS coordinates or incomplete addresses, constrained the precision of modeled flows. We recommend that FFSA prioritize the systematic collection of complete and geocoded donor location data. Enhancing data quality will strengthen the model's ability to generate actionable insights and support more reliable scenario planning. This refinement should be viewed as an investment in long-term operational visibility and network agility. For other organizations considering similar modeling frameworks, establishing standardized processes for geographic and volume-based data collection is essential.

Several recommendations emerge from these findings. First, there is an opportunity to expand the role of underutilized rural infrastructure; warehouses like LIM-WH and NW-WH are well-positioned to absorb additional flows under increased demand or socially prioritized scenarios. Similarly, facilities like EC-WH can serve as high-impact nodes for equity-focused distribution if equipped with more flexible outbound capabilities. Additionally, scenario planning should be utilized to evaluate future network reconfigurations, shifts in donor geography, or changes in community needs. This would allow FFSA to improve preparedness and support data-driven distribution decisions. Finally, embedding social equity metrics, such as SAMPI scores, into routing logic would enable more responsive, vulnerability-informed allocation, especially during times of constrained supply.

These findings underscore the importance of a flexible, location-sensitive distribution strategy. A balanced network that leverages the strengths of both large urban hubs and strategically located rural depots can enable FFSA to reduce costs, lower environmental impact, and improve equity in food access across South Africa. While these recommendations offer strategic guidance, several opportunities exist to expand the model's capabilities and address current limitations, as outlined in the following chapter.

# 6 CONCLUSIONS

## 6.1 General Conclusions

This capstone project sets out to address the real-world challenges food banks face in the mission to fight hunger across the globe. We applied supply chain methodologies to explore improvements in food bank costs, emissions, and social impact via network redesign for FoodForward SA. Our work highlights how optimization can show potential improvements that leaders can use to guide strategic decisions, evaluate tradeoffs, and better align with their mission and constraints. The proposed solution is to apply three separate optimization models to identify operational improvements and identify tradeoffs.

This project's findings include results and recommendations elaborated on in Section 5. Among these findings are the two following takeaways: (1) under the optimized economic model, FFSA's costs consistently drop by ~11% each month compared to the baseline; and (2) under the optimized social model, increasing social impact by 60% would come at the expense of ten times the $CO_2$ emissions.

The first research question in this capstone asks, "What strategies can FFSA use to better serve BOs based on varying network scenarios?" From a purely social perspective, the BOs would benefit more from FFSA adopting a network strategy that is more closely aligned with the output from the social objective function in this capstone. However, that conclusion comes with the assumption that FFSA can maintain its economic ability to operate at increased costs and justify the environmental toll that comes with this model. The social model also favors increased throughput at centrally located warehouses (i.e., EC-WH) where higher SAMPI-weighted coverage is achieved.

The second research question asks, "What improvements in costs, $CO_2$ emissions, food accessibility and coverage can be achieved through an optimized supply chain network?" Each of the three sets of criteria assessed and optimized for can improve significantly. These improvements come from network redesign, where the tightening and relaxing of transportation constraints influence the results of each measure. The economic model favors utilization at centrally located warehouses to reduce donor-to-warehouse costs, while the environmental and social models favor more decentralized warehouses to reduce distances between warehouses and BOs.

The third research question in this capstone asks, "What are the tradeoffs under diverse distribution strategies?" While the models in this capstone show clear room for improvement on each measure, optimizing for one will worsen the performance of the other two objectives within each model. This proves tradeoffs are apparent for food banks when prioritizing economic, environmental, or social objectives. Ultimately, it is within the purview of each food bank to assess their business needs, goals, capabilities, and risk tolerance when toggling their network and investment strategies.

## 6.2 Limitations

This capstone project was subject to several limitations, which influenced the depth and scope of our work. These limitations are related to data availability, geographic access, modeling assumptions, time constraints, and computational scope. Each limitation provides transparency into the boundaries within which our work was conducted concerning research, considerations in modeling, and the point at which potential future work could expand beyond this study.

The aforementioned assumptions in Section 3.3.2 bounded all modeling and subsequent analysis of results in this project. While these assumptions were necessary to keep the capstone manageable and allow for practicality, they also limited the translation into real-world complexities by excluding dynamic variables such as changing demand, perishability factors, and some transportation constraints.

Our data, sourced from FoodForward SA and academic partners at Stellenbosch University, was also a limitation. Piecing together information from multiple files and interview insights was the best methodology for this capstone, but (aside from the literature review in Section 2) constrained our information gathering to a few points of contact. Within the data, one limitation was the lack of GPS coordinates for donor locations, which restricted modeling precision for FFSA. Additionally, the dataset was limited to a single year (March 2023 to February 2024). This constrains the model's ability to account for seasonal variation, long-term trends, or year-over-year performance. Since food donations and demand often fluctuate, a multi-year data set would enable more robust scenario analysis and risk-informed decision-making. The inability to conduct a site visit in South Africa limited firsthand observation of FFSA's facilities and processes.

Expanding on the limited donor data we received, we were not provided with GPS locations or names of specific donors or donor businesses, which limited our ability to analyze donor behavior or optimize based on donor proximity. Furthermore, the quantity and consistency of donations themselves are inherently limited and uncertain, posing challenges for long-term planning.

The timeline for this capstone project was fixed from September 2024 to May 2025. This strict time limitation confined the depth of our research, stakeholder engagement, modeling, and analysis.

Modeling the network within this project's scope required optimization for three separate objectives. While we could build and run models for economic, environmental, and social objectives, we did not implement a full multi-period, multi-objective optimization that balances all objectives and their criteria simultaneously. Including these tradeoffs in a single model would require more time and computational resources than the scope of this capstone allowed.

## 6.3 Future Work

This capstone explored the operational challenges faced by food banks by developing an optimization-based framework that balances economic, environmental, and social objectives. The result is a set of optimization models tailored for FFSA's network and a configurable decision support methodology that other food banks can adapt to align with their networks and strategic goals.

While the current models deliver practical insights, several opportunities exist to extend its capabilities. Incorporating dynamic demand would be allowing beneficiary organization (BO) demand to vary over time, as it does in reality. This would increase the model's ability to capture seasonality or shifting needs across different regions and communities.

Another improvement would be enabling the reconfiguration of the network itself. Allowing users to simulate adding or relocating warehouses and Mobile Rural Depots (MRDs) would expand the model's usefulness in long-term growth planning, emergency response, or strategic restructuring. Enabling food bank network reconfiguration may also provide cost estimates on investments and forecast return on investment as well.

Additionally, future work could account for food waste more accurately. The current models assume food is delivered at the beginning of a period and is fully utilized throughout the month. In reality, food waste occurs progressively over time as perishables approach expiration. Modeling a diminishing usability rate or capping deliverable volumes to reflect spoilage would bring more realism to the analysis and could influence the newly modeled network flows.

Truckload capacity is another limitation that could be addressed. The models could better reflect logistical constraints and improve routing efficiency by introducing vehicle weight, capacity limits, and efficiency. Introducing vehicle type and specifications could also inform on network design.

Lastly, the models could be extended to consider the nutritional value of food. Factoring in product mix and dietary quality would allow food banks to distribute enough food and the right kinds of food, aligned with health and nutritional goals.

These enhancements would improve the model's accuracy, flexibility, and impact, making it a more powerful methodology that can evolve into a decision support system for food banks striving to balance resources while serving their communities with greater precision and equity.

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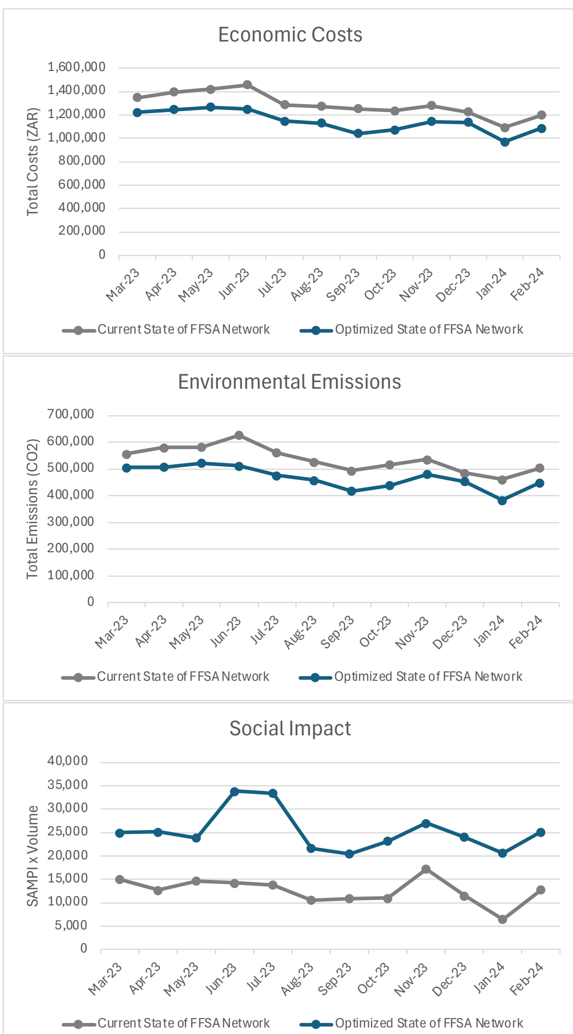
# APPENDIX A

Complete results of the comparative analysis between the current and optimized FFSA network are shown in Figure A1. Monthly data from March 2023 to February 2024 illustrates performance across the three objectives: total economic costs, environmental emissions, and social impact.

The results demonstrate that the optimized network consistently outperforms the current state. Economically, it achieves lower total operational costs across all months. When optimized for environmental objective, the network shows consistent $CO_2$e reductions. The optimized network significantly enhances social impact, delivering greater service to vulnerable areas as reflected in higher SAMPI-weighted volume throughout the year.

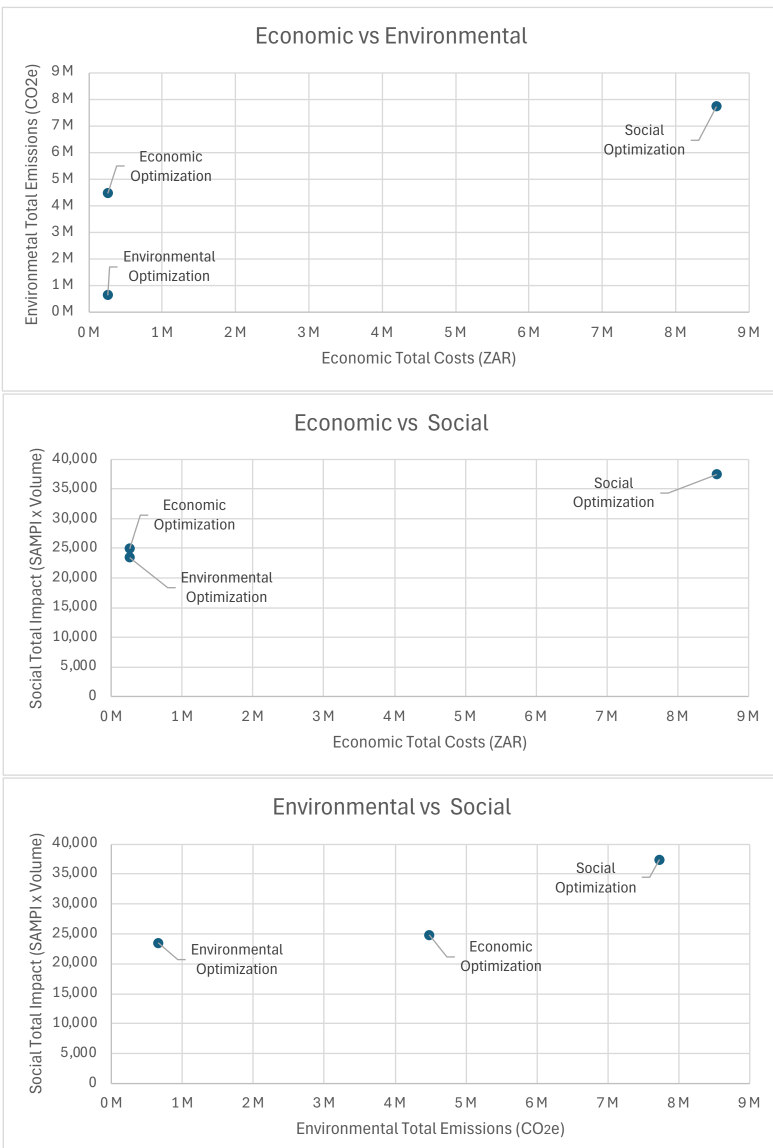
*Figure A1. Monthly Results of Current vs. Optimized FFSA Network Across the Three Objectives*



# APPENDIX B

The scatter plots (shown in Figure B1) illustrate the trade-offs between the three key objectives in the FFSA network optimization: economic cost, environmental emissions, and social impact. Each point represents the optimal solution under a single-objective model. These graphs visualize the inherent trade-offs and between the three objectives by mapping their outcomes across different dimensions. These trade-offs could also be visualized on a 3D XYZ plot to show all three objectives simultaneously.

*Figure B1. Two-Dimensional Trade-Off Plots of FFSA Network Optimization Results*



# APPENDIX C

Appendix C shows the remaining scenario results. Scenario 2: Impact of Activating Rural Province Depots, Scenario 4: Impact of Localized Demand Reduction, and Scenario 6: Stress-Testing Social Coverage Requirements.

## Scenario 2 Results

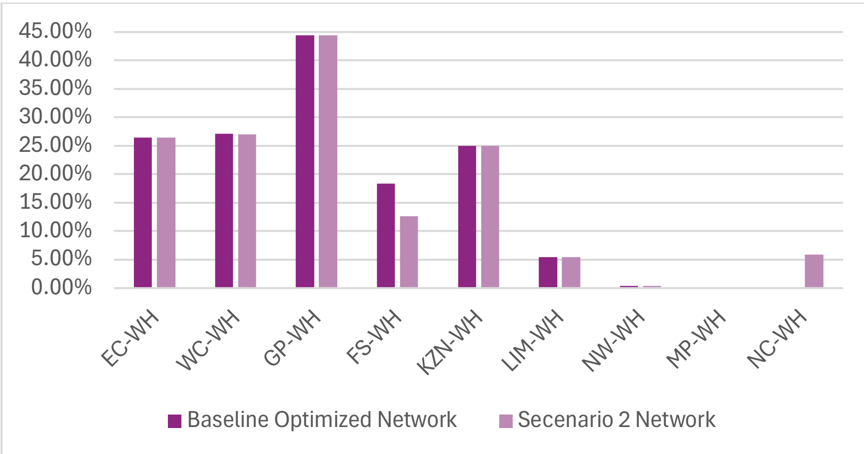
In Scenario 2, introducing two additional Rural Provincial Depots (RPDs) into the network as full-capacity warehouses produced modest but consistent operational improvements. As displayed in Table C1, total economic cost decreased slightly from ZAR 261,374 to ZAR 255,627, a 2.2% reduction, and transportation costs from donors to warehouses fell by 3.5%. Environmental performance also improved marginally, with total emissions declining from 653,859 kg $CO_2$e to 648,095 kg $CO_2$e. Emission reductions were observed across both donor-to-warehouse transport and warehouse-to-BO transport. These results suggest that although expanding the network with RPDs slightly improves flow flexibility, it does not generate significant cost savings or emission reductions under current demand conditions.

*Table C1. Comparative Results of Baseline Optimized Network vs. Scenario 2 Network*

| | Baseline Optimized Network | Scenario 2 Network |
|---|---|---|
| **Economic Total Cost (ZAR)** | **261,375** | **255,627** |
| Total Handling Cost (ZAR) | 99,394 | 99,394 |
| Transportation Cost: Donors to Warehouses (ZAR) | 161,981 | 156,234 |
| **Environmental Total Emissions ($CO_2$e)** | **653,860** | **648,095** |
| Emissions: Donors to Warehouses ($CO_2$e) | 62,041 | 59,874 |
| Emissions: Warehouses to BOs ($CO_2$e) | 481,382 | 477,784 |
| Food Waste Emissions ($CO_2$e) | 110,437 | 110,437 |
| **Social Total Impact Score (SAMPI x Volume)** | **37,388** | **37,388** |

Warehouse utilization patterns, shown in Figure C1, indicate minimal shifts compared to the baseline optimized network. FS-WH declined slightly from 18.42% to 12.64%, suggesting some flow reallocation, but the overall network structure remained highly consistent. The two newly introduced warehouses, MP-WH and NC-WH, absorbed small volumes, with MP-WH reaching only 0.04% utilization and NC-WH reaching 5.93%**.** These results indicate that the transformation of these RPDs into traditional warehouses had limited operational impact. However, this analysis does not take into account the costs of building, buying, or labor for setting up a new warehouse.

*Figure C1. Baseline Optimized Network vs. Scenario 2 Network Capacity Utilization by Warehouse*




## Scenario 4 Results

Scenario 4 tested the network's response to a 12% demand reduction among high-priority beneficiary organizations. Results are summarized in Table C2. While the total number of BOs remained at 1,657, the average volume per BO fell from 533 kg to 325 kg, and the maximum volume dropped sharply from 49,519 kg to 2,795 kg. Flow distribution became more balanced, with the standard deviation decreasing from 2,413 kg to 239 kg and the top 10% of BOs receiving only 26.27% of the total volume. However, the average monthly need coverage declined slightly from 31.38% to 29.08%, and meals per BO dropped from 4.41 to 3.82. These results suggest that while reduced demand improves flow equity and operational consistency, it offers only limited efficiency gains and slightly lowers per-BO service levels.

*Table C2. Baseline Optimized Network vs. Scenario 4 Network BO Flow Volume (kg)*

| | Baseline Optimized Network | Scenario 4 Network |
|---|---|---|
| Total BOs Served | 1,657 | 1,657 |
| Mean Volume (kg) | 533.84 | 325.50 |
| Median Volume (kg) | 273.62 | 269.54 |
| Standard Deviation (kg) | 2,412.67 | 239.42 |
| Min Volume (kg) | 45.00 | 45.00 |
| Max Volume (kg) | 49,518.81 | 2,795.06 |
| Volume to Top 10% BOs (%) | 53.73% | 26.27% |
| Avg. % of Total BO Monthly Need (kg) Covered | 31.38% | 29.08% |
| Avg. Number of BO Meals Covered | 4.41 | 3.82 |

Scenario 4 also altered warehouse utilization across the network (shown in Table C3). As overall demand decreased by 12%, total throughput declined at every warehouse. The largest reductions occurred at EC-WH and WC-WH, whose capacity utilization dropped by ~10%. GP-WH remained the most utilized warehouse but saw a decline from 44.46% to 29.09%. FS-WH, already a lower-volume facility, saw utilization fall to just 7.85%. These results suggest that a moderate reduction in demand not only flattens distribution to BOs but also eases pressure on central nodes, creating slack across the network. However, the decline in utilization was uneven, with urban hubs still absorbing the majority of flow, highlighting their ongoing strategic importance even under constrained conditions.

*Table C3. Baseline Optimization vs. Scenario 4 Network Capacity Utilization % by Warehouse*

| | Baseline Optimized Network | | Scenario 4 Network | |
|---|---|---|---|---|
| Warehouse | Total Flow (kg) | Capacity Utilization | Total Flow (kg) | Capacity Utilization |
| EC-WH | 317,086 | 26.42% | 190,517 | 15.88% |
| WC-WH | 325,833 | 27.15% | 173,736 | 14.48% |
| GP-WH | 533,515 | 44.46% | 349,136 | 29.09% |
| FS-WH | 221,033 | 18.42% | 94,240 | 7.85% |
| KZN-WH | 299,773 | 24.98% | 206,877 | 17.24% |
| LIM-WH | 65,028 | 5.42% | 62,890 | 5.24% |
| NW-WH | 4,732 | 0.39% | - | 0.00% |

## Scenario 6 Results

In Scenario 6, the social optimization model was stress tested by increasing the minimum service threshold from one to six meals per beneficiary organization, representing a significant shift toward deeper baseline support. As shown in Figure C4, the number of BOs served dropped from 1,657 to 865, and unmet demand rose sharply to 1,026,153 kg. While mean and median volumes delivered per BO nearly doubled, from 534 kg to 1,024 kg and from 273.62 kg to 525 kg, respectively, overall flow variability narrowed, and maximum deliveries were capped at 7,986 kg. The volume allocated to the top 10% of BOs decreased from 53.73% to 40.63%, indicating a more equitable spread. Significantly, average need coverage improved from 31.38% to 38.72%, and meals per BO increased from 4.41 to 5.99. These results highlight that enforcing a high minimum service level significantly strengthens support depth, dramatically reduces network reach, and generates substantial unmet demand.

*Table C4. Baseline Optimized Network vs. Scenario 4 Network BO Demand Flow*

| | Baseline Optimized Network | Scenario 6 Network |
|---|---|---|
| Total BOs Served | 1,657 | 865 |
| Mean Volume (kg) | 533.84 | 1,023.75 |
| Median Volume (kg) | 273.62 | 525.00 |
| Standard Deviation (kg) | 2,412.67 | 1,229.63 |
| Min Volume | 45.00 | 60.07 |
| Max Volume | 49,518.81 | 7,986.00 |
| Volume to Top 10% BOs (%) | 53.73% | 40.63% |
| Avg. % of Total BO Monthly Need (kg) Covered | 31.38% | 38.72% |
| Avg. Number of BO Meals Covered | 4.41 | 5.99 |

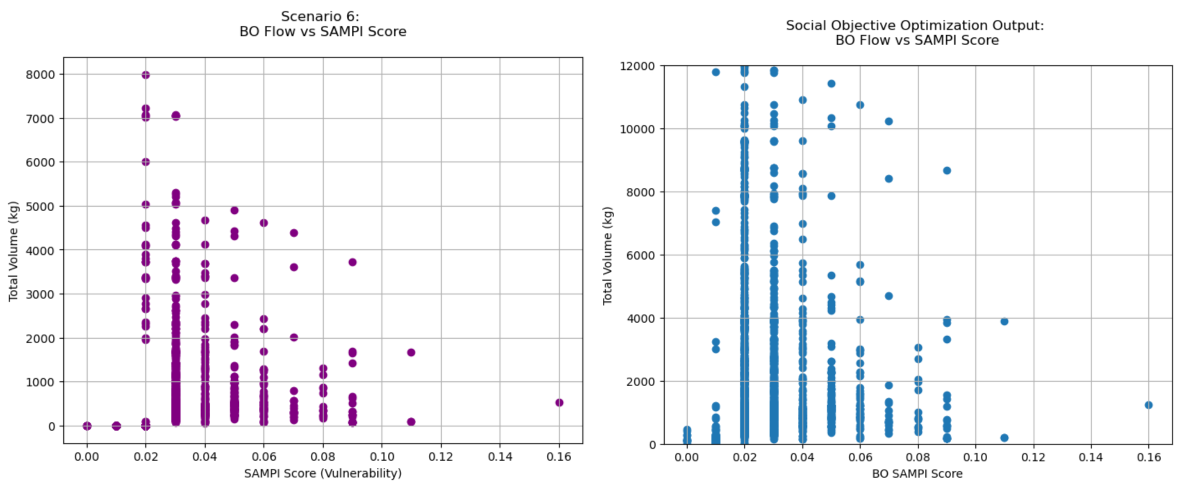
This higher threshold also significantly reshaped warehouse utilization patterns, shown in Table C5. EC-WH reached full capacity (100%), acting as the primary fulfillment node under the socially optimized model. LIM-WH remained a major contributor with over 25% utilization, while usage at WC-WH, GP-WH, and KZN-WH increased from their baseline levels. WC-WH rose from 0.17% to 5.16%, and KZN-WH from 1.22% to 6.13%, indicating broader regional involvement in response to deeper per-BO service requirements. The sharp increase in unmet demand, coupled with near-capacity strain on EC-WH, suggests that enforcing deeper minimum support levels can stretch the network's limits, concentrating volume at key facilities while exposing capacity bottlenecks elsewhere in the network.

*Table C5. Baseline Optimization vs. Scenario 6 Network Capacity Utilization % by Warehouse*

| Warehouse | Baseline Optimized Social Network | | Scenario 6 Network | |
|---|---|---|---|---|
| | Total Flow (kg) | Capacity Utilization | Total Flow (kg) | Capacity Utilization |
| EC-WH | 1,199,428 | 99.95% | 1,200,000 | 100.00% |
| WC-WH | 1,996 | 0.17% | 61,867 | 5.16% |
| GP-WH | 22,791 | 1.90% | 44,519 | 3.71% |
| FS-WH | 2,312 | 0.19% | 22,117 | 1.84% |
| KZN-WH | 14,679 | 1.22% | 73,545 | 6.13% |
| LIM-WH | 327,652 | 27.30% | 306,339 | 25.53% |
| NW-WH | 198,141 | 16.51% | 58,613 | 4.88% |

From a social prioritization standpoint, The BO Flow vs. SAMPI Score plots (see Figure C2) how increasing the minimum meals constraint to six meals in Scenario 6 dramatically compressed volume distribution. Compared to the baseline, where flows often exceeded 8,000 kg and reached up to 12,000 kg, Scenario 6 flows capped near 8,000 kg, with most BOs receiving between 0 and 4,000 kg. The distribution shifted to become more uniform, with fewer extreme high-volume outliers, while maintaining a similar spread across SAMPI vulnerability scores. This reflects a network prioritizing deeper, more equitable baseline support but with a reduced ability to deliver very large volumes to any single BO.

*Figure C2. Social Objective Optimization and Scenario 5: BO Volume Flow (kg) vs. SAMPI Score*



# APPENDIX D

Appendix D presents visual maps of FFSA's current network, highlighting the geographic reach and location of donors, beneficiary organizations, and warehouse facilities (both traditional and RPDs). The maps help contextualize the operational environment and regional service patterns discussed throughout this report.

*Figure D1. Locations of FFSA Donors (Blue Markers)*

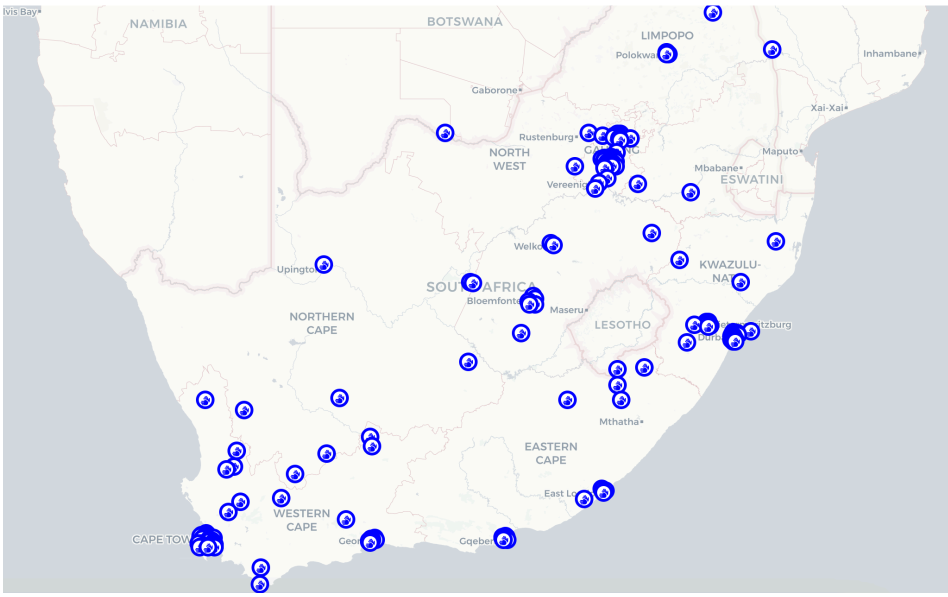



*Figure D2. Locations of FFSA Beneficiary Organizations (Green Markers)*

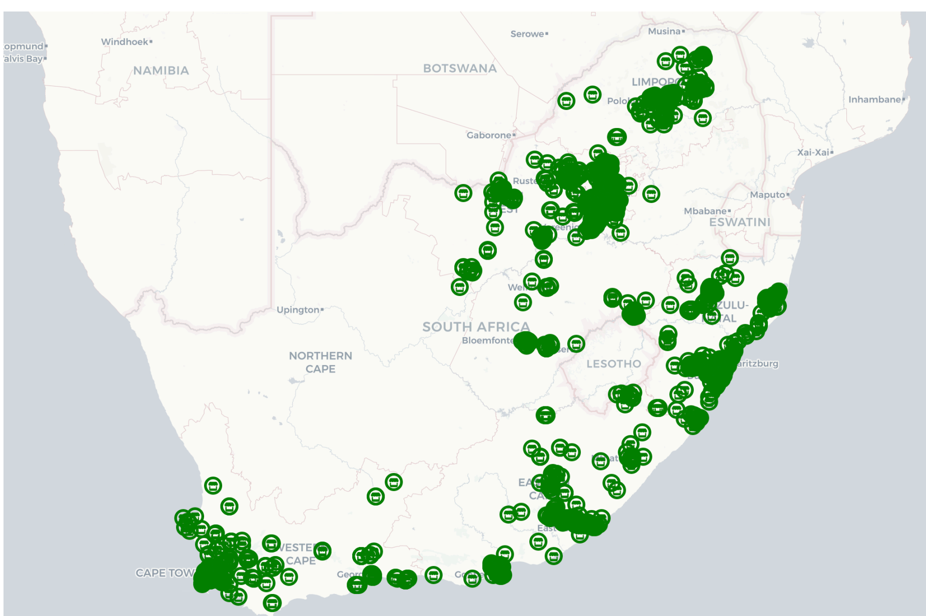


*Figure D3. Locations of FFSA Traditional Warehouses (Red Markers) and RPDs (Purple Markers)*