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Elicitation of Preference among Multiple Criteria in Food Distribution by Food Banks

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The United Nations Sustainable Development Goals provide a road map for countries to achieve peace and prosperity. In this study, we address two of these sustainable development goals: achieving food security and reducing inequalities. Food banks are nonprofit organizations that collect and distribute food donations to food-insecure populations in their service regions. Food banks consider three criteria while distributing the donated food: equity, effectiveness, and efficiency. The equity criterion aims to distribute food in proportion to the food-insecure households in a food bank's service area. The effectiveness criterion aims to minimize undistributed food, whereas the efficiency criterion minimizes the total cost of transportation. Models that assume predetermined weights on these criteria may produce inaccurate results as the preference of food banks over these criteria may vary over time, and as a function of supply and demand. In collaboration with our food bank partner in North Carolina, we develop a single-period, weighted multi-criteria optimization model that provides the decision-maker the flexibility to capture their preferences over the three criteria of equity, effectiveness, and efficiency, and explore the resulting trade-offs. We then introduce a novel algorithm that elicits the inherent preference of a food bank by analyzing its actions within a single-period. The algorithm does not require direct interaction with the decision-maker. The non-interactive nature of this algorithm is especially significant for humanitarian organizations such as food banks which lack the resources to interact with modelers on a regular basis. We perform extensive numerical experiments to validate the efficiency of our algorithm. We illustrate results using historical data from our food bank partner and discuss managerial insights. We explore the implications of different decision-maker preferences for the criteria on distribution policies.

Key words: food bank; equity; multi-criteria optimization; preference elicitation; humanitarian operations; UN Sustainable Development Goals
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1. Introduction

Achieving food security and reducing inequalities are among the Top 10 United Nations' (UN) Sustainable Development Goals for 2030 (United Nations 2020a). Food insecurity, defined as the inability of a household to provide a sufficient amount of nutritious food to its members for normal growth and development (Feeding America 2015), is ubiquitous and affects countries worldwide. According to the UN, an estimated 690 million people worldwide suffered from food insecurity in 2019 (United Nations 2020b). Underdeveloped countries may suffer from scarcity of food, or famine, whereas the main reason for food insecurity in developed countries such as the United States (US) is income inequality (Elmes 2018). The impact of COVID-19 on the state of food insecurity has been significant. In the US, 10.5% of households were food insecure in 2019 (United States Department of Agriculture 2020). With the spread of COVID-19, food insecurity has significantly increased. The Feeding America (FA) COVID-19 Impact Assessment Report shows a 28% increase in need in 2020, which translates to an additional 10 million people in need (Feeding America 2021). Appendix A shows the weekly increase in food distribution by FA between March and April 2020 compared to 2019.

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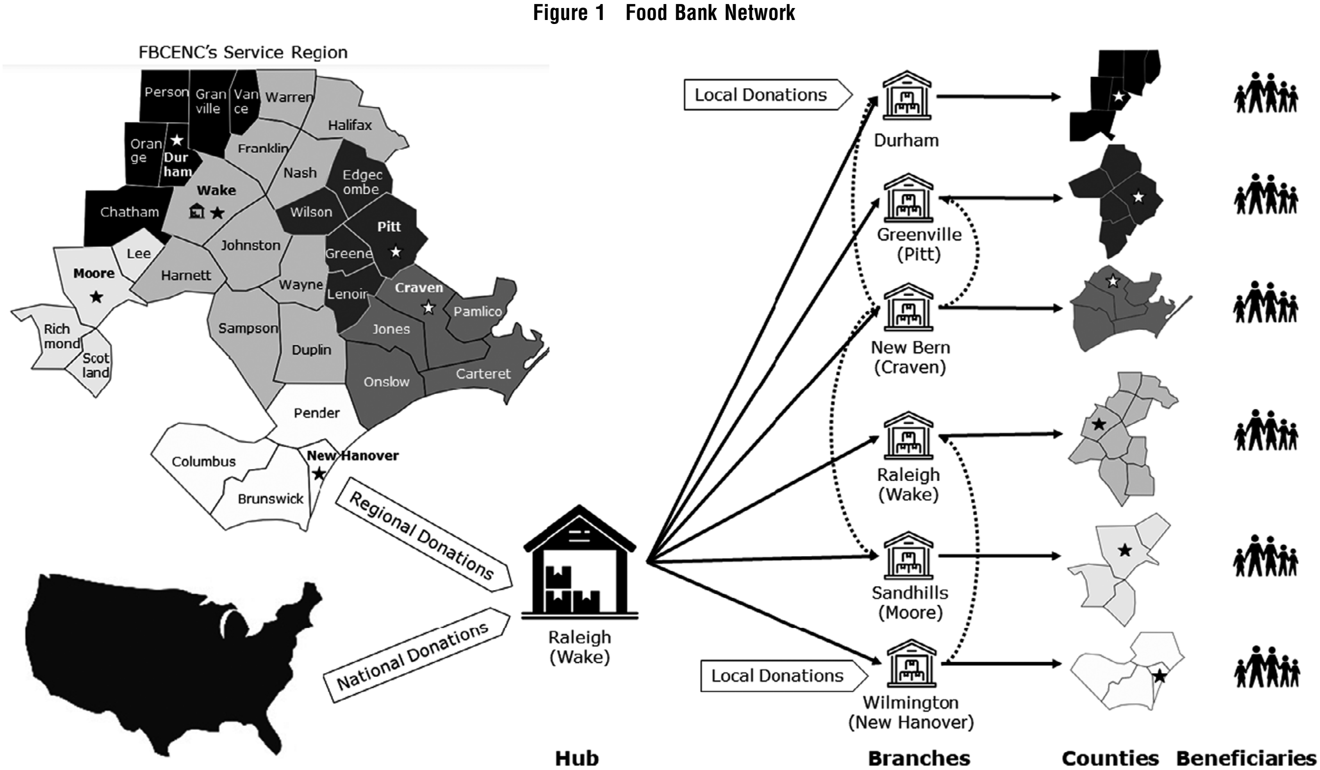
In this study, we address two of the UN Sustainable Development Goals (UNSDGs) related to food insecurity: Zero Hunger (Goal 2) and Reduced Inequalities (Goal 10). Due to the complexities of the UNSDGs, they cannot be considered in isolation and solutions must address the interconnection between these goals (United Nations 2020a, United Nations Development Programme 2020). To address the Zero Hunger goal, developed countries should focus on operations due to the abundance of food and subsequent food waste. Specifically, they should focus on preventing usable food from being wasted and facilitating the equitable allocation of food to the population in need, which is aligned with Goal 10. The concurrent consideration of these goals requires modeling approaches that aim to achieve an equitable, effective, and efficient allocation of usable food.

Feeding America is the largest nonprofit hunger-relief organization in the US, operating through a nationwide network of 200 food banks and 60000 agencies. In 2019, they helped provide 4.2 billion meals to over 40 million people (Feeding America 2020a). The organization collects food donations from national food and grocery manufacturers, retailers, and governmental agencies and distributes the donations to its member food banks. The food banks then distribute the food they receive from FA and other sources such as local grocers, state and federal government agencies, and individuals to charitable agencies in their service regions. These nonprofit agencies, such as food pantries, churches, and soup kitchens, distribute to food-insecure households in their local area.

Our study is motivated by our decade-long collaboration with the Food Bank of Central and Eastern North Carolina (FBCENC), an affiliate member of Feeding America. The FBCENC network, shown in Figure 1, is representative of food bank supply chains in the US and many developed countries (Sengul Orgut et al. 2016a, Zobel et al. 2015). FBCENC is one of the seven FA-affiliated food banks working to alleviate food insecurity in the state of North Carolina (NC) and the largest food bank in NC in terms of annually distributed food. It was established in 1980 in Raleigh, NC, and serves food-insecure households in 34 of the 100 counties[1] in NC. FBCENC distributes food donations from national and regional sources to more than 900 agencies through six distribution centers (branches) (FBCENC 2021).

Unlike for-profit organizations, where maximizing profit and meeting consumer demand are usually the central criteria, food banks try to ensure an equitable, effective, and efficient distribution of donated food. The *equity* criterion refers to the "fair" distribution of donated food to people who need it. Since demand typically exceeds supply in this environment (Sengul Orgut et al. 2016b), food banks aim to ensure that each county receives food in proportion to the

Figure 1 Food Bank Network



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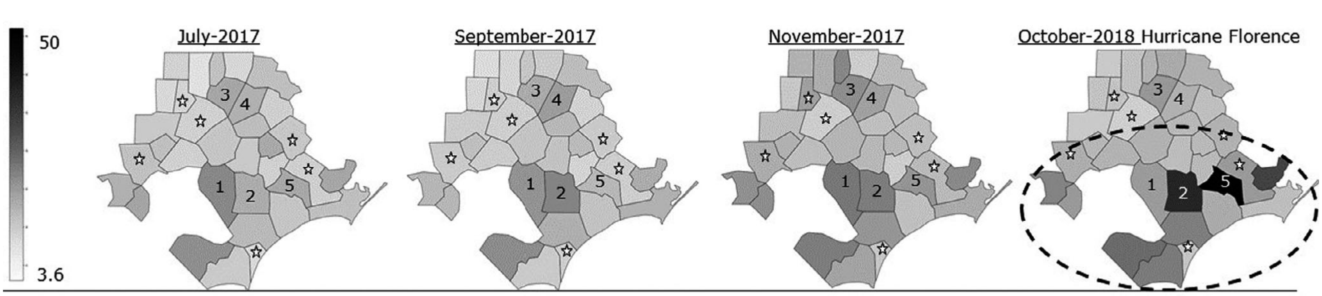
demand they serve, which is the equity metric used by FA (Feeding America 2020c). This allocation of food according to each county's demand proportion is also referred to as "perfect equity." The *effectiveness* criterion refers to the minimization of food waste within the food bank distribution network. As the supply of donated food is less than the actual demand, food banks attempt to distribute the maximum amount of donated food, minimizing potential food waste. However, like other organizations, food banks require staff (paid and volunteer) and overhead to support their operations. They also have limited operating budgets, as such high distribution costs may force them to limit operations over time. The *efficiency* criterion refers to the minimization of the distribution costs. Although food banks do not seek to generate profit, they try to achieve their goals of equitable and effective food distribution for a minimum cost. This enables a food bank to focus its budget on improving food security within its network. Money saved by minimizing the cost of distribution can be used to feed more people in need, as one dollar equates to ten meals (Feeding America 2020d). At the same time, an efficient distribution policy would allow a food bank to continue its daily operations without significantly constraining staffing and overhead. In humanitarian organizations such as food banks, donors may also be concerned about how their monetary donations are allocated (Burkart et al. 2016) and may like to see the minimum amount spent on overhead and logistical operations and the maximum amount spent on acquiring donations. Each of these priorities influences food distribution policy.

Food banks face two major challenges considering the criteria of equity, effectiveness, and efficiency simultaneously in their operations. First, these criteria may contradict. For example, to lower distribution costs, a food bank may decide to distribute all available food so that the counties closer to their warehouses receive more food. While this policy is effective and efficient, it is inequitable as more distant counties receive less than their fairshare. Second, a food bank's preferences for equity, effectiveness, and efficiency may not be stationary and may shift based on fluctuations in supply and demand. Figure 2 shows the distribution actions taken by FBCENC over July 2017, September 2017, November 2017, and October 2018. As shown in the figure, Meals per Person In Need (MPIN) is a county-level equity measure used by FBCENC and is calculated by dividing the pounds of food received by the county in a given time period (month) by 1.2 times the food-insecure population estimate for that county. Note, 1.2 pounds of food is equivalent to one meal (Feeding America 2020d). When the MPIN values for all counties are the same, perfect equity is achieved. If the MPIN value of a county is lower than other counties, this indicates that a food-insecure person in that county received less food than a food-insecure person residing in the other counties in the service region.

Figure 2 highlights the variability in distribution actions over the four months. For example, Figure 2 shows that Sampson (1) county had a higher MPIN than its neighbor, Duplin (2) county, in July 2017, whereas Duplin had a higher MPIN than Sampson in September 2017. A similar observation can be made for Franklin (3) and Nash (4) counties. FBCENC usually receives more donations in November (8.7 million pounds) than other months (e.g., this was 2 million pounds more than July 2017), as the month marks the start of the holiday season. The additional food resulted in higher MPIN values across all counties compared to July 2017; however, there was also greater variability in the MPIN values suggesting that

Figure 2 **Changes in FBCENC's Distribution over Time; the Geoplots Show the MPIN (Meals Per Person In Need) Across Counties where Darker Shading means a Higher MPIN or more Pounds were Distributed within that County Per Person in need Relative to the Other Counties; MPINr: the Range of MPIN Values Across the Counties, Supply (lbs): Available Food Supply in Pounds at FBCENC Warehouses, %: Percentage of Food Distributed; Dashed Circle Indicates the Counties Most-Impacted by Hurricane Florence in 2018; 1: Sampson, 2: Duplin, 3: Franklin, 4: Nash, 5: Jones**



MPINr	3.60 – 15.35	4.03 – 16.12	5.81 – 18.01	5.65 – 49.61
Supply(lbs)	6.7 Million lbs	7.4 Million lbs	8.7 Million lbs	10.38 Million lbs
Dstr%	72%	68%	76%	71%

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a lower level of equity was achieved in order to distribute the large amount of donations. Likewise, FBCENC's preference may change drastically during the time of a disaster, such as Hurricane Florence in 2018. The counties within the circle in the rightmost geoplot in Figure 2 are those most impacted during Hurricane Florence as designated by the US Department of Homeland Security Federal Emergency Management Agency (FEMA 2019). We can see that the MPINs within the most impacted counties were noticeably higher than the other counties (highly variable MPIN, 5.65–49.61), suggesting a decrease in FBCENC's preference for equity or an increase in demand. The county in black, Jones (5) county, had the highest MPIN. This variability illustrates that a food bank's priorities are dynamic and may change over time (e.g., seasonality) and in response to extreme events (e.g., hurricane). Appendix B contains an analysis of FBCENC's monthly operations (donations, distribution, etc.) from July 2017 to June 2019.

Considering these challenges, our research questions are threefold: *1.a. How do food bank decision-maker preferences and priorities with respect to equity, efficiency, and effectiveness affect optimal distribution policy? 1.b. How should a food bank distribute food donations to their beneficiaries according to their preferences for the criteria of equity, efficiency and effectiveness?* To address these research questions, we develop a single-period, multi-criteria network flow model, *Model EEE*, that considers the weighted scalarized deviations from perfect equity, effectiveness, and efficiency (EEE). Specifically, our model minimizes the sum of three components: the total weighted absolute deviation from a perfectly equitable distribution (equity criterion), the total holding cost associated with undistributed food supply (effectiveness criterion), and the total distribution cost (efficiency criterion). The scalarization for each criterion, also known as linear normalization (Ransikarbum and Mason 2016), is performed such that each criterion is on a uniform, dimensionless scale. The weight assigned to each criterion can be interpreted as the preference placed on the criterion by the decision-maker, for example, food bank manager. This approach allows us to capture a food bank's objectives and explore the trade-offs while providing the flexibility for a food bank to adjust its preferences over the three criteria and understand the implications of such changes. We assume a food bank's actions are driven by food bank management which we refer to as the food bank manager who is the decision-maker.

Our second research question is: *2.a. What can be learned about food bank decision-maker priorities and preferences with respect to equity, efficiency, and effectiveness from their historical distribution behavior? 2.b. Can we capture a decision maker's shifting preferences (weights) for the three criteria in a non-interactive manner using the historical distribution decisions by the food bank?* To address this research question, we develop a non-interactive "preference elicitation" (PE) algorithm that can extract the weights the decision-maker places on the criteria by analyzing their actual distribution actions during a single period. This algorithm only requires the historical data as input, can be solved iteratively over multiple periods, and is non-interactive.

In multi-criteria optimization models (MCOM), it is important to capture the decision-maker's preferences for the considered criteria in order to obtain results that are suited to the needs of the decision-maker (Gralla et al. 2014). This is usually done by testing all weight combinations, developing an efficient frontier, and asking the decision-maker to select weights based on the efficient frontier (Karwan et al. 1985, Keeney and Raiffa 1976). However, such an approach is not sustainable in food bank operations for two reasons. As illustrated above, a food bank's preferences are dynamic and food bank managers may not have the time and resources to explore complex efficient frontiers regularly. In addition, it may be difficult for food bank managers to interpret the trade-offs between three contradictory criteria and capture their preferences for these abstract concepts among the pairs of non-dominated solutions. Hence, the novelty of the PE algorithm is that it allows us to capture a food bank's priorities for each of these criteria as reflected by their distribution actions in a non-interactive manner and to significantly reduce the set of weights to be explored by food bank managers. This algorithm can inform food bank managers how their actions align with their perceived preferences and support future distribution decision-making for achieving their strategic goals.

Our last research question is: *3.a. What insights can be learned about the impact of food bank manager preferences on their distribution decisions from exploration of historical distribution behavior? 3.b. How can these insights be used to provide guidance to improve distribution with respect to the criteria of equity, effectiveness, or efficiency?* To address this research question, we use the developed multi-criteria model and non-interactive algorithm concurrently to perform an extensive case analysis using data from our collaborating food bank, FBCENC. We explore how the distribution policies shift for varying weights placed on the three criteria, elicit FBCENC's preferences on the three criteria based on their actions, and characterize the impact of the criteria on distribution actions.

The next section provides a review of the relevant literature. Sections 3 and 4 present Model EEE

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and the PE algorithm, respectively. Section 5 presents the FBCENC case study and discusses corresponding managerial and policy insights. Section 6 provides directions for future research.

2. Literature Review

Our work is related to two literature streams: (i) Modeling of Equity, Effectiveness, and Efficiency in Humanitarian Operations and (ii) Preference Elicitation Methods for Multi-criteria Optimization Problems.

2.1. The Modeling of Equity, Effectiveness, and Efficiency in Humanitarian Operations

Often in humanitarian aid distribution problems, decision-makers consider multiple and contradictory criteria to identify optimal distribution policies for relief aid in short-term and long-term problems. Short-term problems in the humanitarian context usually refer to disaster relief operations (Van Wassenhove 2006), whereas long-term problems refer to ongoing processes such as the hunger relief activities of a food bank. Although the criteria of equity, effectiveness, and efficiency are commonly studied in both short-term and long-term problems, they typically have different definitions and importance (Beamon and Balcik 2008, Marsh and Schilling 1994). Table 1 presents an overview of studies in disaster relief and food banking operations that consider equity, effectiveness, or efficiency as a criteria or as a constraint (marked with *). If weights are placed on the criteria, we also indicate the method for determining weights, that is, assumed, determined through an interactive method, or determined through a non-interactive method, and highlight how our model contributes to this literature.

Table 1 **A review of disaster relief, food rescue, and food bank operations literature Eq: Equity, Effec: Effectiveness, Effic: Efficiency, Int: Interactive, Non-int: Non-interactive**

	Criteria			Weights		
Paper	**Eq**	**Effec**	**Effic**	**Assumed**	**Int**	**Non-int**
Disaster Relief						
Abazari et al. (2021)		×	×	×		
Anaya-Arenas et al. (2018)	×		×			
Aslan and Çelik (2019)	×					
*Balcik et al. (2008)		×	×			
Carland et al. (2018)			×		×	
Döyen et al. (2012)		×	×			
Ferrer et al. (2018)	×		×	×		
Ghasemi et al. (2020)	×		×			
Gralla et al. (2014)	×	×	×		×	
Holguín-Veras et al. (2013)	×		×			
Hong et al. (2015)			×			
*Huang et al. (2012)	×	×	×			
*Huang et al. (2015)	×	×		×		
Kilci et al. (2015)	×					
McCoy and Lee (2014)	×		×			
*Noham and Tzur (2018)	×	×				
Rawls and Turnquist (2011)		×	×			
Rezaei-Malek et al. (2016)		×	×			
Tzeng et al. (2007)	×		×			
Viswanath and Peeta (2003)			×	×		
*Vitoriano et al. (2011)	×		×	×		
Yilmaz and Kabak (2020)			×		×	
Yu et al. (2018)	×	×	×	×		
Yu et al. (2019)	×	×	×	×		
Food Rescue Operations						
*Balcik et al. (2014)	×	×		×		
Eisenhandler and Tzur (2019a, b)	×	×				
Gonçalves et al. (2013)		×	×			
Gunes et al. (2010)			×			
Lien et al. (2014)	×	×				
Nair et al. (2017)	×		×			
*Nair et al. (2018)		×	×			
Rey et al. (2018)	×		×			
Solak et al. (2014)			×	×		
Food Bank Operations						
*Ahire and Pekgün (2018)			×			
*Alkaabneh et al. (2020)		×	×			
*Blackmon et al. (2021)		×	×			
Fianu and Davis (2018)	×					
Granillo-Macías (2021)			×			
Grover et al. (2020)		×	×		×	
*Islam and Ivy (2018, 2021)	×	×	×			
Kretschmer et al. (2014)	×	×	×			
Martins et al. (2019)	×	×	×	×		
*Mogale et al. (2018)		×	×			
Mohan et al. (2013)		×				
Park and Berenguer (2020)	×		×			
Sahinyazan et al. (2021)			×	×		
*Sengul Orgut et al. (2013, 2016a, b, 2017, 2018)	×	×				
Our work	×	×	×			×

Notes: Papers with "asterisks" consider at least one criteria as constraint.

<u>**Disaster Relief Operations**</u>: Beamon and Balcik (2008) review disaster relief operations criteria, while Gutjahr and Nolz (2016) and Balcik and Smilowitz (2020) present an overview of multi-criteria optimization models in humanitarian aid distribution. In disaster relief operations literature, several papers focus on equity optimization, which they define as a function of demand fill rates (e.g., Anaya-Arenas et al. 2018), travel time (e.g., Aslan and Çelik 2019), or a measure of suffering (e.g., Yu et al. 2018). It is also common in the disaster relief literature to implement equity as a constraint by limiting the maximum deviation from a target value based on demand fill rates (e.g., Noham and Tzur 2018). Note that these definitions of equity focus on satisfying demand or minimizing travel time, which are not relevant goals in food bank operations as supply is much lower than demand and the goal is to distribute the available food as fairly as possible rather than as quickly as possible (Sengul Orgut et al. 2016b).

Effectiveness has also played a significant role in the disaster literature and has been defined as holding cost minimization (e.g., Döyen et al. 2012), maximization of relief deliveries (e.g., Hong et al. 2015), and maximization of service quality (e.g., Yu et al. 2018). Given the importance of timely response in the disaster literature, efficiency has been represented by minimizing the number of trips between distributor and beneficiaries (e.g., Anaya-Arenas et al. 2018), minimizing transportation costs (e.g., Balcik et al. 2008), travel time (e.g., Huang et al. 2012), or travel distance (e.g., Abazari et al. 2021). Our work is inherently different from disaster relief operations due to our definition of equity and the ongoing nature of food bank operations (lack of urgency). Among the above papers, only Gralla et al. (2014) and Yu et al. (2018, 2019) consider simultaneously in the objective function. In addition to the differences in our definition of equity, none of these papers consider non-interactive elicitation of the decision-maker's preferences.

Food Rescue Operations: Some operational-level food distribution literature focuses on food rescue, that is, collecting food from donors and immediately distributing them to charitable agencies without considering storage or location distribution problems. These papers may be categorized based on which and how many of the three criteria they consider. As summarized in Table 1, this literature incorporates one or two of the equity, effectiveness, and efficiency criteria to guide food rescue operations. These studies differ from our study in several areas. First, none of these studies simultaneously considers equity, effectiveness, and efficiency in the objective function. In addition, they focus on food rescue operations, which eliminate the need to consider food storage. Although food banks may also be involved in food rescue operations, their primary operations are the collection and sorting of donations in their warehouses and distribution of donations to charitable agencies, which in turn distribute food to beneficiaries. Furthermore, these studies focus on the routing element of this problem, whereas our model makes decisions on food storage and allocation rather than routing.

Food Bank Operations: Equity, effectiveness, and efficiency are commonly considered criteria in the food bank operations management literature that focuses on identifying optimal food distribution policies over the long-term. We summarize the research in long-term humanitarian operations management that has focused on tactical decisions associated with allocating food within service regions by food banks, which is similar to the problem studied in this study. Sengul Orgut et al. (2013) study a deterministic, capacity-constrained network flow problem considering equity and effectiveness. Distribution is defined to be equitable if every county receives food proportional to their demand, while effectiveness refers to maximizing the distribution quantity or minimizing waste at the food bank warehouse. They consider effectiveness as the objective and enforce equity through constraints. Sengul Orgut et al. (2016b) study a similar problem where the absolute deviation from perfectly equitable distribution for each county's service region is bounded above by a user-defined value. Sengul Orgut et al. (2017) and Sengul Orgut et al. (2018) extend Sengul Orgut et al. (2016b) by considering stochastic county capacities through a two-stage stochastic model and a robust optimization model, respectively. Fianu and Davis (2018) study a discrete-time discrete-state Markov decision process (MDP) model with stochastic supply, deterministic demand, and an equity-based objective, where they define equity as a function of the Pounds distributed Per Person in Poverty (PPIP).

There are fundamental attributes that distinguish our work from these previous studies. First, none of these papers incorporate the objective of efficiency (cost minimization). This is limiting because some food banks, especially those in areas with a high cost-of-living have to consider cost minimization to maintain their employees and pay their overhead while aiming to maximize their distribution. Second, some criteria are optimized in objective function in these papers while the other criteria are modeled as constraints. Sengul Orgut et al. (2013, 2016b, 2017, 2018) enforce equity as constraints which prioritizes equity, whereas we model equity as a criterion in the objective function. Fianu and Davis (2018) consider equity as the sole objective. These papers also do not consider the relative preference of a food bank with respect to the criteria of equity, effectiveness, and efficiency. In contrast, our work considers all three criteria simultaneously in the objective function. Placing all three criteria in the objective function allows us to develop a generalized model which enables a food bank to operate according to their varying preferences, and hence applies to most food banks in developed countries. Because the model has a generalized form, the numerical results and insights are also applicable to various nonprofit donation distribution settings. Lastly, the supply chain structure that we utilize in our model is general and applicable to different food banks. This extends the work of Sengul Orgut et al. (2013, 2016b, 2017, 2018) that model the entire food bank (hub and branches) as a single entity and do not consider distribution or allocation between different branches in order to obtain policies at the tactical level. This study considers a more general supply chain structure with three echelons, allowing inter-branch flows and a county to be served by multiple branches. Hence, our study represents the underlying system that considers both tactical and operational decisions.

A few food banking operations papers consider all three criteria—equity, effectiveness, and efficiency—in their studies. Islam and Ivy (2018, 2021) define equity to be the absolute difference in the proportion of demands fulfilled between pairs of service regions, which is enforced as a constraint. Efficiency, that is, distribution cost, and effectiveness, that is, waste minimization, are equally weighted criteria in the objective function. Kretschmer et al. (2014) develop a theoretical supply chain framework for school food programs to study the impact of different factors such as demand, suppliers, and donors, on equity, effectiveness, and efficiency. Alkaabneh et al. (2020) consider effectiveness (i.e., nutritional service maximization) and efficiency (i.e., maximization of the total amount of distributed food) in the objective function and argue that equity can be achieved when an effective and efficient allocation identified by the model is proportionally allocated. Martins et al. (2019) study a strategic supply chain redesign problem where they consider a total of nine criteria, including equity by minimizing the least satisfied demand, effectiveness by minimizing waste, and efficiency by minimizing travel by agencies. However, they do not consider transportation cost minimization by the food bank. Our paper is unique relative to these papers as none considers equity, effectiveness, and efficiency simultaneously in the objective function. Furthermore, these studies do not consider the elicitation of preference for the equity, effectiveness, and efficiency criteria for hunger relief operations. Given that ending hunger is one of the most important UNSDGs and food banks play a significant role in achieving this goal, understanding their operating objectives and exploring the impact of these objectives on food distribution is a key component to improving their operations.

2.2. Preference Elicitation for Multi-criteria Optimization Problems

Multi-criteria optimization model studies that consider decision-maker's preference for the criteria can be traced back to Keeney and Raiffa (1976), and more recently in papers such as Karwan et al. (1985) and Karakaya and Köksalan (2020). The approach taken in these papers is based on selecting pairs of solutions from the non-dominated set of solutions, known as the Pareto front. For any two non-dominated solutions on the Pareto front, neither of the solutions is better than the other across all criteria. To elicit the decision-maker's preferences, the decision-maker is asked to choose between the solution pairs via "choice" questions (Karwan et al. 1985). Rating methods have been used to develop the Pareto front as the model is solved for several combinations of weights (Ransikarbum and Mason 2016). Algorithms developed based on the answer to "choice" questions may not be practical in cases where the decision-maker is not available to answer the choice questions or when the choice questions cannot be answered easily.

To circumvent this issue, Sumpsi et al. (1997), Amador et al. (1998), André and Riesgo (2007), Andre et al. (2010), and Gómez-Limón et al. (2016) have developed non-interactive algorithms to elicit the preferences of a decision-maker over multiple criteria based on their observed values. These algorithms consider the observed values of the objective function in any given period and seek to elicit the preferred weights of the criteria. They typically employ inverse optimization methodologies as they usually deal with an objective function and criteria that are well defined and known. While the objective function value is not known in our problem context, the historical actions of the decision-maker can be tracked easily. Therefore, we have developed a non-interactive PE technique that considers only the actions taken by the decision-maker, that is, the distribution actions taken by the food bank manager, and does not require the objective function value.

Preference Elicitation in Disaster Relief and Food Banking Operations: Several papers in disaster relief and food banking operations elicit the weights on the criteria using interactive approaches. Gralla et al. (2014) conduct a conjoint analysis survey to estimate the preference of 18 experts over five different metrics to elicit the trade-offs between equity, effectiveness, and efficiency for disaster relief operations. They have found that effectiveness was the most preferred criteria, followed by equity and then efficiency. In their study of private-sector humanitarian organizations, Carland et al. (2018) use the swing weight method to elicit the preferences of decision-makers. This method involves asking decision-makers about their swing ranges for each attribute, that is, the highest and lowest levels of each attribute assigned by the decision-makers when making decisions. Yilmaz and Kabak (2020) apply an Interval type-2 fuzzy sets Analytic Hierarchy Process (IT2FS AHP) to identify the weights placed on three criteria: transportation cost, infrastructure, and security. Grover et al. (2020) elicit the implicit criteria for grain distribution by government bodies in India and the weights on the criteria by surveying experts. These papers consider PE techniques that require interaction with the decision-maker while we develop a non-interactive technique. These studies identify the decision-maker preference for multiple criteria based on experts' perception, while we develop a method to learn the preference from the actions taken by the decision-maker. The main difference between these humanitarian operations PE studies and the work in this study is the

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development of an algorithm that elicits the preferred weights from the actions taken by the decision-maker without observing the objective function value.

This study makes several methodological and practical contributions to the literature:

1. ***Food Bank Operations Management.*** To our knowledge, this is the first paper in food banking operations management literature that concurrently formulates the criteria of equity, effectiveness, and efficiency in the objective function, where each criterion is expressed as a function of the allocation policy. This approach allows us to develop a flexible model which better captures the variability in food banking operations and thoroughly examines the relationships and trade-offs between these criteria. Furthermore, our model is a three-echelon model which considers the layers of hub, branches, and counties. Although not all food banks have these three layers, formulating the model this way allows us to incorporate the complex structure of larger food banks such as FBCENC. The model can easily be scaled to smaller food banks with two echelons by eliminating the hub or branch echelon (or assigning zero donations to those locations).
2. ***Preference Elicitation for MCOM.*** We have developed a novel algorithm that does not require direct interaction with the decision-maker to identify the inherent preference for the criteria in a multi-criteria optimization model associated with the decision-maker's actions. To the best of our knowledge, this algorithm is the first approach that identifies a decision-maker's preference non-interactively and by only observing the actions rather than observing the objective function value. This approach is especially applicable to humanitarian operations problems where decision-makers may not be readily available to state their preferences or make selections of weights. The non-interactive nature of the algorithm is fundamental for food bank operations as the staff are usually too busy to engage in interactive approaches such as Analytical Hierarchy Approach, regularly (Gralla et al. 2014).
3. ***Food Bank Management Insights.*** Our proposed algorithm and MCOM, in combination, can inform food bank decision-makers about their implied preference for the criteria by analyzing actual distribution actions and providing recommendations on distribution policies. This would allow food bank managers to evaluate their current distribution actions and policies and modify them to better align with their strategic goals. Our case study analyses highlight managerial insights to help food bank managers understand the impact of their decisions and external factors, such as costs, on their objectives. Furthermore, we examine the trade-offs between the equity, effectiveness, and efficiency criteria and the implications of different decision-maker preferences for these criteria on distribution actions.

3. Equitable, Effective, and Efficient Food Distribution Model

We formulate a single-period, uncapacitated, multi-echelon network flow model with the goal of identifying optimal distribution policies for food banks. The model objective function is defined as the weighted sum of the functions of three individual criterion: equity, f_1, effectiveness, f_2, and efficiency, f_3. The general form of the objective function can be written as

$$min \quad w_1 f_1 + w_2 f_2 + w_3 f_3 \tag{1}$$

where f_1, f_2, and f_3 are defined as the scaled deviations from perfect equity, perfect effectiveness, and perfect efficiency, respectively. The weights assigned to equity, effectiveness, and efficiency are w_1, w_2, and w_3, respectively. The model assumptions are introduced below. Section 3.1 defines the notation for the model and provides the formulation. Section 3.2 discusses the analytical formulations of the individual crietrion.

The food bank network is assumed to be composed of three echelons: (i) hub, (ii) branch, and (iii) county (see Figure 1). It is assumed that food cannot flow upstream. This network is assumed to operate under the following assumptions:

1. *Food donations are received at the hub or any branch location and constitute the food supply.* This assumption reflects the actual operations of a food bank as donors typically donate food to a location, which can be the hub or a branch, that is most convenient or closest to them and within their community.
2. *Transshipments between the branches are one-way and are allowed at a positive cost.* A branch cannot simultaneously distribute to another branch and receive food from another branch. From a managerial perspective, the food bank is headquartered at the hub location and considered a single entity that includes the hub and the branches. For this reason, all costs are incurred at the hub.

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3. *All parameters are deterministic*. In food banking operations, demand is typically considered to be a function of the food-insecure population. Feeding America estimates the food-insecurity rate of a county, that is, the percentage of individuals facing food insecurity in the county, using a mixed-effects model (Feeding America 2020b). This model includes the following variables for which state and county-level data are available: unemployment rate, poverty rate, median income, percent Hispanic, percent African American, and percent of individuals who are homeowners. Using the food insecurity rates, the food need in terms of pounds across the counties served by a food bank is calculated by multiplying the MPIN and the poverty population of each county. The MPIN estimate is used to calculate the equitable distribution of the donated food received by a food bank. The estimated equitable distribution serves as a benchmark for the food bank to understand the deviation from perfect equity in the distribution of donated food in any given period. In this study, we use this deterministic MPIN definition and the poverty population of the counties to estimate demand in the food bank's service region. We also assume that supply is deterministic as we are considering a single-period problem where distribution decisions are made after food donations have been received at the food bank warehouses. In our case study, we examine the sensitivity of our results to the incoming supply using actual donation data from FBCENC for different months.
4. *Donated food is non-perishable*. FBCENC categorizes the in-kind donations received as: Dry Goods ($\approx 51\%$), Refrigerated Food ($\approx 23\%$), Frozen Food ($\approx 13\%$), and Produce ($\approx 13\%$)[2]. In this study, we do not explicitly consider the perishability of the food items, that is, we do not model the varying shelf lives and storage requirements for the different food types. Hence, our models are most applicable to dry goods. However, the models can be modified to include varying holding costs by food type as discussed in Section 6.
5. *All food is distributed through point-to-point (P2P) distribution*. Point-to-point distribution refers to the one-way distribution of food from a serving entity to a receiving entity. A serving entity can be a hub or a branch, where a receiving entity can be a county or a branch receiving shipments from another branch or the hub.
6. *Although the charitable agencies in a food bank's network are the last food distribution points, in our model, we aggregate the agencies in terms of the counties they are located in and consider counties to be the smallest demand points*. This aligns with how FBCENC evaluates equity, that is, by county, not by agency. We allow for one county to be served by multiple branches if such a connection exists in the real life system to achieve a more accurate representation of the food bank operations.

3.1. Multi-Criteria Optimization Model

Table 2 defines the model notation. The model parameters include the holding costs at the hub and branches; the P2P distances between the hub, branches, and counties; the per-pound per-mile shipping cost, the demand at the counties, and the supply to the hub and the branches. The holding cost represents the cost of holding one pound of food at the hub or a branch. Holding food at the food bank for longer periods increases the risk of spoilage. Hence, food banks aim to have short turnaround times which can be represented through higher holding costs. Supply represents the food available for distribution at the hub and branches, which is the sum of the starting inventory available

Table 2 Notations

Field	Description	Unit
Sets		
o	The hub	
$\mathbf{B}$	Set of branches in the branch echelon, where $\mathbf{B} \equiv \{1, \ldots, b, \ldots, \lvert\mathbf{B}\rvert\}$	
$\mathbf{A}$	Set of counties in the county echelon, where $\mathbf{A} \equiv \{1, \ldots, a, \ldots, \lvert\mathbf{A}\rvert\}$	
$\mathbf{A}_b$	Set of counties served by branch b, where $\mathbf{A}_b \subseteq \mathbf{A}$	
$\mathbf{W}$	Set of weights assigned to the objectives, where $\mathbf{W} \equiv \{w_1, w_2, w_3\}$, where w_1, w_2, w_3 are the weights for equity, effectiveness, and efficiency attributes, respectively and $w_1 + w_2 + w_3 = 1$.	
Parameters		
h_o	Holding cost at the hub o	(\$)
h_b	Holding cost at branch $b \in \mathbf{B}$	(\$)
d_{ob}	Distance between the hub o and branch b	(miles)
$d_{bb'}$	Distance between branches b and b'	(miles)
d_{ba}	Distance between branch b and county a	(miles)
δ_a	Demand at county $a \in \mathbf{A}$	(*lbs*)
p_a	Demand proportion of county $a \in \mathbf{A}$, $\frac{\delta_a}{\sum_{a \in \mathbf{A}} \delta_a}$	(null)
S_o	Total supply available at the hub o	(*lbs*)
S_b	Total supply available at branch $b \in \mathbf{B}$	(*lbs*)
K	Per-mile cost of distribution for one pound of food	$\left(\frac{\$}{lb-mile}\right)$
Decision variables		
X_{ob}	Pounds of food to be distributed from hub o to branch $b \in \mathbf{B}$	(*lbs*)
Y_{ba}	Pounds of food to be distributed from branch $b \in \mathbf{B}$ to county $a \in \mathbf{A}_b$	(*lbs*)
$Z_{bb'}$	Pounds of food to be transshipped from branch $b \in \mathbf{B}$ to branch $b' \in \mathbf{B} \setminus \{b\}$	(*lbs*)

at the warehouse and donations. Demand is defined according to FA's MPIN definition discussed above. Our decision variables include the pounds of food shipped from the hub to each branch, transshipment flows between branches, and distribution from each branch to the counties in the food bank's service region.

Model EEE identifies an optimal distribution policy for a food bank given the decision-maker's preference weights for equity, effectiveness, and efficiency. First, we consider the general form of the objective function. Section 3.2 discusses the analytic formulation of each criterion, f_i.

Model EEE

$$\textit{Min} \quad w_1 \cdot f_1 + w_2 \cdot f_2 + w_3 \cdot f_3 \tag{2}$$

$$\text{S.t.} \sum_{b \in \mathbf{B}} X_{ob} \leq S_o \tag{3}$$

$$\sum_{a \in \mathbf{A}_b} Y_{ba} \leq S_b + X_{ob} + \sum_{b' \in \mathbf{B} \setminus \{b\}} Z_{b'b} - \sum_{b' \in \mathbf{B} \setminus \{b\}} Z_{bb'}, \quad \forall b \in \mathbf{B} \tag{4}$$

$$\mathbf{X}, \mathbf{Y}, \mathbf{Z} \geq 0 \tag{5}$$

The objective function in Equation (2) is expressed as the weighted sum of scaled deviations from perfect equity, effectiveness, and efficiency, which will be defined in the next section. Constraints (3) and (4) ensure that the hub and branches cannot distribute more pounds of food than they receive, respectively. Finally, Constraints (5) ensure that distributions are non-negative.

3.2. Structure of the Objective Function

In this section, we develop the analytical formulations of the three criteria: equity, effectiveness, and efficiency in the objective function. We denote the non-scaled criteria as π_i, $\forall\, i \in \{1, 2, 3\}$. Using the notation in Table 2, we first formulate the non-scaled form of each criterion. Then, we discuss scalarization of each objective separately.

3.2.1. Equity. Perfect equity is defined as the case when each county receives their fairshare of food, that is, $p_a \cdot \left(\sum_{b \in \mathbf{B}} \sum_{a \in \mathbf{A}_b} Y_{ba}\right)$ which is similar to Sengul Orgut et al. (2016b). The deviation from perfect equity is expressed as the sum of the absolute differences between the fairshare of each county and the pounds of food they have received:

$$\pi_1 = \sum_{a \in \mathbf{A}} \left| \sum_{b \in \mathbf{B}} Y_{ba} - p_a \cdot \sum_{b \in \mathbf{B}} \sum_{a \in \mathbf{A}_b} Y_{ba} \right| \tag{6}$$

To linearize Equation (6) for Model EEE, we define a variable $\hat{Y}_a$ for each $a \in \mathbf{A}$ and develop Constraints (8) and (9):

$$\pi_1 = \sum_{a \in \mathbf{A}} \hat{Y}_a \tag{7}$$

$$\text{S.t.} \; \hat{Y}_a \geq \left(\sum_{b \in \mathbf{B}} Y_{ba} - p_a \cdot \sum_{b \in \mathbf{B}} \sum_{a \in \mathbf{A}_b} Y_{ba} \right), \quad \forall a \in \mathbf{A} \tag{8}$$

$$\hat{Y}_a \geq -\left(\sum_{b \in \mathbf{B}} Y_{ba} - p_a \cdot \sum_{b \in \mathbf{B}} \sum_{a \in \mathbf{A}_b} Y_{ba} \right), \quad \forall a \in \mathbf{A} \tag{9}$$

3.2.2. Effectiveness. Perfect effectiveness refers to the distribution of all food donations, that is, there is no waste. The deviation from perfect effectiveness is defined by the total holding cost of the leftover inventory at the hub and branches as follows:

$$\pi_2 = h_o \cdot \left(S_o - \sum_{b \in \mathbf{B}} X_{ob} \right) + \sum_{b \in \mathbf{B}} h_b \cdot \left(S_b + X_{ob} - \sum_{a \in \mathbf{A}_b} Y_{ba} + \sum_{b' \in \mathbf{B}/\{b\}} Z_{b'b} - \sum_{b' \in \mathbf{B}/\{b\}} Z_{bb'} \right) \tag{10}$$

3.2.3 Efficiency. Perfect efficiency corresponds to a solution that results in zero distribution cost, which, in this context, is a solution where no food is distributed from the hub or branches. Any amount of food distributed will result in a deviation from perfect efficiency, which is expressed as the cost to distribute the donated food to counties from the hub and branches. For each P2P transaction, the cost is calculated as the product of the following terms: (i) the pounds of distributed food, (ii) the distance covered in miles, and (iii) the per-mile cost K to deliver one pound of food.

$$\pi_3 = K \cdot \left(\sum_{b \in \mathbf{B}} X_{ob} \cdot d_{ob} + \sum_{b \in \mathbf{B}} \sum_{a \in \mathbf{A}_b} Y_{ba} \cdot d_{ba} + \sum_{b \in \mathbf{B}} \sum_{b' \in \mathbf{B}} Z_{bb'} \cdot d_{bb'} \right) \tag{11}$$

3.3. Scalarization of the Criteria

In multi-criteria optimization modeling, the individual criteria functions are scaled to ensure that the criteria have the same units and range. In this study, scalarization is performed using the linear normalization technique (Ransikarbum and Mason 2016). This technique converts the objective function to values between zero and one based on the best and worst-case scenarios of the criteria in the form of:

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$$f_i = \frac{\pi_i - \pi_i^{zen}}{\pi_i^{nad} - \pi_i^{zen}},\ \forall i \in \{1,\ 2,\ 3\} \tag{12}$$

where π_i^{zen} and π_i^{nad} are the best (zenith) and worst (nadir) case scenarios for criterion i, where $i = 1$ for equity, $i = 2$ for effectiveness, and $i = 3$ for efficiency. Since we aim to minimize all three criteria in this study, the zenith and nadir points refer to the minimum and maximum values of the respective functions.

Given the definitions of perfect equity, effectiveness, and efficiency, the minimum value of each criterion is equal to zero. In a perfectly equitable solution, each county receives its fairshare of food, resulting in a zero deviation from perfect equity. A trivial solution to this is to ship zero pounds of food, which is a feasible solution of Model EEE and results in perfect equity. In a perfectly effective solution, no food is held at the hub or the branches, thus the holding cost is equal to zero. Shipping all food from the hub to the branches, and from the branches to the counties is a feasible solution and results in perfect effectiveness. In a perfectly efficient solution, no food is distributed, thus the cost of distribution is equal to zero. Hence, we have $\pi_i^{zen} = 0, \forall\ i\ \in \{1, 2, 3\}$.

In contrast, identifying the maximum value (worst-case scenarios) of each criterion is more challenging. The worst-case scenarios for each criterion can be developed by searching for the maximum values of the functions in Equations (6), (10), and (11), which we discuss next.

Lemma 1 states the conditions for obtaining the worst-case equity for a given set of donations at the hub and the branches. The proof is provided in Appendix C.

LEMMA 1. *For a given set of donations at the hub and the branches, the worst-case equity occurs when all food available in the network is distributed to the county with the lowest demand proportion, that is,*

$$\pi_1^{nad} = \left| \left(S_o + \sum_{b \in \boldsymbol{B}} S_b \right) - p_a^{min} \cdot \left(S_o + \sum_{b \in \boldsymbol{B}} S_b \right) \right| + \sum_{a \in \boldsymbol{A} | p_a \neq p_a^{min}} \left| 0 - p_a \cdot \left(S_o + \sum_{b \in \boldsymbol{B}} S_b \right) \right| \tag{13}$$

where $p_a^{min} = \min_{a \in \boldsymbol{A}} p_a$.

The worst-case value for the effectiveness criterion corresponds to the case where no food is distributed to counties and food is held at the location(s) with the highest holding cost. The worst-case effectiveness can vary with holding cost differences by location, that is, hub and branches. We introduce Lemma 2 which states the worst-case effective scenario. The proof is provided in Appendix D.

LEMMA 2. *The maximum deviation from perfect effectiveness can be expressed as,*

$$\pi_2^{nad} = max(h_o,\ h_b^{max}) \cdot S_o + h_b^{max} \sum_{b \in \boldsymbol{B}} S_b \tag{14}$$

where $h_b^{max} = \max_{b \in \boldsymbol{B}} h_b$.

The upper bound on efficiency refers to the policy that results in the maximum cost to distribute all of the available food. We have developed a mixed-integer linear programming (MILP) model, $WC_{Efficiency}$, to estimate the worst-case efficiency for a given set of input parameters, that is, supply, per-mile cost to ship a pound of food, and the distances between the nodes within the network. The model is as follows.

$$\text{Model} \quad WC_{efficiency}$$

$$\text{Max} \quad \pi_3^{nad} = K \cdot \left(\sum_{b \in \mathbf{B}} X_{ob} \cdot d_{ob} + \sum_{b \in \mathbf{B}} \sum_{a \in \mathbf{A}_b} Y_{ba} \cdot d_{ba} + \sum_{b \in \mathbf{B}} \sum_{b' \in \mathbf{B} \setminus b} Z_{bb'} \cdot d_{bb'} \right) \tag{15}$$

$$S.t. \sum_{b \in \mathbf{B}} X_{ob} \leq S_o \tag{16}$$

$$\sum_{a \in \mathbf{A}_b} Y_{ba} \leq S_b + X_{ob} + \sum_{b' \in B \setminus \{b\}} Z_{b'b} - \sum_{b' \in B \setminus \{b\}} Z_{bb'}, \quad \forall b \in \mathbf{B} \tag{17}$$

$$\sum_{b' \in \mathbf{B} \setminus \{b\}} Z_{bb'} \leq M \cdot \eta_b \quad \forall b \in \mathbf{B} \tag{18}$$

$$\sum_{b' \in \mathbf{B} \setminus \{b\}} Z_{b'b} \leq M \cdot (1 - \eta_b) \quad \forall b \in \mathbf{B} \tag{19}$$

$$X_{ob},\ Y_{ba},\ Z_{bb'} \geq 0,\ \forall (b,\ b') \in \mathbf{B},\ \forall a \in \mathbf{A},\ \boldsymbol{\eta} \in \mathbb{B}$$

The objective function in Equation (15) maximizes the total cost of food distribution within the network. Constraints (16) and (17) ensure that the hub and branches cannot distribute more than the total pounds of available food at their respective warehouses. Constraints (18) and (19) ensure that if a branch receives food from the hub then the branch will not be allowed to transship to the other branches, that is, if $\eta_b = 1$ for a given branch b, then, branch b is allowed to transship to other branches (constraint 18), but not allowed to receive food from the other branches (constraint 19). The opposite conditions hold if $\eta_b = 0$. This condition prevents redundant movement of the food available at the hub within the branches. This set of constraints also prevents the model from being unbounded. Note that since the per-mile per-pound distribution cost K appears in the criteria and the nadir values (both numerator and denominator of f_3), it mathematically cancels out. However, we keep that parameter in the original formulation to be able to estimate the distribution costs in dollars. Here, M is a large number.

We have presented the general form of Model EEE, defined the analytical formulations of the criteria, and developed methods to scalarize the criteria. A complete formulation of Model EEE is provided in Appendix E, which includes the analytical formulation of the criteria and constraints. We now discuss structural properties of Model EEE.

3.4. Structural Properties for Criteria Trade-offs

In this section, we characterize the structure of the solutions for different combinations of weights on the criteria. In addition, we study the implications of including only one or two of the criteria in the objective function (assigning a weight of zero for the other criteria) to better understand the trade-offs.

First, we consider the case when only one criterion is considered. If a food bank manager only considers equity and puts 100% weight on the equity criteria, then there are infinite solutions possible, as the distribution decision variables are continuous. Any amount of food that is distributed can be distributed according to the demand proportions of each county, zero distribution being one trivial solution. If only the effectiveness criterion is considered, then all food will be distributed. Similarly, this scenario has an infinite number of solutions as all available food can be distributed to any set of counties. Lastly, if only the efficiency criterion is considered, then no food will be distributed, which is a unique yet trivial solution.

Let us now consider the inclusion of only two criteria in the objective. First, consider the scenario where equity and effectiveness are considered in the objective function. Lemma 3 states the solution structure for this scenario and its proof is provided in Appendix F.

LEMMA 3. *When only equity and effectiveness are considered in the objective function, all available food in the network will be distributed to the counties equitably.*

Now, consider the equity and efficiency criteria in the objective function, placing zero weight on effectiveness. Lemma 4 states the solution structure and its proof is provided in Appendix G.

LEMMA 4. *When only equity and efficiency are considered in the objective function, a zero distribution policy is optimal.*

Finally, consider the case where only effectiveness and efficiency are considered in the objective function by assigning a zero weight to the equity criterion. For this scenario, we develop a formulation to identify the "critical" weight of effectiveness. The critical weight of effectiveness, w_i^{crit}, for a given serving entity $i \in \{o, b \in \mathbf{B}\}$ is defined as the minimum weight on effectiveness required to distribute all food available at the serving entity i. The analytical formulation for the critical weights of effectiveness for a branch $b \in \mathbf{B}$ and the hub are stated in Lemma 5, and their proofs are given in Appendix H.

LEMMA 5. *Consider the case where only effectiveness and efficiency are included in the objective function. Let w_2, w_o^{crit} and w_b^{crit} be the weight assigned to effectiveness, the critical weight of effectiveness for hub o, and the critical weight of effectiveness for branch $b \in \boldsymbol{B}$, respectively. Hub o will distribute all available food if,*

$$w_2 \geq w_o^{crit} = \min_{b \in \boldsymbol{B}} \left(\frac{K \cdot d_{ob}}{h_b - h_o + K \cdot d_{ob}} \right) \tag{20}$$

where h_o and h_b are the holding costs per pound of food at the hub o and branch $b \in \boldsymbol{B}$, and d_{ob} refers to the distance between hub o and branch $b \in \boldsymbol{B}$. Branch b will distribute all available food if,

$$w_2 \geq w_b^{crit} = \frac{K \cdot d_{ba}^{closest}}{h_b + K \cdot d_{ba}^{closest}} \tag{21}$$

where h_b is the holding cost per pound of food at branch b, and $d_{ba}^{closest}$ is the distance from branch b to the closest agency $a \in \boldsymbol{A}$.

Lemma 5 states that a branch will distribute all food if the marginal cost of distribution $\left(K \cdot d_{ia}^{closest}\right)$ exceeds the marginal holding cost (h_i) for that entity. Note that since only efficiency and effectiveness have positive weights in this scenario, a given branch will either ship all of its available food, or ship nothing. Likewise, if the branch is shipping food, it will be shipped to the closest agency. The critical weight w_b^{crit} can be considered as the relative cost of distribution to holding per pound of food. A similar argument can be made for the hub.

The optimal distribution policies depend on the weights placed on the equity, effectiveness, and efficiency criteria. To accurately capture the trade-offs between criteria and various potential preferences of decision-makers, a model formulation must make it possible for all three scaled criteria to be considered simultaneously by food bank managers. In the next section, we introduce a PE algorithm that learns the inherent weights placed on these criteria by a food bank through their distribution decisions.

4. Preference Elicitation Algorithm

In Model EEE, the decision-maker's preference weights on the three criteria w_1, w_2, w_3 are assumed to be known parameters. In fact, these values are difficult to estimate in practice. Although many interactive methods are available for estimating preference weight parameters (Karakaya and Köksalan 2020, Karwan et al. 1985), an interactive algorithm is not suitable in a food bank setting for several reasons: (i) the decision-makers may have difficulty quantifying their inherent preferences for these three criteria, (ii) a food bank's preferences may be dynamic, as illustrated in Section 1, and (iii) policy makers may not be available to interact with modelers on a regular basis. For these reasons, we develop a non-interactive PE algorithm that uses the food distribution decisions made by the decision-maker to determine their underlying weights. As input, the algorithm requires a set of distribution actions made by the decision-maker (e.g., the distribution decisions over at least one period) and the Model EEE parameter values (i.e., supply, demand ratios, and costs). The algorithm starts by considering all discretized combinations of possible weights in the set $\boldsymbol{W}$ for a given step size, s, and reduces the set of weights by learning from the decision-maker's distribution actions. The step value, s, determines the precision of the weight estimation; a smaller s provides more precise estimates of the underlying preferences of the decision-maker but increases the computational complexity of the algorithm. For each weight combination in the set $\boldsymbol{W}$, the algorithm solves Model EEE for the given set of parameters and stores the criteria values. The algorithm then considers the single-period allocation action made by the decision-maker and calculates the corresponding observed criteria values. The algorithm continues this process of generating sets of criteria values for all elements in the initial weight set, $\boldsymbol{W}$. These criteria values are compared to the observed criteria values. The weight combinations for which the absolute difference between each pair of criteria values are less than a small threshold, ε, are saved in the set W' for the next iteration. We denote this newly formed set of weights as the "truncated" set. Using the truncated set and setting $W = W'$, the algorithm continues the same procedure for the next iteration, which has a new set of supply and distribution decisions. For example, in our illustration, supply and distribution decisions from the next period (month) are used. In doing this we are implicitly assuming that the decision-maker's preferences are relatively robust within a small time frame. If the cardinality of the truncated set reduces to one after an iteration, that is, if the truncated set has only one combination of weights, the algorithm terminates. If the cardinality of the truncated set reduces to zero after an iteration, we consider the weights from the previous iteration and define them as the "nearly convergent" weights. The convergence to a zero cardinality set may be attributed to the variability of supply and distribution among the periods. For example, if we start the PE Algorithm from July 2017 and it converges to a zero cardinality weight set in October 2017, we can infer that the supply and distribution actions in October 2017 are significantly different from the July 2017, August 2017, and September 2017 data. Algorithm 1 provides the corresponding pseudo-code.

The PE Algorithm has some limitations. The algorithm may fail to converge to a single set of weights when a given distribution policy can be generated from multiple sets of criteria weights. Another limitation of the algorithm is its dependence on the step size. There is a clear trade-off between the granularity of the step size and the computational performance of the algorithm. For example, if $s = 0.1$, the number of possible combinations of positive weights across all the criteria is 36, which increases to 4,885 when $s = 0.01$ and almost 50,0000 when $s = 0.001$. In our numerical experiments, we have considered a step size of $s = 0.01$ to develop the starting weight sets. Another challenge with the step size when the algorithm is implemented in practice is that the discrete weight combinations evaluated may not include the inherent weights of the decision-maker. Moreover, the algorithm requires a minimum allowable threshold, ε, between the observed criteria values and the solved criteria values to reduce the cardinality of the initial weight set. If ε is too small, the algorithm may be unable to find a weight combination for which the difference between the solved criteria and the observed criteria is lower than this threshold.

5. Results

In this section, we provide the numerical results. Section 5.1 presents the case study based on our food bank partner, FBCENC, and explores how a food bank's preferences on equity, effectiveness, and efficiency impact their distribution policies and actions. In Section 5.2, we apply the PE Algorithm to FBCENC data which allows us to learn FBCENC's preferences with respect to the three criteria from their historical distribution behavior. Section 5.3 discusses managerial and policy insights obtained from the case study including how distribution policies may be adjusted based on varying preferences.

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Algorithm 1: PE Algorithm

initialization
$t \leftarrow 1$
$W \leftarrow \{[w_1, w_2, w_3]$ where $w_i = (0 : s : 1), \forall i \in \{1, 2, 3\}, s \equiv$ step size$\}$
$W' \leftarrow []$
while $|W'| \neq 1$ **do**
  Observe supply parameters of period t
  Observe decision-maker's actions in period t for
    $[X^*, Y^*, T^*] \leftarrow \{X^*_{ob}, Y^*_{ba}, T^*_{bb'}, \forall (b, b') \in \mathbf{B}, \forall a \in \mathbf{A}\}$
  for $[w_1, w_2, w_3] \in W$ **do**
    Solve EEE for $[X, Y, T] \leftarrow \{X_{ob}, Y_{ba}, Z_{bb'}, \forall (b, b') \in \mathbf{B}, \forall a \in \mathbf{A}\}$
    $Z \leftarrow R(X, Y, T)$
    $[X', Y', T'] \leftarrow [X^*, Y^*, T^*]$;
    $Z' \leftarrow R(X', Y', T')$;
    if $|Z - Z'| < \epsilon$ **then**
      $W'[end + 1] \leftarrow [w_1, w_2, w_3]$
    else
      $W' \leftarrow W'$
    end
  end
  $W \leftarrow W'$
  $t \leftarrow t + 1$
end

5.1. Case Study: The Food Bank of Central and Eastern North Carolina (FBCENC)

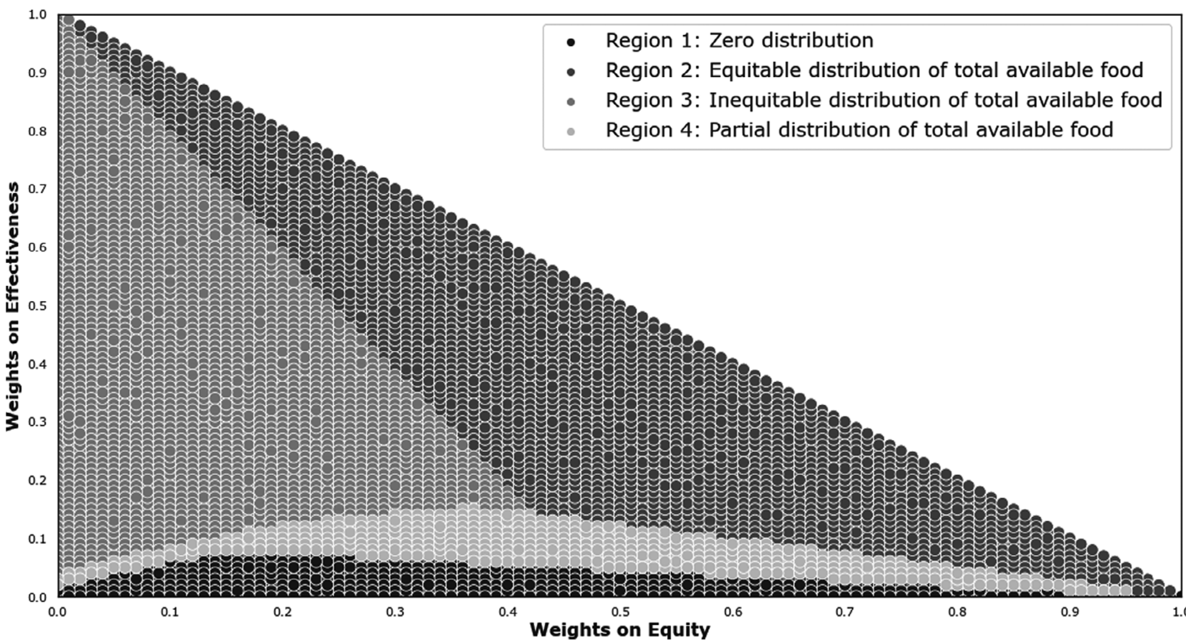
In this section, we provide the results of Model EEE on the network of FBCENC and share key insights for the food bank's distribution policies for varying weight combinations on the three criteria.

5.1.1. FBCENC Network. The FBCENC network is composed of a hub, located in Raleigh, and six branches, located in Raleigh, Durham, Greenville, New Bern, Sandhills, and Wilmington, serving 34 counties in North Carolina (FBCENC 2021). Figure 1 shows the FBCENC network including the locations of the hub and branches and the counties they serve. Although each county has a primary branch from which they receive food, some of the counties may receive food from more than one branch. For example, during the 2017 fiscal year, Duplin county received 90% of its food from the Raleigh branch, and the remaining 10% from the Greenville branch. We preserve this structure in solving our models by creating dummy counties for the counties that are served by more than one branch. All calculations are performed across four Windows machines with the following specifications: Machine 1: Intel(R) Core(TM) i7 - 10750 CPU @ 2.60 GHz, 16.0 GB RAM, 64-bit operating system; and Machines 2, 3, 4: Intel(R) Core(TM) i7 - 6700 CPU @ 3.40 GHz, 32.0 GB RAM, 64-bit operating system.

5.1.2. FBCENC Data. We use the operations data from FBCENC for the 2017–2018 fiscal year for the monthly donations received by the hub and branches; the monthly distribution quantities shipped by the hub to the branches and the branches to each county; and the monthly transshipment quantities between the branches. The P2P great circle distances (Bullock 2007) between the network entities are calculated using the distances between the population-weighted centroids of each county using MatLog, a toolbox in MATLAB (Matlog 2020). We set $h_0 = h_b = 0.5$ for all $b \in \mathbf{B}$, $K = \frac{1}{1000}$ as nominal values and perform sensitivity analyses by varying the holding cost and donations. To estimate the proportion of demand for each county, we use the MPIN estimates FBCENC uses to report their monthly achieved fairshare to Feeding America as discussed in Section 3. We use the 2017–2018 Fiscal Year beginning inventory for the network as reported in the FBCENC Audit report (Food Bank of Central and Eastern North Carolina 2019). We develop a heuristic to calculate the starting inventory for each month from July 2017 to June 2018 at the hub and at the branches, which is presented in Appendix I.

5.1.3. Model EEE Optimal Distribution Policies as a Function of the Decision-Maker's Preference Weights. This section explores the effect of the

Figure 3 Weight Distribution Across Policy Regions Generated by Model EEE

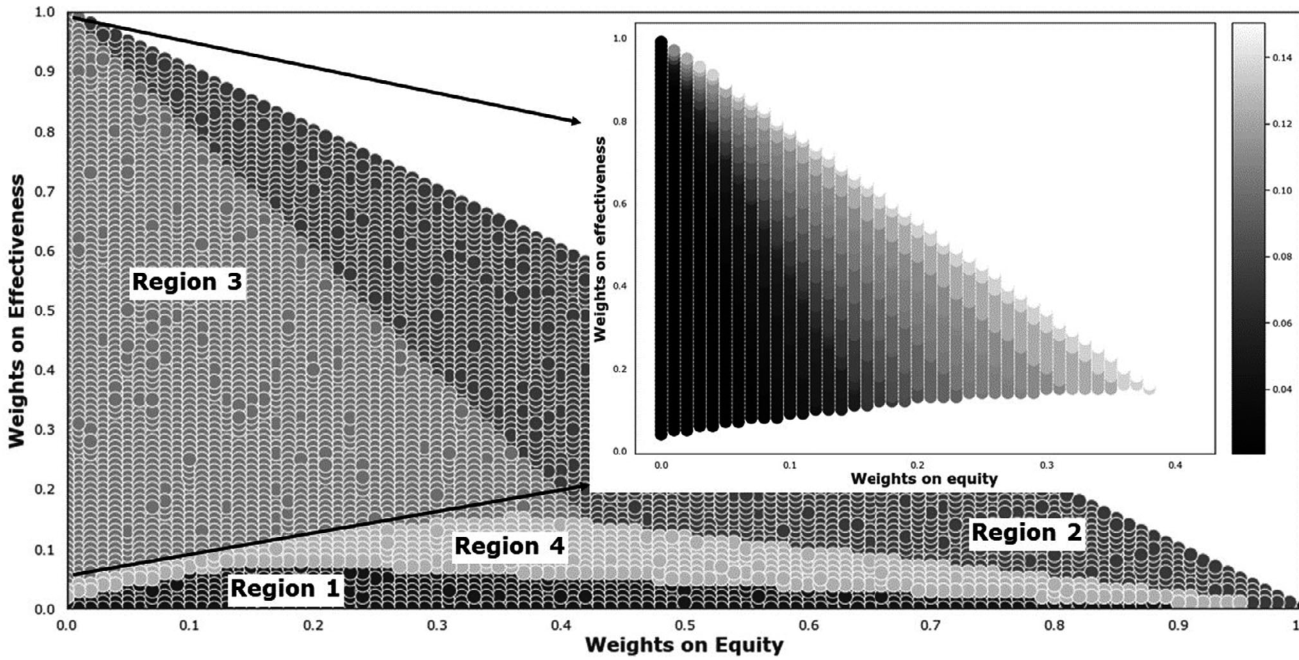


weights placed on the equity, effectiveness, and efficiency criteria on food distribution policies. We solve Model EEE for varying weight combinations and discuss the implications of the weights on food distribution.

We generate the set of weights on equity, effectiveness, and efficiency criteria for a step size of 0.01, where the resultant set of weights has a cardinality of 5151. Our analysis shows that the computational time for solving EEE for any combination of the criteria in the objective function is negligible (less than one second). For each element in the weight set, we solve Model EEE for July 2017 data and analyze the corresponding distribution policies. There are groups of weight combinations that result in the same distribution policies. For the entire set of weight combinations, we calculate the number of unique distribution solutions. Of the 5151 weight combinations, we generate 153 unique distribution policies. For any two unique policies, the sum of absolute pairwise shipment differences is more than epsilon of one, that is, for two distribution solutions α and β, $\sum_{b\in\mathbf{B}} \left|X^{\alpha}_{ob}(b) - X^{\beta}_{ob}(b)\right| + \sum_{b\in\mathbf{B}}\sum_{a\in\mathbf{A}}\left|Y^{\alpha}_{ba}(b,\, a) - Y^{\beta}_{ba}(b,\, a)\right| + \sum_{b\in\mathbf{B}}\sum_{b'\in\mathbf{B}}\left|Z^{\alpha}_{bb'}(b,\, b') - Z^{\beta}_{bb'}(b,\, b')\right| > 1$. These unique distribution policies are divided into several policy regions based on their distribution attributes, that is, pounds of food distributed (all, some, or none, corresponding to whether the food was distributed effectively), whether the food was distributed equitably, and whether the food was distributed efficiently. The policy regions are shown as a function of the weights on equity (horizontal axis) and effectiveness (vertical axis) in Figure 3 (note that one minus the sum of the weights on equity and effectiveness corresponds to the weight on efficiency). In Figure 3, each dot represents a weight combination where the coloring is based on the policy regions (1, 2, 3, or 4).

Region 1 refers to the weight combinations for which the optimal solution is to ship no food to the counties and instead, hold all food at the branch or hub locations. Regions 2 and 3 refer to weight combinations where all available food is distributed to the counties according to perfect equity and imperfect equity, respectively. The weight combinations in Region 4 result in partial distribution of the food, which we explore in more details later. Policy Regions 1, 2, 3, and 4 contain 469, 2245, 1972, and 465 weight combinations, respectively. Note, these regions may have more than one distribution solution. For example, in Region 3, the shipments vary according to the weight combinations although they all result in the distribution of all available food with a deviation from perfect equity. Different regions can have weights with similar preference relationships while the same region can have weights with different preference relationships. For example, a set of weights with a higher weight on effectiveness than efficiency can be observed in multiple regions (e.g., Region 2: [0.09, 0.89, 0.02] and Region 3: [0.15, 0.65, 0.2]). On the other hand, Region 4 contains both weight sets, [0.05, 0.06, 0.89] and [0.06, 0.05, 0.89], where the

Figure 4 Scaled Efficiency Values for Varying Weights on Equity and Effectiveness in Region 3 (Inset)



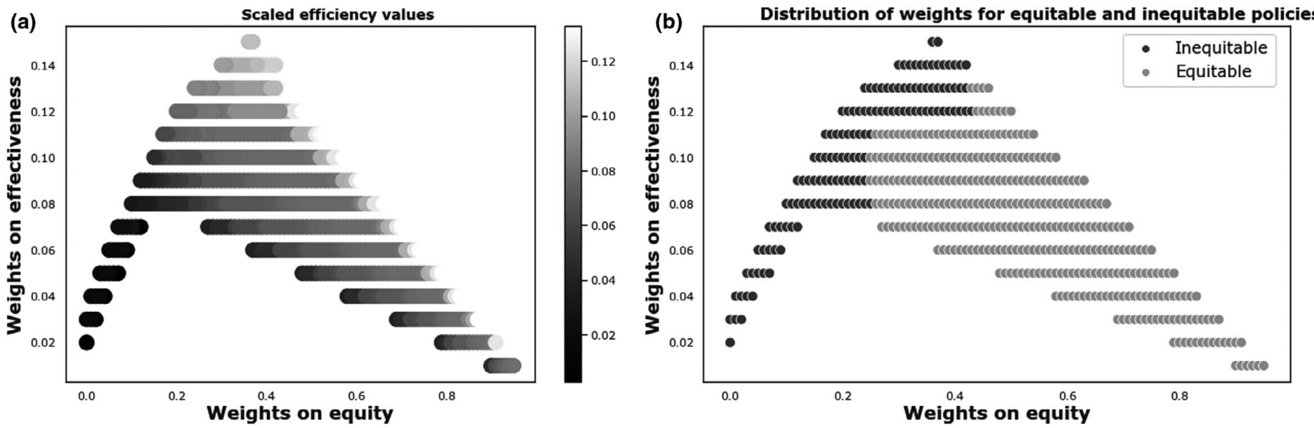
former has a higher weight on effectiveness than equity and the latter has the reverse relationship. The regions illustrate the trade-offs between equity, effectiveness, and efficiency and the corresponding effect on food bank distribution.

Consider a scenario where the weight on equity is set equal to 0.2. From Figure 3, we can see that for weights on effectiveness close to zero, there is no distribution in the network (Region 1). As the weight on effectiveness increases, corresponding to a decrease in the weight on efficiency, and crosses a threshold, Model EEE starts to distribute some (but not all) of the available food, which we define as Region 4. This is intuitive as a higher weight on effectiveness would drive food distribution in the network. As the weight on effectiveness increases, the distribution increases to the point where all food is distributed inequitably (Region 3). This suggests that the weight of 0.2 on equity is not high enough relative to efficiency to drive equitable distribution of all food in this region. However, if the weight on effectiveness increases more because the weight on efficiency becomes very low, all food starts to be distributed equitably since cost minimization loses its importance due to the low weight on efficiency. The changes in criteria weights can significantly alter the distribution policy as illustrated by the policy regions, which highlights the importance of eliciting the preference of the food bank manager over the criteria.

To provide greater insight regarding the effects of the criteria weights on distribution, we analyze the policy regions separately. We will not discuss Region 1 as zero food distribution in a given month never happens in practice. In Region 2, all food is distributed equitably to the counties. Thus, all combinations of weights will have the same distribution solutions and criteria values. Insights about Regions 3 and 4 are more complex as the amount of food distributed and the level of inequity evolves with the criteria weights within these regions. In the following discussion, we take a deeper look at these two regions.

In Region 3, all of the available food in the network is distributed to the counties with a deviation from perfect equity. Model EEE sacrifices equity to distribute food more cheaply. Figure 4 is an enlarged view of Region 3 where the color of the markers represents the scaled efficiency values, darker means a lower efficiency value and hence a lower cost solution. Note that scaled efficiency is the value of the efficiency criterion divided by the upper bound of the criterion as defined in Section 3.3. As the weight on equity increases, the need for a more equitable distribution causes the cost of distribution, and hence the scaled efficiency value, to increase as well. For example, since there may be rural counties which are farther from food bank branches, it may be more costly to serve those counties, yet necessary if equity must be satisfied. Keeping the weight on equity fixed, the scaled value of efficiency also increases as the weight on effectiveness increases, as this causes the weight on efficiency to decrease; resulting in the same

Figure 5 **Scaled Efficiency Values for Varying Weights on Effectiveness and Equity (5a) and Distribution of Weights on Equity and Effectiveness Corresponding to Equitable and Inequitable Distribution (5b) in Region 4**



amount of food being distributed in a more equitable way at a higher cost.

Another observation can be made from Figure 4 about the importance of the weight on equity on the distribution policies. When the weight on equity is comparatively low, it allows a larger range of effectiveness weights for which the optimal policy is to distribute all food inequitably (it remains in Region 3), that is, height of bars increases as the weight on equity decreases. This is in part driven by the relative increase in the importance (weight) of efficiency relative to equity. When the weight on equity is higher, the range of possible effectiveness weights such that all food is distributed inequitably (the distribution decisions remain in Region 3) is smaller. When equity is more important, the trade-off between effectiveness and efficiency becomes more pronounced and the resulting distribution policies are more likely to move to the other regions. For a higher weight on equity, if the weight on effectiveness is also high, the optimal distribution policy falls in Region 2 (equitable distribution of all food), whereas if the weight on effectiveness is low, the optimal distribution policy falls in Region 4 (partial distribution).

In contrast to Regions 2 and 3 where all food is distributed either equitably or inequitably, in Region 4 only a portion of the available food is distributed. To understand the trade-off between equity and effectiveness in Region 4, in Figure 5a, the scaled efficiency values determine the coloring where the x and y axes correspond to the weights on equity and effectiveness, respectively for this region, and lighter color means higher efficiency value, that is, higher cost. Note that a more efficient solution can be achieved in two ways: (i) by distributing less food or (ii) distributing the same amount of food along a cheaper (shorter distance) path which typically corresponds to sacrificing equity. Based on this, we see that, keeping the weight on effectiveness fixed, as the weight on equity increases, the scaled efficiency values, that is, the cost of distribution, increases due to the increased importance of the equitable distribution of food, causing the food to be distributed in a more expensive way. Instead, if we keep the weight on equity fixed and increase the weight on effectiveness, efficiency values also increase, now due to the need to distribute more food.

To further understand the impact of the weights of equity and effectiveness on the equity of the distribution policies, we color code the weights within Region 4 according to equitable (perfect equity—lighter) and inequitable (deviation from perfect equity—darker), based on their corresponding achieved equity in Figure 5b. As shown, there is a clear boundary between the equitable and inequitable weight regions. A minimum threshold on the equity weight is satisfied for a partial distribution to be equitable for a given effectiveness weight. This threshold is higher if there is a higher weight placed on effectiveness. For higher effectiveness weights, the model sacrifices equity to reduce the cost of distribution and improve the overall objective function value of Model EEE.

We have also studied several modifications of Model EEE where we consider one or two criteria in the objective function and assign the other criterion as a constraint to explore the effect of placing all three criteria in the objective function. These analyses highlight bounds on the criteria that constrain distribution and illustrate the interactions between the criteria that drive distribution. Furthermore, one of the strengths of the Model EEE formulation is that it is possible to use Model EEE to identify the weights and regions that allow for corresponding levels of efficiency, equity, and effectiveness as described below.

1. ***Equity & Effectiveness in the Objective with Efficiency as a Constraint.*** As discussed earlier, the weights on efficiency influence the

amount of food distributed and how food is distributed. If efficiency is modeled as a constraint with equity and effectiveness in the objective function, it is binding for all values of scaled efficiency less than 0.257. In other words, FBCENC would have to either sacrifice equity or distribute less to maintain the efficiency bound. This implies if the bound on efficiency is greater than 0.257, it is possible to distribute all food equitably. It is possible to use Model EEE to identify the corresponding weight combinations for which scaled efficiency is greater than 0.257, these weights likely are within Region 2.

2. ***Effectiveness & Efficiency in the Objective with Equity as a Constraint.*** As discussed earlier, like efficiency, equity can influence both the amount of food distributed and the cost to distribute it. If equity is modeled as a constraint with effectiveness and efficiency in the objective function, it is binding for all values of equity less than 0.532. Consequently, FBCENC would either have to distribute less or incur higher cost of distribution to satisfy this equity requirement. This implies if the bound on equity is greater than 0.532, it is possible to distribute all of the food supply along the cheapest path. It is possible to use Model EEE to identify the corresponding weight combinations for which scaled equity is greater than 0.532 and these weights likely are within Region 3.
3. ***Effectiveness in the Objective with Efficiency as a Constraint.*** If there are no requirements associated with equity, that is, the weight on equity is zero, and the focus is on effectiveness, it is possible to distribute all the food supply if the bound on scaled efficiency is greater than 0.0208. If the bound is tighter, FBCENC would have to distribute less food.
4. ***Effectiveness in the Objective with Equity as a Constraint.*** If there are no requirements associated with efficiency, that is, the weight on efficiency is zero, and the focus is on effectiveness, it is possible to distribute all the food supply. But if the bound on scaled equity is less than 0.07, the food must be distributed equitably. For any value higher than 0.07, distributing all food does not require perfect equity, that is, the equity constraint is not binding. In this case, a food bank is willing to sacrifice a relatively small level of equity in order to distribute the food.

The cases discussed above highlight that placing one of the criteria as a constraint in the model may inadvertently result in that criteria being prioritized depending on how tight the bound is, which may not reflect the inherent preferences of a food bank. While the constrained models provide some insights on the boundary conditions of equity, effectiveness, and efficiency, the models do not allow a decision-maker to explore her total spectrum of preferences. By placing the criteria in the objective function, we are able to achieve a more flexible model that can better reflect the inherent preferences of a food bank, which may vary dynamically.

Sensitivity Analyses: We have performed sensitivity analyses to explore the effect of changes in holding costs and monthly donations on the policy regions. We have observed that the policy regions remain robust for small changes in the holding cost and for relatively large changes in donations. For example, keeping the holding cost at the hub constant, if we increase the holding cost at the branches by 20%, then the cardinality of Policy Region 4 increases by 8%, and the cardinality of Policy Region 1 decreases by 10%. The changes to Policy Regions 2 and 3 are insignificant (Appendix J.1, Table 2). On the other hand, if we consider the donations from August 2017 to December 2017 compared to the donations in July 2017 (baseline), the changes in the cardinality for each policy region are within 1%, except Policy Region 4 which decreases by 5% (Appendix J.1, Table 3). Readers are referred to Appendix J.1 for a detailed discussion on the sensitivity results.

5.2. PE Algorithm Results

While policy regions presented in Section 5.1.3 provide insights about the relationships between weight combinations and resulting distribution policies, distribution decisions are highly dependent on the decision-maker's preferred set of weights as illustrated by the behavior within Regions 3 and 4. We apply the PE Algorithm to FBCENC data to learn their preferred weights as suggested by their distribution actions. We use our base case parameter settings in our initial results. We also perform sensitivity analyses on model parameters which are presented in Appendix J.2.

Before we discuss the PE Algorithm results, we provide a summary of the actual distribution actions taken by FBCENC over July 2017. The total amount of available food in the FBCENC network in July 2017 was 6.72 million pounds, comprised of 5.55 million pounds of donations and 1.17 million pounds of starting inventory. A total of 4.84 million pounds of food were distributed within the network, with an ending inventory of 1.88 million pounds. We observe that in July 2017, FBCENC distributed less than the total available food in the network with a deviation from perfect equity. Based on the insights from the different policy regions in Section 5.1.3, we expect that the

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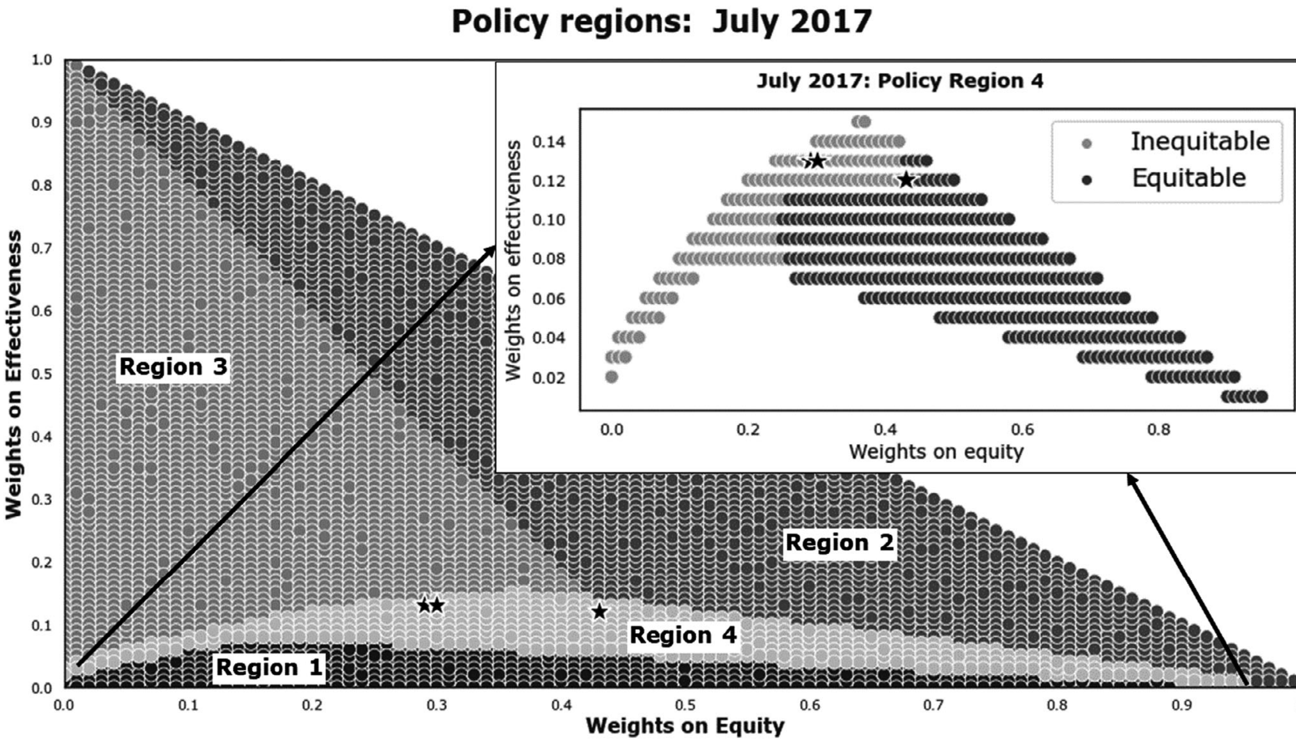
Figure 6 Policy Region for Nearly Convergent Weights from PE Algorithm (Inset: Elicited Weights Plotted over Policy Region 4); "*" Marks the Elicited Weights



preferred set of criteria weights will fall in Region 4. Next, we apply the PE Algorithm to the FBCENC data and characterize the weights identified, including their corresponding region(s).

To apply the PE Algorithm, we set $s = 0.01$ and $\varepsilon = 0.07$. We select the value of ε iteratively, starting from 0.01 and increasing by increments of 0.01 until the algorithm can reduce the cardinality of the weight set. For values smaller than 0.07, the algorithm is unable to reduce the weights. We start the PE Algorithm from the July 2017 period. We solve Model EEE for the starting set of weights and reduce the cardinality of the weight set using the cutoff condition. We move forward to the next month and apply the same procedure on the new set of data considering the reduced set of weights. We plan to run the PE Algorithm until June 2018, but the PE Algorithm may converge in an earlier month. Here, the PE Algorithm does not converge to a single set of weights on equity, effectiveness, and efficiency. The weight cardinality is reduced to zero by September 2017. However, the algorithm reduces the cardinality of the weight set to three elements by August 2017. We denote this as "near-convergence," where the algorithm reduces the starting set of weights to a set of reduced cardinality instead of converging to a weight set of unit cardinality. The total computational time required for the algorithm was 152 seconds. The three weight combinations are: (i) [0.29, 0.13, 0.58], (ii) [0.3, 0.13, 0.57], and (iii) [0.43, 0.12, 0.45]. To characterize the preferred weights, we plot the nearly convergent weights from the PE Algorithm in Figure 6. We can see that all three sets of weights in the nearly convergent set belong to Region 4, partial distribution of available food.

Examining the distribution of the weights on each criterion suggests that FBCENC prioritized efficiency first and then equity followed by effectiveness, in making their distribution decisions. Although FBCENC has indicated that they prioritize equity first in our historical correspondences, their actions suggest a different preference during the considered time period. This may be due to the fact that although FBCENC considers equitable distribution to be very important, they must consider cost minimization to be able to continue their operations. Furthermore, as highlighted in the inset of Figure 6, while these weight sets suggest an inequitable distribution, at least one of the weights is close to the border of equity and inequity. As we met with our FBCENC partners to present our findings, they reflected on their priorities. They indicated that while equity is important, they prioritize not wasting food, and in order to sustain operations, they prioritize having a non-zero ending inventory. As a result, when they saw where their current actions placed on the distribution triangle, it made sense to them and they indicated that it aligned well with their behavior and priorities. We discuss the policy implications of this further in Section 5.3, along with other managerial and policy insights.

Our result also differs from the findings of Gralla et al. (2014). While they have found operational cost to be the least important in the context of disaster relief, we find the opposite. This can be attributed to the urgency of a disaster relief problem, which is the focus of Gralla et al. (2014). In contrast, we study a food bank's problem where a long-term service is considered, and minimizing the cost of distribution can be significantly more important than in a disaster relief framework particularly given the need to sustain operations. In Appendix J.2, we summarize the results of our sensitivity analysis based on the holding costs and examine the scenarios where (i) the holding cost at the hub is greater than the branch and (ii) vice versa. We find that the nearly convergent weights are robust to small deviations in the holding costs. The nearly convergent weights remain within Policy Region 4 if the percentage difference between the holding cost at the hub and at the branches is within 5% of each other. The nearly convergent weights may shift to other policy regions when the percentage difference between the holding cost at the hub and at the branches is 10% or greater (Appendix J.2, Table 4). We perform sensitivity analysis on the algorithm with respect to the donations (or starting inventory) by implementing the algorithm for different months and observe that the nearly convergent weights remain in the same region (Appendix J.2, Table 5).

We also perform experiments on a toy network and test its convergence performance. Details of that analysis are provided in Appendix K. We find that although in some instances the PE Algorithm may never converge (e.g., weights that correspond to zero-distribution policy), on average the PE Algorithm converges to a reduced set of weights polynomially.

5.3. Managerial and Policy Insights

The policy regions discussed in Section 5.1.3 provide tangible insights for food bank managers about their distribution policies. A food bank manager may have high-level goals regarding equity, effectiveness, and efficiency to guide her distribution decision-making. Given the starting inventory level, the effectiveness-equity distribution triangle (Figure 3) can provide insight regarding the corresponding optimal distribution region, alternative distribution policies, their commonalities, and respective criteria values.

Figure 7 A Numerical Study of Equity, Effectiveness, and Efficiency Among FBCENC's Distribution Policy and Policies in Regions 2, 3, and 4; MPINr: Range of MPIN, PctDev: Percentage Deviation from Perfect Equity, EndInv: Ending Inventory in Pounds, DstrCost: Cost of Distribution; "*" Indicates a Branch Location; 1: Sampson, 2: Granville, 3: Wake (Raleigh branch), 4: Durham (Durham branch)

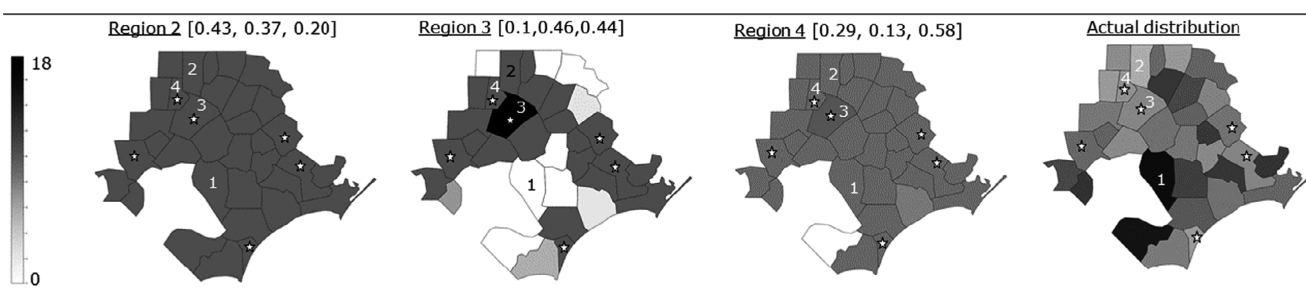


Fig 7(a): (From the left) MPIN for policy regions 2, 3, 4 and actual distribution

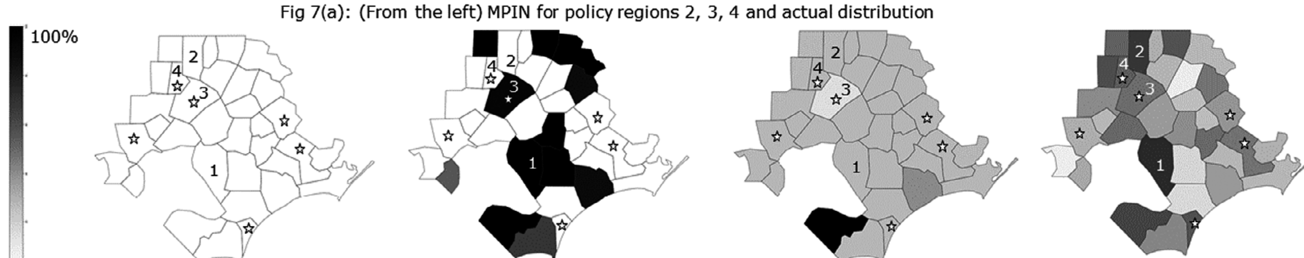


Fig 7(b): (From the left) Absolute percentage deviations from perfect equity for policy regions 2, 3, 4 and actual distribution

MPINr	9.19 - 9.19	0 – 17.7	0 – 8.48	3.6 – 15.35
PctDev	0% - 0%	0% - 100%	8% - 100%	4% - 67%
EndInv(lbs)	0 Million	0 Million	1.18 Million	1.88 Million
DstrCost	$299,052	$124,160	$174,883	$288,140

Alternatively, a food bank manager may realize that the weights implied by their distribution actions as identified by the PE Algorithm differ from their strategic goals. In that case, she may be interested in understanding how distribution should be changed to better align with her priorities. A comparative analysis of distribution policies associated with each policy region can inform the manager's decision-making process.

To illustrate the impact of the policy regions further, we compare four scenarios for July 2017 where the ordering of the weights corresponds to equity, effectiveness, and efficiency, respectively: (i) distribution resulting from a weight combination in Region 2 with the highest weight on equity ([0.43, 0.37, 0.20]), (ii) distribution resulting from a weight combination in Region 3 with the highest weight on effectiveness ([0.1, 0.46, 0.44]), (iii) distribution resulting from one of the weight combinations in the nearly convergent set identified for July 2017 by the PE Algorithm, ([0.29, 0.13, 0.58]; this weight combination is from Region 4 and has the highest weight on efficiency), and (iv) the actual distribution made by FBCENC in July 2017. For these distribution policies, Figure 7 illustrates the MPIN and the MPIN range (MPINr) across counties; deviations from perfect equity and the equity deviation range across counties; the undistributed food or the ending inventories at the food bank warehouses; and the total distribution cost. We define the percent deviation from equity at county a as $e_a = \frac{|Y_{ba} - p_a \cdot \sum_{b \in \mathbf{B}} \sum_{a \in \mathbf{A}} Y_{ba}|}{p_a \cdot \sum_{b \in \mathbf{B}} \sum_{a \in \mathbf{A}} Y_{ba}}$. The county maps are color-coded by the corresponding MPIN (Figure 7a) and the e_a (Figure 7b) value for each county where a lighter color represents lower MPIN and lower absolute deviation from perfect equity, respectively.

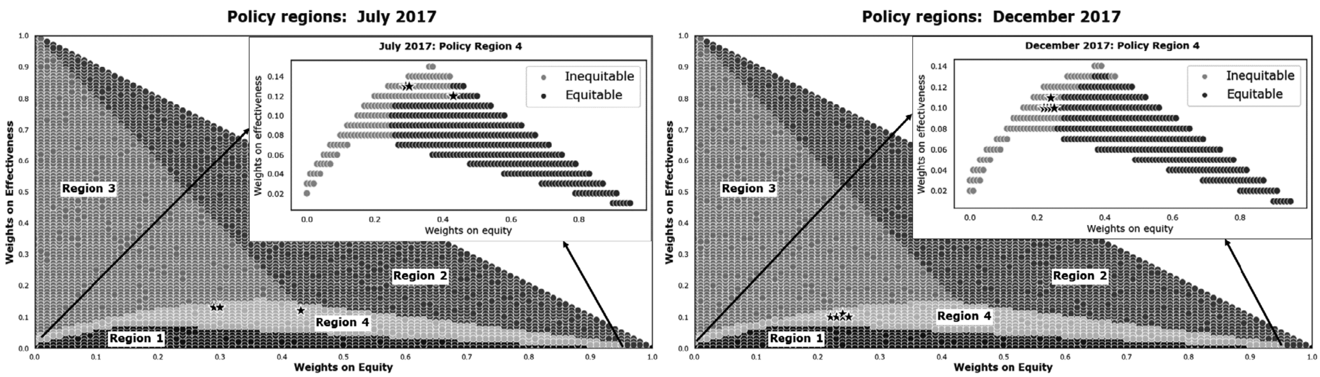
The cost of equitable and effective distribution. Examining the leftmost map in Figure 7 (Region 2), we see that if FBCENC prefers to distribute all available food in the network in a perfectly equitable manner, they incur an estimated distribution cost of \$299,052. In the actual distribution (the rightmost map in Figure 7), FBCENC retains 1.88 million pounds in ending inventory, has a wider MPINr and an estimated distribution cost of \$288,140. Several factors drive the difference between these two distribution schemes. First, FBCENC is sometimes willing to sacrifice equity if a county is experiencing hardship, as discussed in Section 1. During June 2017, Sampson (1) county was declared a disaster region following a tornado (North Carolina Department of Public Safety 2020). We see that Sampson has the highest MPIN value of 15.35 (darkest color) on the actual distribution. Since Sampson is also farther from the branches, this results in FBCENC spending \$3,424 more to distribute 38,925 pounds more food to Sampson compared to the equitable distribution case.

In contrast, some counties are underserved in the actual distribution compared to the equitable distribution. For example, Granville (2) county has the lowest MPIN value of 3.6 despite being close to both the Raleigh (Wake-3) and Durham (Durham-4) branches. We anticipate that this may be due to capacity limitations in Granville county. In the equitable distribution, an additional 62,829 pounds of food is distributed to Granville for an additional cost of \$3,471. Overall, if FBCENC prefers to achieve an equitable and effective distribution while keeping their distribution costs low, they can decrease their distribution costs by adding additional or satellite branch warehouses to the network that are closer to the consistently underserved counties.

The equity implications of efficient and effective distribution. Alternatively, if FBCENC prefers to distribute all food but at a lower distribution cost, they can choose the distribution policy from Region 3. For this case, FBCENC's distribution cost decreases by 57%, but they realize greater inequity across their service region. Specifically, Wake county, where FBCENC hub is located, receives almost 1.36 million pounds of food more than their fairshare, that is, $e_a = 94\%$, under this scenario. The total deviation from perfect equity equals 5.54 million pounds of food. Similar to the findings associated with equitable and effective distribution discussed above, one way a food bank may achieve efficient distribution with high levels of effectiveness would be to decrease their holding costs by investing in additional or larger storage facilities (interestingly, since Hurricane Florence, FBCENC has maintained additional warehouse storage at select locations within their network).

Potential benefits to food bank managers. The importance of the PE Algorithm is not limited to identifying the preferred set of criteria weights corresponding to the distribution actions taken by the food bank manager. The preferences associated with a food bank's distribution actions may differ from the organization's operational priorities. For example, we have seen in Section 5.2 that, based on the distribution actions taken over the 12-month horizon, FBCENC's highest priority is on efficiency, followed by equity and effectiveness. However, FBCENC's historically stated preference places more weight on equity. This inconsistency suggests that the actions taken by FBCENC may not align with their stated preference. After our findings were shared with FBCENC, they acknowledged the role that both efficiency and effectiveness played in their distribution decision-making, sometimes at the expense of equity. While they prioritized turning their inventory as quickly as possible, they acknowledged that it was vital to maintain some level of ending inventory to sustain operations. FBCENC

Figure 8 Elicited Weights Generated by PE Algorithm for July 2017 and December 2017 FBCENC Data



(a) Elicited weights for July 2017 data; Supply = 6.72 million lbs; Distribution% = 72%

(b) Elicited weights for December 2017 data; Supply = 7.6 million lbs; Distribution% = 70%

also identified their target or aspirational region in the equity-effectiveness distribution triangle as lying near the intersection of Regions 2, 3, and 4.

Given the preferences corresponding to their distribution actions elicited from the PE Algorithm, FBCENC can plan their distribution policies strategically to align with their stated preference. For example, suppose that FBCENC prefers to put more emphasis on equity, but budget limitations restrict their ability to distribute the available food equitably among the 34 counties. Under this scenario, they can explore Region 4 in Figure 3. It is possible for them to increase their weight on equity by maintaining some inventory and remain within Region 4. FBCENC can use Model EEE to identify the optimal distribution policies for the candidate weight combinations that align with their preferences. FBCENC can apply a range of these weight combinations, compare the corresponding distribution policies (such as the map for Region 4 in Figure 3), and choose a policy that best fits their preference. Model EEE is computationally inexpensive, as discussed in Section 5.1.3. Therefore, the evaluation of multiple weight combinations and the selection of a suitable distribution policy would not be time-consuming for FBCENC.

The benefits of Model EEE and the PE Algorithm are even more significant considering the dynamic nature of FBCENC's preferences over the three criteria. To evaluate how FBCENC's elicited preferences on equity, effectiveness, and efficiency have changed over time, we have applied the PE Algorithm to FBCENC data for December 2017. In this case, the PE algorithm was able to reduce the cardinality of the weight set to the following five elements: (i) [0.22, 0.1, 0.68], (ii) [0.23, 0.1, 0.67], (iii) [0.24, 0.1, 0.66], (iv) [0.24, 0.11, 0.65], and (v) [0.25, 0.1, 0.65]. All five weight combinations fall within Policy Region 4. The ordering of the weights corresponds to the criteria of equity, effectiveness, and efficiency, respectively. These nearly convergent weights are plotted over policy regions which can be found in Figure 8b. Comparing these weight combinations with those for July 2017 (Figure 8a), we see that the efficiency weights are higher and equity weights are lower for December 2017. This may be attributed to the fact that FBCENC receives more food in December, as this is during the holiday season, and FBCENC may sacrifice equity to distribute the additional food. This example of time-varying preference highlights the potential benefit of Model EEE's flexibility, allowing FBCENC to change the weights on the criteria according to their current preferences and obtain distribution policy suggestions accordingly. In addition, the PE Algorithm could be used to alert FBCENC of potential changes in their preferences reflected by their distribution actions.

6. Conclusion and Future Work

This study aims to address two of the UNSDGs: achieving food security and reducing inequalities. In developed countries, food banks commonly work to reduce food insecurity by distributing donations to food-insecure people in their service regions in an equitable manner. In this study, we study three commonly used criteria considered by food banks: equity, effectiveness, and efficiency. To provide insight regarding the optimal distribution policies for food banks and improve the understanding of the trade-offs between different criteria, we formulate a single-period, uncapacitated, multi-echelon multi-criteria network flow model, denoted as Model EEE. The objective function of the model is defined as a weighted sum of the three criteria. We use real data from our partner food bank to illustrate results and characterize the trade-offs between the criteria based on different weight combinations.

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Understanding the preferences of decision-makers, that is, the food bank managers, is critical for accurately and meaningfully informing the development of pragmatic distribution policies for the donated food. A food bank's preferences for the criteria of equity, effectiveness, and efficiency may vary based on supply and demand patterns. A distribution model that assigns predetermined weights to the criteria may not be able to produce a distribution policy that is acceptable and implementable. We have proposed a preference elicitation algorithm, namely the PE Algorithm, which uses the distribution actions taken by a food bank over time to elicit the inherent preference of the food bank over the criteria. The PE Algorithm considerably reduces the number of possible discrete weight combinations over these criteria that correspond to the distribution actions taken by the food bank. Further, food banks, such as FBCENC, can use this algorithm to demonstrate the differences between their current and strategic preferences on equity, effectiveness, and efficiency for soliciting funding from federal agencies and donors.

To the best of our knowledge, the PE Algorithm is the first approach in the humanitarian aid distribution literature to identify the decision-maker's preference for the criteria based on only observing their distribution actions. A unique aspect of the PE Algorithm relative to many non-interactive preference elicitation methods is that it uses only the distribution actions and the corresponding criteria estimates but does not require knowledge of the objective function value. We perform an extensive numerical case study to evaluate the algorithm's computational efficiency and provide managerial insights for FBCENC based on their historical distribution behavior and operations data. Although the algorithm does not always converge to a unique set of weights, it can reduce the cardinality of the weights set significantly, providing a range of feasible weights that represent the preferences of FBCENC based on their distribution actions. We discuss the policy implications of FBCENC's preferred weights and the expected influence of these preferences on equity, total food distribution, and transportation costs.

Furthermore, we presented our findings to the FBCENC managers. They agreed that their preference for equity, effectiveness, and efficiency fell within Policy Region 4, that is, partial distribution of the available food. FBCENC managers also indicated that their future goal was to have a distribution policy that is closer to Region 2, that is, equitable distribution of all available food. We shared our recommendations on how that could be achieved and the potential implications, based on our discussion in Section 5.3. FBCENC managers found our comparative analyses on the policy regions and actual distribution in terms of MPIN, cost of holding food, and cost of distribution insightful and easy to understand. These analyses allowed them to better understand and explore the impact of their actual distribution actions visually using their operational performance metrics.

This study can be extended in several ways. Our model considers a single period that can be extended to a multi-period setting to provide optimal distribution decisions over time. In addition, although our model assumes that the parameters are deterministic, some parameters, such as supply, are stochastic. A possible extension would be to model stochastic supply. Furthermore, the model can be extended to consider the receiving and distribution capacity of the counties and food bank hub and branches, respectively. We believe adding capacity constraints may make achieving equity more difficult, creating a more pronounced trade-off with effectiveness and efficiency. Finally, the perishability of some food items has not been explicitly considered in this study. Two approaches may be taken to consider perishability: the holding cost may vary by food type, or a time limit may be imposed on how long food items can be stored. If we consider a preference-based quality dimension, then a utility-based approach can be taken.

Although our models are motivated by the operations of our food bank partner, they are directly applicable to other food banks. Different food banks likely have different operating priorities and assign different weights to the criteria of equity, effectiveness, and efficiency when making distribution decisions. A given food bank may prioritize equity over effectiveness and efficiency, while another food bank may prioritize effectiveness to minimize food waste and reduce the cost of waste disposal. For example, a food bank that operates in an area with a high cost of living may prioritize minimizing operating costs to continue their operations, whereas another food bank may be more concerned with the quick turnaround of food due to limited storage. Given these variations in preference, solutions and policies that are based on predetermined criteria weights, or those that ignore one or more of these criteria, may overlook or inaccurately represent the preferences of a food bank in a given period. The models presented in this study have the flexibility to adjust to food banks' shifting preferences and needs. At a larger scale, Feeding America, which collects and distributes food donations to its food bank affiliates in an equitable, effective, and efficient manner, can use the model to determine their optimal distribution policies according to their preference.

Furthermore, the developed methods can potentially be applied to global humanitarian relief efforts. One of the UNSDGs addressed in this study, reducing food insecurity, is also a primary strategic goal of World Food Programme (WFP) (World Food

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Programme 2017). Under WFP, the United Nations Humanitarian Response Depot (UNHRD) is a global network of depots located in Ghana, Italy, United Arab Emirates, Malaysia, Spain, and Panama that procures, manages, and transports emergency supplies for the humanitarian community (The United Nations Humanitarian Response Depot 2017). UNHRD usually considers two criteria in distributing donated food: (i) maximization of demand met and (ii) minimization of travel distances (Miraç and Eren 2020). UNHRD's first criterion can be related to Model EEE's equity and effectiveness criteria, whereas UNHRD's second criterion can be related to Model EEE's efficiency criterion. Therefore, the model developed in this study can be applied to a broader framework to address the complex challenges posed by UNSDGs. Finally, our results can be used for short-term humanitarian relief operations, where the goal is usually to distribute relief items to the affected population in an equitable (each person's demand is met), effective (minimal waste of relief items), and efficient (minimal distribution cost) manner. International humanitarian organizations such as Red Cross, Doctors Without Borders, and Oxfam could also use the PE Algorithm to elicit their inherent preferences over the criteria.

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Notes

[1]In the US, a county refers to an administrative subdivision of a state. There are over 3000 counties in the US.
[2]Percentages based on FBCENC food donations data from July 2013 to May 2020.

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Supporting Information

Additional supporting information may be found online in the Supporting Information section at the end of the article.

Appendices.

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