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Predicting and optimizing the fair allocation of donations in hunger relief supply chains

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ABSTRACT

Non-profit hunger relief organizations primarily depend on donors' benevolence to help alleviate hunger in their communities. However, the quantity and frequency of donations they receive may vary over time, thus making fair distribution of donated supplies challenging. This paper presents a hierarchical forecasting methodology to determine the quantity of food donations received per month in a multi-warehouse food aid network. We further link the forecasts to an optimization model to identify the fair allocation of donations, considering the network distribution capacity in terms of supply chain coordination and flexibility. The results indicate which locations within the network are under-served and how donated supplies can be allocated to minimize the deviation between overserved and underserved counties.

1. Introduction

1.1. Background

Whenever the accessibility of nutritionally safe and adequate food is uncertain for an individual, they are considered food insecure (Haering & Syed, 2009). In the United States, food insecurity affects an estimated 10.2% of total U.S. Households (Coleman-Jensen, Rabbitt, Gregory, & Singh, 2022). Several federal, private, and non-profit interventions exist to assist individuals facing hunger. The U.S. Food and Nutrition Services offers programs targeted at all population segments, including those specific to pregnant women, children, and seniors. Many people also receive assistance from private and non-profit organizations that rescue surplus food from suppliers, distributors, and retailers associated with the for-profit food supply chain. The food is then redistributed to other charitable organizations focused on providing direct assistance to individuals in need. This paper focuses on food rescued (or donated) to non-profit hunger relief organizations (NPHROs), specifically food banks.

Food banks receive food that otherwise might be discarded but is still safe for human consumption. Some significant contributors to the donated food supply are retail grocers, "big-box" stores (e.g., Wal-Mart, Sam's Club), farmers, and food manufacturers. Food is distributed to people in need directly by the food bank or through a network of smaller local non-profit organizations called partner agencies (e.g., soup kitchens and food pantries). Food banks are committed to alleviating hunger in their service areas and depend mainly on the benevolence of donors to help them achieve their goals. While food banks receive both monetary and in-kind donations, more than 70% of the food distributed comes from donations. As the quantity and frequency of donations may vary over time, the mission of alleviating hunger is challenging.

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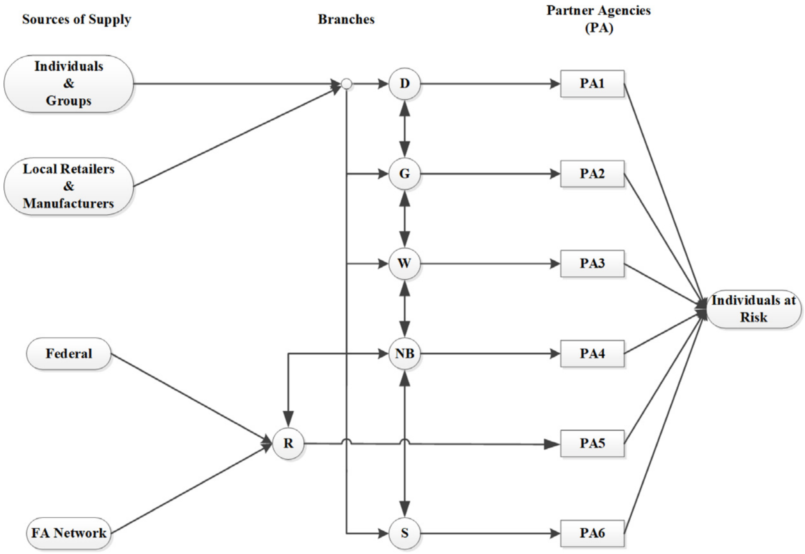


Fig. 1. Supply flow in the food bank network with branch locations Raleigh (R), Durham (D), Greenville (G), Wilmington (W), New Bern (NB), and Sandhills (S).

In addition to uncertain supply, distribution capacity affects the ability of food banks to achieve their mission. Distribution capacity encompasses two forms. The first relates to the number of agencies in the network, which can be considered the last-mile capacity. This limits what can be distributed to individuals. The second form of distribution capacity is at the warehouse level, which limits what can be received and, subsequently, what can be distributed. The distribution network of food banks can vary significantly, and many food bank practitioners often state, "If you have seen one food bank...you have seen one food bank". Some food banks operate from a single warehouse and serve a specific geographic area (e.g., counties, zip codes). Other food banks may have a large service area that necessitates having multiple smaller warehouses strategically positioned closer to the people/agencies they serve.

In addition to dealing with uncertain supply and capacity constraints, the demand for food typically exceeds what is available. Thus, food banks make distribution decisions focusing on achieving equity (Orgut et al., 2016). In this paper, we explore the relationship among these three factors by linking forecasts of donated supply to equitable distribution of the supply, taking into consideration the capacity imposed by the network structure. In for-profit supply chains, demand predictions drive production planning decisions. We posit that supply predictions inform distribution decisions in the non-profit hunger relief setting. Therefore, we aim to link these two activities. Prior research in food aid supply chains has largely ignored the supply uncertainty aspect and determined distribution and allocation decisions based on known supply in a single period. While these models have provided important insight, strategic decisions are made over a longer time horizon and should reflect the uncertain nature of supply. Our paper tries to bridge this gap meaningfully, informed by our interactions with a local food bank.

1.2. Motivation

Feeding America is one of the largest U.S.-based NPHROs engaged in the mission to feed hungry Americans. This mission is achieved through a collaborative network of 200 food banks located throughout the country.[1] In this study, we mainly focus on a food bank located in the state of North Carolina. North Carolina is one of several states with a food insecurity rate above the national average and is served by seven Feeding America-affiliated food banks. The analysis and models presented in this study are based on the operations and supporting data of one of the seven food banks, The Food Bank of Central and Eastern North Carolina (FBCENC). FBCENC serves 34 of the 100 counties in North Carolina and is the biggest food bank in the area. Their distribution network consists of six branch warehouses and over 800 partner agencies (e.g., soup kitchens, food pantries) addressing the hunger needs of more than 600,000 individuals in their service area.[2] Fig. 1 depicts the flow of food within this network. Food donations come from the U.S. Department of Agriculture programs (e.g., The Emergency Food Assistance Program), retail stores and supermarkets, food manufacturers, partner food banks, and local food drives. Branches can receive donations directly from donors near their location. Still, the bulk of the federal commodities go through the warehouse located in Raleigh (denoted as *R*) and are subsequently transferred to other locations. The branch warehouses can share food donations among themselves (as depicted by the bi-directional flows). FBCENC also receives monetary donations and supplements their donated food with purchased food based on available funds.

1 https://www.feedingamerica.org/our-work/food-bank-network

2 fbcenc.org

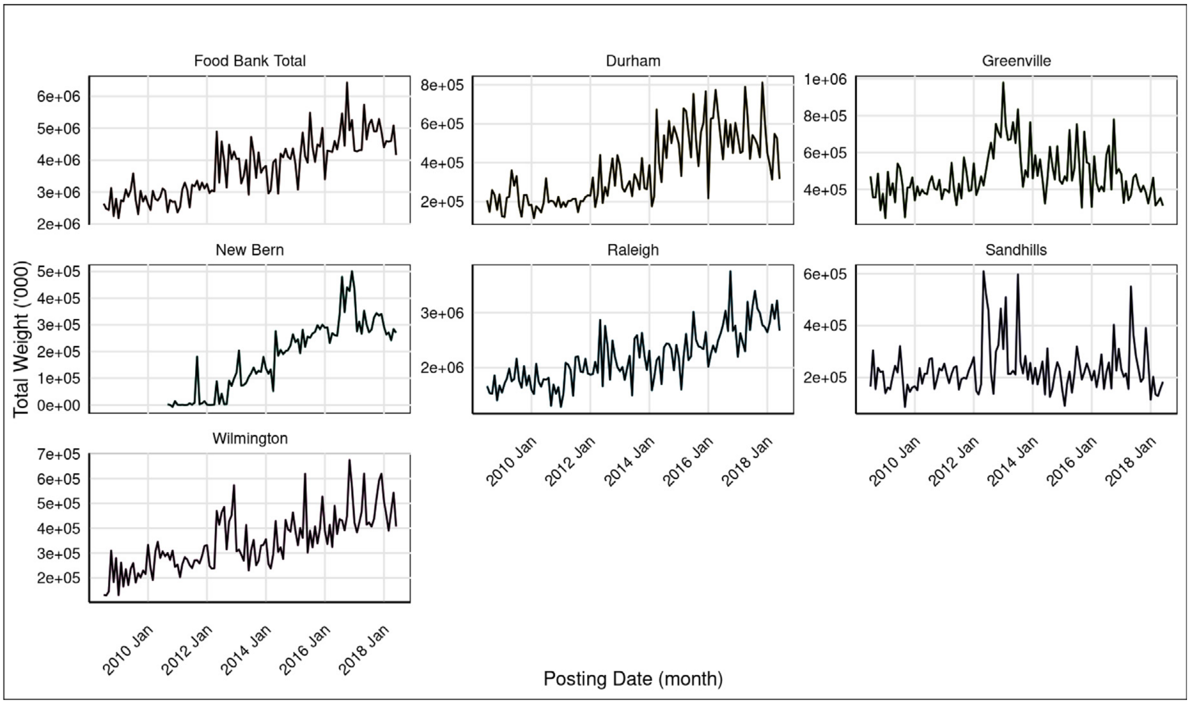


Fig. 2. Time series plots of food donations within the network, excluding TEFAP commodities.

Donations are transferred to individuals in need through partner agencies such as soup kitchens and food pantries. Each branch warehouse primarily serves a distinct set of partner agencies within specific counties close to the branch. Sometimes, other branches can serve partner agencies based on need and proximity.

In this network, the main warehouse receives the majority of food donations because it has the largest storage capacity, illustrated by the time series graphs of food donations in Fig. 2. The graphs show an overall increasing trend in donations at the network level (*Food Bank Total graph*). The graphs exhibit variability in the quantity received within a branch and the variability received among the branches due to the warehouse capacity restrictions. Another operational change that impacts variability is the new warehouse that the Durham branch received in 2014, which increased its capacity to receive food. Additionally, New Bern was a branch that was added in 2010.

1.3. Study aims

This research aims to estimate and optimize the fair allocation of in-kind donations in a multi-product, multi-warehouse food aid distribution network. The following research questions guide our study aim:

Research Question 1: What is the best way to estimate the amount of in-kind donations that will be received at a specific location in a multi-warehouse food aid network?

As indicated in our motivation, each branch receives donated items, which vary in frequency, quantity, and type of food (Davis, Jiang, & Terry, 2013). Therefore, in addition to understanding the potential supply that may arrive in a given time period for the entire network, a decision-maker may be interested in a location-specific assessment of potential supply. This location-specific assessment may influence the amount of food that will be transferred among branches to satisfy demand and identify which counties should be served by the branches. In practice, some counties are served by a primary and secondary branch.

Research Question 2: How can predictions of in-kind donations be used to identify geographic areas that may be over-served or under-served by potential distribution activities? As noted in Davis, Jiang, Morgan, Nuamah, and Terry (2016), FBCENC routinely evaluates the performance and impact of its operational activities. One key performance metric is pounds of food distributed within their partner agency network (by county and over a 12-month rolling horizon). This allows decision-makers to identify (i) if food is being distributed equitably, (ii) where there are counties of unmet need (i.e., under-served) relative to other counties within their service area, and (iii) make decisions on how to fill the gaps through other activities like direct distribution or additional sourcing. This assessment is primarily done using historical distribution data from prior months; however, more proactive decisions can be made if forecasts of donations are considered in the decision-making process.

Research Question 3: How does supply chain structure (specifically the level of coordination and flexibility) impact the equitable distribution of supply? Flexible supply chains can adapt to disruptions in supply and changes in demand while maintaining customer service levels. Several definitions of supply chain flexibility are proposed in the literature (Tiwari, Tiwari, & Samuel, 2015); however, the work proposed in this paper aligns with studies where flexibility is characterized by adaptability, alignment, and agility (Lee et al., 2004). Adaptability measures the degree to which the supply chain's design can adapt to structural changes in the market and modify supply network designs. This definition is also described in Stevenson and Spring (2007) as network-level flexibility, referred to as re-configuration. For food bank supply chains, adaptability and re-configuration flexibility are exhibited by the degree to which (agency) demand can be sourced from multiple warehouse locations. Essentially, the degree to which the network is structured to accommodate dual sourcing is one way to increase flexibility. While there is no unique definition for supply chain coordination, the consensus is that supply chain coordination involves multiple stakeholders working together to achieve mutually defined goals and can involve mechanisms such as information sharing, joint decision-making, and resource sharing (Kanda et al., 2008). In our study, we quantify the degree of coordination from a resource-sharing perspective. Specifically, food bank warehouses that receive donations independently can share food donations with other warehouse locations to meet needs and reduce waste. This form of coordination is described in Davis, Samanlioglu, Qu and Root (2013) in the context of disaster relief.

We propose a two-phase approach to integrate predictions of donated supply with a decision model of equitable food distribution, considering the distribution capacity imposed by the network structure. We present a hierarchical forecasting framework that integrates bottom-level donor-giving frequency and food type forecasts into location-specific forecasts. We evaluate several time series models, including an ensemble of multiple time series models, to identify the approach that yields the lowest forecast error. We then use the predicted location-specific forecasts to identify the optimal food distribution within the multi-warehouse, multi-demand point network. We consider supply chain flexibility, coordination behavior, and operational goals of fair distribution and minimizing waste. We measure fairness relative to the meals served per person in need (MPIN), a standard metric used by food banks.

The remainder of this paper is outlined as follows. Section 2 summarizes the relevant literature. Section 3 presents the model framework and corresponding notation. The results and analysis are summarized in Section 4. Section 5 summarizes our key findings and the practical implications of our work.

2. Literature review

We summarize the related literature on forecasting, emphasizing applications within humanitarian relief since food assistance is a humanitarian endeavor. We also discuss our specific contributions to the donations forecasting problem.

2.1. Forecasting in humanitarian relief applications

Forecasting in traditional supply chains plays an important role in matching available supply with demand and can provide similar benefits in humanitarian supply chains. It is well documented that logistics decisions in humanitarian supply chains are made in the face of uncertainty (Hoyos, Morales, & Akhavan-Tabatabaei, 2015). Some of those uncertainties come in the form of uncertain demand, uncertain supply, and uncertain damage to the transportation network used to move the supply to the areas in need. Furthermore, given that some disasters occur suddenly and little information may be available, forecasting in this context may prove challenging. However, slow-onset and predictable disasters (such as hurricanes) provide information and time that may more readily lend itself to forecasting for logistics activities.

Table 1 summarizes the key forecasting problems investigated in the humanitarian logistics domain, differentiated by sudden-onset (e.g., hurricanes, earthquakes) and slow-onset disasters (e.g., famine, flood, drought). We position the related literature in this manner because Famine, drought, and poverty are classified as slow-onset disasters (see Figure 1 in Van Wassenhove, 2006). It is well documented in the literature the correlation between food insecurity in the U.S. and poverty (Drewnowski, 2022; Hossfeld, Kelly, & Waity, 2018). Chronic hunger is an outcome of an individual's poverty condition, which can be intensified during disasters and other disruptive events (e.g., job loss, sudden change in health).

We note that there are several papers related to predicting donor intention and behavior (Ülkü, Bell, & Wilson, 2015; Zagefka, Noor, & Brown, 2013); however, we limit our summary to papers that predict donation quantities. The use of predictive modeling to address these uncertainties has been limited to problems related to forecasting disaster occurrences. The reader is referred to Hoyos et al. (2015) and Altay and Narayanan (2020) for a comprehensive summary of articles on this situation. Forecasting models for relief supply is a growing area of research, particularly with respect to slow-onset disasters such as famine. Most work done for forecasting slow-onset disasters has centered on food donations received by non-profit hunger relief organizations, similar to the one investigated in this paper.

The primary studies for forecasting food donations come from two different settings: U.S food banks part of the Feeding America Network (Brock & Davis, 2015; Davis et al., 2016; Phillips et al., 2013) and a food rescue organization in Sydney, Australia (Nair et al., 2017). As illustrated in Table 1, machine learning and classical time series models have been used (i.e., ARIMA and smoothing-based forecasting approaches). The predictions have been constructed under different scenarios considering all possible donors within a service area (Davis et al., 2016; Nair et al., 2017), a subset of donors such as retail suppliers (Brock & Davis, 2015; Phillips et al., 2013), and in pre and post-disaster-settings (Pérez et al., 2023). The time horizon for predicted quantities consist of daily (Phillips et al., 2013), weekly (Brock & Davis, 2015; Sharma et al., 2021) and monthly (Davis et al., 2016; Pugh & Davis, 2017; Sharma et al., 2021) periods.

The problem data and predicted variables vary across the different studies and the inherent differences in the data make it difficult to draw conclusions about the best

Table 1
Classification of forecasting problems in humanitarian logistics.

Disaster type	Problem context	Approach	Authors
Sudden-onset	Monetary Donations	social network analysis	Korolov et al. (2016)
	Food donations	ES, MA, ARIMA, Econometric	Pérez, Marthak, and Mediavilla (2023)
	Food demand	ARIMA-Hybrid Grey method	Xu, Qi, and Hua (2010) Wang (2013)
	Medical Resources	Machine Learning, simulation	Papadopoulos and Korakis (2018)
	Relief demand	Data fusion, entropy-based weighting	Sheu (2007)
Slow-onset	Food demand	Regression Random forest	Okore-Hanson, Winbush, Davis, and Jiang (2012) Odubela, Jiang, and Davis (2022)
	Food supply	ES, MA, ARIMA Neural Networks & Regression Extreme value Theory, Monte–Carlo simulation Support Vector regression (SVR) ES, ARIMA, Machine Learning ES, MA, ARIMA, Econometric model ES and SVR ensemble	Davis et al. (2016) Brock and Davis (2015) Nair, Rashidi, and Dixit (2017) Phillips, Hoenigman, Higbee, and Reed (2013) Pugh and Davis (2017) Sharma, Davis, Ivy, and Chi (2021) Pérez et al. (2023) Paul and Davis (2021)

approach. However, we do note the following observations. Time series models work well when the data is aggregated across all donors, food types, or donation-receiving locations, with mean absolute percentage errors as low as 9% (Davis et al., 2016). However, forecasting for a specific receiving location and types of food produces larger forecast errors as the variability observed in the data is quite high compared to an aggregated dataset. More sophisticated forecasting techniques that capture external factors related to donor behavior and operating environment can lead to more promising predictions for specialized forecasts by a subset of the donors, type of food provided, and shorter prediction intervals (Brock & Davis, 2015). In particular, both Brock and Davis (2015) and Nair et al. (2017) use neural networks to predict donated supply and achieve R^2 values as high as 0.7.

Davis et al. (2016) note the importance of decentralized forecasts, particularly since the food bank considered in their study operates a multi-warehouse network where donations can be received at individual warehouse locations and shared across the food bank network. This paper focuses on developing models to address decentralized forecasts in this environment. We specifically extend the prior study of Davis et al. (2016) to investigate additional prediction models for the *food donations forecasting problem*. The application of state-space models to this forecasting problem is of particular interest.

2.2. Research contribution

Our paper contributes to the existing literature on humanitarian relief forecasting in slow-onset disasters in several ways. Our work builds upon the work of Davis et al. (2016), whose main objective was to introduce the food donations forecasting problem, discuss its complexity, and explore the efficacy of the traditional time series approach. In this paper, we expand the scope and scale of the data investigated and consider additional forecasting techniques. Furthermore, we incorporate the forecast into an optimization model that identifies the optimal allocation of the donated supply that is equitable and balanced against the constraints of the supply chain structure. More specifically, we introduce measures of supply chain flexibility and coordination to isolate the conditions by which supply uncertainty and supply chain structure impact equitable distribution. To the best of our knowledge, the open literature has not addressed the application of a state-space modeling approach to estimate and equitably allocate in-kind donations. There is, however, an extensive amount of literature relating to optimization models exploring operations of humanitarian relief organizations (Hoyos et al., 2015).

Most of the work done on the operations of humanitarian organizations is in the field of relief supply allocation. The allocation decisions are made for in-kind donations of relief items such as food or other equipment (Altay, 2012). The objective is to allocate the supply in a way that minimizes transportation costs and addresses needs by satisfying demand. While cost is a typical objective when performing distribution activities, a few papers consider service-based objectives like minimizing deprivation costs (Pérez-Rodríguez & Holguín-Veras, 2016) or maximizing social benefit (Das & Hanaoka, 2014). Within the food bank operations literature, service-based objectives such as minimizing waste (Orgut, Ivy, Uzsoy, & Wilson, 2016) or maximizing fill rate (Lien, Iravani, & Smilowitz, 2014) are also considered. An important issue to address when allocating supply, particularly if it is constrained, is equitable allocation or distribution (Balcik, Iravani, & Smilowitz, 2014).

Our approach to addressing the research questions consists of two components. First, We develop a methodology for predicting food donations at each branch within the food bank network, which is subsequently used to quantify the degree to which this potential supply can meet the demand equitably, considering the unique structure and coordination within this food bank network. Our approach focuses on examining the role of supply uncertainty and capacity will further restrict our ability to meet demand equitably. However, we seek an idealized estimate of what is equitable because we note that additional distribution capacity can be achieved operationally through activities such as mobile distribution (Stauffer, Vanajakumari, Kumar, & Mangapora, 2022) and off-site

Table 2
Summary of key fields.

Field	Description	Levels
Posting Date	Date donation was received in the warehouse	–
Donor ID	Unique identifier of the donor	–
Gross Weight	The donation amount (in pounds)	–
Branch Code	Warehouse location where donation was received	6
Storage Code	Classification of donation based on warehouse storage (e.g., Dry, Frozen, Produce)	5
Donor Class of Trade	Classification of donor (e.g. MFG)	4
Item Number	Product identifier, similar to a SKU number	–

warehouse storage (Hasnain et al., 2023). The reader is referred to the studies of Orgut et al. (2016) to understand the impact of capacity on equitable distribution.

3. Methodology

We aim to determine the best approach for developing location-specific predictions of in-kind donations for each branch warehouse reflected in Fig. 1. This includes consideration of two aspects: (ii) the best way to construct the time series data (aggregated versus dis-aggregated) and (ii) identifying the best model. Based on our relationship with a local food bank, we obtained ten fiscal years of data (Fiscal Year 2008–2009 to Fiscal Year 2017–2018), where a fiscal year runs from July to June of the subsequent year. Table 2 summarizes the key fields in the data that are relevant to this study.

3.1. Data preparation

We first prepare our data for analysis by identifying and correcting misclassification errors. We identified 1187 entries from 2014 to 2018 that were misclassified as "DRY", while in reality, these entries were "PRODUCE" items. A total of 99 donors were affected by this incorrect classification, most of which were large-volume donors with total donations by weight ranging from 4% to 18% per month. We correctly classified the data before proceeding.

Another thing to note is that, within the time frame of our data, Hurricane Matthew occurred. Hurricane Matthew, spanning from September 28 to October 9, 2016, left a devastating path of destruction across the Caribbean and southeastern United States, claiming over 1000 lives and causing billions of dollars in damages. Its fierce winds and torrential rains triggered widespread flooding, displacing thousands and leaving communities in ruins. To help those in need, food banks received donations from various donors during the last quarter of 2016. These donation items are coded as Disaster "DR" in our dataset. A total of 271 entries fell under this category. However, these are high-volume donations. To obtain better prediction results, we remove those one-time donations from FY2016-17 from the donation data.

We then prepare our data by creating multiple time series dis-aggregated according to the structure presented in Fig. 3. For each branch in the network, this corresponds to 9 to 12 distinct series (60 series in total). One of the challenges associated with dis-aggregating the data by location, food type, and donor frequency is that it may increase the occurrence of gaps in the data for specific periods of time. We utilize several techniques to reduce this effect. First, we consider predictions on a monthly rather than weekly or daily time scale. This is consistent with the prior literature and how some food bank operations managers evaluate the performance of their distribution activities. Second, a donor may give one time (i.e., community food drive) or sporadically, causing donor-specific predictions to be problematic. To overcome this phenomenon, we cluster donors based on their giving frequency, also referred to as a donor reliability score in Paul and Davis (2021). In particular, we create a binary variable (E_{dt}) for each donor d that takes on the value of 1 if at least one donation was made in period t, 0 otherwise. Then, the reliability for donor d is determined according to Eq. (1). The reader is referred to Fig. 12 in the Appendix for a histogram of the donor reliability for each branch. A reliability score closer to 0 implies a donor does not give every month. It should be noted that there are very few consistent donors, thus strengthening our justification for aggregation.

$$r_d = \frac{\sum_{t=1}^{T} E_{dt}}{T} \tag{1}$$

We then perform *k-means* clustering to partition the donors into groups as a function of their giving frequency. We use the elbow method to identify the optimal number of clusters. In addition to performing clustering based on the *k-means* algorithm, we also collapse some of the levels associated with the *Storage Code* key field because we observe temporal changes in the classification of donated produce. Initially, donated produce was classified under the storage code PRODUCE. However, in subsequent years, the items were more frequently classified as refrigerated (REF). This classification change causes gaps in time series data, making lower-level forecasting problematic. Therefore, we merge the two codes (REF and PRODUCE) into one code (REF).

We next determine if there are any outliers by calculating the interquartile range (IQR) (Hyndman & Athanasopoulos, 2023) and identifying points that are within 0.8–2 IQRs from the central 50% of the data. The acceptable range for outliers varied by branch as indicated in Table 9 in the Appendix. Outliers are replaced with the median of the series.

Lastly, for any month in the clustered series with no corresponding donation amount, we enter the value of 0. It should be noted that for the highest level of aggregation (by Branch), there is a non-zero donation amount for every month in the time series. Thus, transformation of the data is unnecessary.

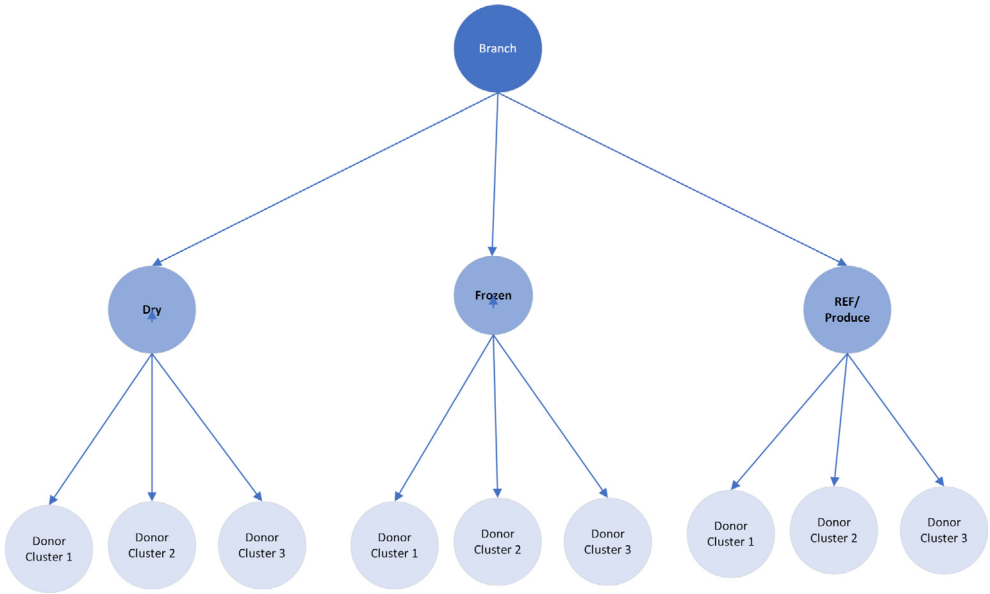


Fig. 3. Hierarchy of donation data where the first level is the food type and the second level is donor clustered by monthly donation frequency.

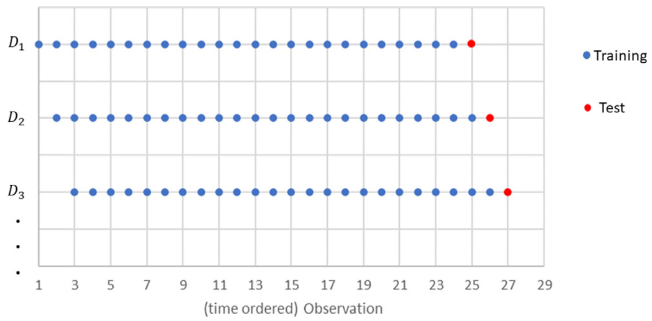


Fig. 4. Illustration of data set (D_i) partitioning for time series cross-validation with origin at $t = i$ and the set of one period forecasting time periods $T = \{25, 26, 27\}$.

3.2. Forecast model selection

We split our data into two sets: (i) A training set consisting of data points from the fiscal year 2008–2009 (FY0809) to FY1617; (ii) a holdout set consisting of data from FY1718, which is used to validate our forecasting approach. The training set is subdivided into multiple training/test sets for performing time series cross-validation as illustrated in Fig. 4. We utilize a sliding window approach consisting of a fixed window size of 24 months based on the findings in Pugh and Davis (2017). We then generate one-step ahead forecasts at the lowest level in the hierarchy and utilize a bottom-up approach to generate the corresponding branch forecast. In addition to the branch forecast generated for a specific model m, we construct a composite model comprising the best forecast model for each bottom-level series.We identify the best forecast model as the one that generates the lowest mean absolute percentage error (MAPE).

Our approach is outlined in algorithm 1, using the following notation. Let M denote the set of forecast models, S the set of food types, and G the set of donor-giving frequency groups. Let $\mathcal{C}^k_{sg}$ denote a time-ordered data set associated with branch k that is grouped by giving frequency g and food type s. $\mathcal{C}^k_{sg}$ represents a leaf node in the data hierarchy depicted in Fig. 3, where $\mathcal{C}^k$ represents all leaf node (terminal tree node) datasets associated with branch k. Let T_{sg} represent the set of all time periods where one-step ahead forecasts are generated during cross-validation. This is essentially the time horizon associated with the test data sets (the reader is referred to Fig. 4 as an illustration). We similarly define T_s as the set of all time periods where aggregated one-step ahead forecasts are generated for the product type. $\tilde{y}^k_{sg,t}(m)$ is a forecast for branch k at time t for product type s and donor group g using model m. Then the forecast for a specific product type $\tilde{y}^k_{s,t}(m)$ and the branch $\tilde{y}^k_t(m)$ is given by equations below, according to the bottom-up approach.

$$\tilde{y}^k_{s,t}(m) = \sum_{g\in G} \tilde{y}^k_{sg,t}(m) \tag{2}$$

$$\tilde{y}^k_t(m) = \sum_{s\in S} \tilde{y}_{s,t}(m) \tag{3}$$

Our algorithm is implemented in Python, and we describe the models and accuracy measures in subsequent sections.

Algorithm 1: Model selection procedure for a branch k

Step 1. Bottom-level model fitting
foreach $\mathcal{C}_{sg}^k \in \mathcal{C}^k$ **do**
1 $n \leftarrow |\mathcal{C}_{sg}^k| - w$
2 generate n test sets using sliding window of size w $\rightarrow \hat{\mathcal{C}}_{sg}^k = \{D_{t_i}, D_{[t_i+1]}, \ldots D_{t_i+n-1}\}$
3 **for** $m \in M$ **do**
4 **foreach** $D_t \in \hat{\mathcal{C}}_{sg}^k$ **do**
5 Fit model m to time series D_t
6 Generate 1 step-ahead forecast, $\tilde{y}_{sg,t+24}^k(m)$, from data set D_t with origin at t
7 $\tilde{\mathbf{y}}_{sg}^k(m) \leftarrow \tilde{\mathbf{y}}_{sg}^k(m) \oplus \{\tilde{y}_{sg,t+24}(m)\}$
8 **end**
9 **for** $j \in \mathcal{A}$ **do**
Compute accuracy measure j for model m for data set $\mathcal{C}_{sg}^k$
10 $z_{sg,j}(m) \leftarrow f_j(\mathbf{y}_{sg}^k(m), \tilde{\mathbf{y}}_{sg}^k(m))$
11 **end**
12 **end**
13 **end**
Step 2. Bottom-up model forecast and evaluation
for $m \in M$ **do**
14 Compute $\tilde{y}_{s,t}(m) \leftarrow \sum_{g \in G} \tilde{y}_{sg,t}(m)$ $\forall s \in S, t \in \bigcap_{g \in G} T_{sg}$
15 Compute $\tilde{y}_t(m) \leftarrow \sum_{s \in S} \tilde{y}_{s,t}(m)$ $\forall t \in \bigcap_{s \in S} T_s$
16 $\tilde{\mathbf{y}}_s^k(m) \leftarrow \tilde{\mathbf{y}}_s^k(m) \oplus \{\tilde{y}_{s,t}(m)\}$ $\forall t \in \bigcap_{g \in G} T_{sg}$
17 $\tilde{\mathbf{y}}^k(m) \leftarrow \tilde{\mathbf{y}}^k(m) \oplus \{\tilde{y}_t(m)\}$ $\forall t \in \bigcap_{s \in S} T_s$
18 **for** $j \in \mathcal{A}$ **do**
19 $z_{sj}(m) \leftarrow f_j(\mathbf{y}_s^k(m), \tilde{\mathbf{y}}_s^k(m))$
20 $z_j(m) \leftarrow f_j(\mathbf{y}^k(m), \tilde{\mathbf{y}}^k(m))$
21 **end**
22 **end**
Step 3. Ensemble model forecast and evaluation
foreach $\mathcal{C}_{sg}^k \in \mathcal{C}^k$ **do**
23 $m_{sg}^* \leftarrow \arg\min_{m \in M} z_{sg,j}(m)$
24 **end**
25 Compute $\tilde{y}_{s,t}(m^*) \leftarrow \sum_{g \in G} \tilde{y}_{sg,t}(m_{sg}^*)$ $\forall s \in S, t \in \bigcap_{g \in G} T_{sg}$
26 Compute $\tilde{y}_t(m^*) \leftarrow \sum_{s \in S} \tilde{y}_{s,t}(m^*)$ $\forall t \in \bigcap_{s \in S} T_s$
27 Similarly, compute accuracy measures are described in lines 18- 21.

3.3. Description of model pool

The set of forecasting models (M) used in algorithm 1 consists of the following classical time series methods: Simple Moving Average (SMA), Autoregressive Integrated Moving Average (ARIMA), and time series decomposition. The reader is referred to Hyndman and Athanasopoulos (2023) for a formal presentation of these models. We briefly discuss important modeling assumptions considered in this study.

Assumption 1. For **simple moving average**, one-step ahead forecasts are generated using the prior 24 months of observations. In Davis et al. (2016), simple moving average models outperformed the other models for four out of the five branches in the study. Therefore, we incorporate SMA in our model pool.

ARIMA models are appropriate if time series data are correlated with prior observations and/or random shocks. The ARIMA model can generally be described in terms of the number of auto-regressive terms, the number of past forecast errors, and the number of terms needed to make a non-stationary time series stationary (i.e., differencing parameter). Manual selection of these model parameters involves a number of tasks, including plotting the data, potentially transforming the series, and checking auto-correlation and partial auto-correlation plots.

Assumption 2. In our study, **ARIMA** models are fit to the data using the automatic selection procedure defined in Hyndman and Khandakar (2008) and as implemented in the python package *pmdarima*.

Time series decomposition involves extracting a series's seasonality, trend, and cyclic components. Forecast models can be constructed for the components and incorporated in an additive or multiplicative fashion (Hyndman & Athanasopoulos, 2023).

Assumption 3. Our study considers forecasting with time series decomposition based on the season and trend decomposition using LOESS (locally weighted regression and scatterplot smoothing). We utilize the STL procedure from the python *statsmodel* package.

We also incorporate exponential smoothing state-space (ETS) models. ETS modeling approach provides several advantages over simple exponential smoothing, specifically the ability to model error, trend, and seasonality in a linear (additive) or nonlinear (multiplicative) fashion. There are two main forms of state space models: conventional and innovations. The conventional state space model has multiple sources of error, while the innovations state space model has a single source of error. There are 24 (linear and nonlinear) state-space representations of exponential smoothing models, and both point forecasts and prediction intervals can be generated. We refer the reader to Hyndman, Koehler, Ord, and Snyder (2008) and Hyndman and Athanasopoulos (2023) for a more formal presentation of the linear and nonlinear state space models.

Assumption 4. For **ETS** model fitting, we use the *ETSmodel* procedure in the python *statsmodels* package. We fit models with multiplicative and additive error, trend, and seasonality.

3.4. Description of accuracy measures

The set of accuracy measures ($\mathcal{A}$) used in algorithm 1 are mean absolute percentage error (MAPE), root mean square error (RMSE), and mean absolute error (MAE). These measures are consistent with those presented in related studies (Nair et al., 2017; Pérez et al., 2023; Sharma et al., 2021) Eqs. (4)–(6) define the measures of forecast

Table 3
Optimization model notation.

Index Sets	I	Set of Branches $i, k \in \{1, \ldots, N_B\}$
	J	Set of demand points $j \in \{1, \ldots, N_D\}$
Parameters	$\tilde{y}_i$	The forecast of available in-kind donations at branch $i \in I$
	P_j	The number of people in poverty at demand point $j \in J$
	D_j	Prior period distribution for demand point $j \in J$
	v_{ij}	1 if shipments can be made from branch $i \in I$ to demand point $j \in J$, 0 otherwise.v_{ij} quantifies supply chain flexibility.
	c_{ik}	1 if supply can be transferred (shipped) from branch $i \in I$ to branch $k \in I$, 0 otherwise. c_{ik} quantifies supply chain coordination.
	w_i	Weight of objective i
	T	Target MPIN distribution goal for each county
	M	large number
Decision Variables	m_j	meals distributed per person in need (MPIN) for demand point $j \in J$
	a^+	The maximum over target MPIN for all demand points $j \in J$.
	a_-	The maximum under target MPIN for all demand points $j \in J$.
	x_{ij}	The amount of in-kind donations shipped to demand point j from branch $i \in I$
	b_{ik}	The amount of in-kind donations shipped from branch i to branch k, $(i, k) \in I$
	u_i	The undistributed supply from branch $i \in I$
	o_j^+	The MPIN over target quantity for demand point $j \in J$
	o_j^-	The MPIN under target quantity for demand point $j \in J$

accuracy for a time series of length T as a function of the forecast error $e_t = (\tilde{y}_t - y_t)$.

$$MAPE = \sum_{t=1}^{T} 100 * |e_t|/y_t \tag{4}$$

$$MAE = \frac{\sum_{t=1}^{T} |e_t|}{T} \tag{5}$$

$$RMSE = \sqrt{\frac{\sum_{t=1}^{T} (e_t)^2}{T}} \tag{6}$$

3.5. Supply distribution prediction

We use our forecast of supply to develop a prediction of equity within the network under the assumption that the decision-maker acts optimally. We develop a linear programming (LP) model to represent the decision-maker's equitable distribution decision. We adopt an equity measure presented in Marsh and Schilling (1994) and introduce supply chain design parameters that reflect network flexibility and coordination to investigate the supply chain structure's role in equitable donations allocations. As a result of our formulation, we construct nine different supply chain structures. We first present the mathematical model and then discuss the supply chain structures induced by our formulation.

3.5.1. Model formulation

$$\text{Min} : z = w_1(a^+ + a_-) + w_2 \sum_{i \in I} u_i \tag{7}$$

$$\text{s.t} : \sum_{j \in J} v_{ij} x_{ij} + \sum_{k \in I/i} c_{ik} b_{ik} - \sum_{k \in I/i} c_{ki} b_{ki} = \tilde{y}_i - u_i \quad \forall i \in I \tag{8}$$

$$\sum_{i \in I} v_{ij} x_{ij} (16/19) = m_j P_j \quad \forall j \in J \tag{9}$$

$$(16/19) D_j / P_j + m_j - o_j^+ + o_j^- = T \quad \forall j \in J \tag{10}$$

$$b_{ki} \le M r_{ki} \quad \forall i, k \in I \tag{11}$$

$$b_{ik} \le M(1 - r_{ki}) \quad \forall i, k \in I \tag{12}$$

$$o_j^+ \le a^+ \quad \forall j \in J \tag{13}$$

$$o_j^- \le a_- \quad \forall j \in J \tag{14}$$

$$a^+, a_- \ge 0 \tag{15}$$

$$r_{ik} \in \{0, 1\} \quad \forall i, k \in I \tag{16}$$

$$o_j^+, o_j^-, p_j, m_j \ge 0 \quad \forall j \in J \tag{17}$$

$$u_i \ge 0 \quad \forall i \in I \tag{18}$$

$$x_{ij} \ge 0 \quad \forall i \in I, j \in J \tag{19}$$

$$b_{ik} \ge 0 \quad \forall i, k \in I \tag{20}$$

Table 3 describes the model sets, parameters, and decision variables. We define the total number of branch warehouses as N_B and the total number of demand points as N_D. Branch warehouses are locations where donations are received. Within the food bank problem context, demand points are agencies served by food banks, aggregated at the county level. The first component of the objective function, Eq. (7), minimizes the difference between the worst-case over-target meals per person in need (MPIN) and the worst-case under-target MPIN. Since the worst-case under-target is a negative deviation quantity, the difference between the worst-case over-target and worst-case under-target is additive. MPIN is a measure Feeding America food banks use to track the efficacy of their distribution activities. The second objective represents the undistributed supply. Constraints (8) ensure a particular branch does not allocate more than its available in-kind donations. Constraints (9) calculate the meals per person in need based on the amount of food distributed to each demand point. The factor (16/19) is a standard measure to convert pounds to meals. Constraints (10) determine the number of meals distributed over the entire planning horizon, with the first component representing the food distributed before the current period. The amount over and under a specified target (T) is also determined. Constraints (11–12) ensure that a branch is either a receiver of food or a supplier of food from another branch, but not both. Constraints (13) determine the worst case over the target MPIN quantity. Constraints (14) determine the worst-case under-target MPIN quantity. Constraints (15–20) define the bounds of the decision variables. We model the problem using AMPL and solve it with the CPLEX solver.

3.5.2. Supply chain structure

Supply chain coordination is defined by the level of product sharing among the branch warehouses. A fully coordinated network implies that branches share donated products among the warehouses as the need arises, whereas no branch sharing implies there is no coordination. Supply chain flexibility defines the structure by which county-level partner agency demand can be met. A fully flexible network can serve counties (i.e. meet the demand of partner agencies) from any branch warehouse, whereas a low or limited-flexibility network implies that branch warehouses only serve a distinct set of counties. Three levels representing supply chain flexibility and three levels representing supply chain coordination are considered to investigate the effects of a supply chain structure on equitable allocation estimates. We define supply chain flexibility by $S_F(z_B, z_D) \rightarrow V$ where z_B represents the number of demand points each branch can allocate in-kind donations to, z_D is the distance limit restricting demand points each branch can allocate in-kind donations to, and $V = (v_{ij})$ is an $N_B x N_D$ covering matrix where each element (v_{ij}) satisfies the following:

Condition 1. $\sum_{j\in J} v_{ij} = z_B$

Condition 2. $\delta_{ij} v_{ij} <= z_D$.

Recall that the parameter v_{ij} in the LP model defines the allocation from branches to demand points. Fig. 5 illustrates the three levels of supply chain flexibility for a network consisting of five branch warehouses and five demand points. Under a low flexibility structure, $z_B = 1, z_D = 100$, a branch can only distribute to 1 demand point and must be the closest demand point that does not exceed the distance limit of 100 miles. This implies for each branch i, there exists a unique j' where $\delta_{ij'} \leq z_D$ such that $v_{ij} = 1$ for j' and 0 for $j \neq j'$. High flexibility implies any branch can serve any demand point. Therefore $z_B = N_B$ and $z_D = \infty$. Partial Flexibility is between the two extremes since any branch can allocate in-kind donations to a demand point within their city and other cities 100 miles or less apart. In this case, $\sum_{j\in J} v_{ij} \leq z_B = N_B$ and $z_D = 100$.

Supply chain coordination represents the level of coordination between branches. It is denoted by a mapping function $S_C(n_B) \rightarrow T$ where n_B represents the number of branches that can share their available in-kind donations with other branches and $C = (c_{ik})$ is an $N_B x N_B$ matrix where each element c_{ik} satisfies the conditions below. B_{i0} represents a subset of branches for which transfers are not possible for branch i:

Condition 1. $\sum_{k\in I} c_{ik} = n_B$

Condition 2. $c_{i_k} = 0 \; \forall k \in B_{i0}$

Fig. 6 illustrates the three levels of supply chain coordination among branches within the network. $S_C(0)$ is the lowest level of coordination since branches do not share in-kind donations. A fully coordinated system is defined by $S_C(n_B - 1)$, reflecting that in-kind donations can be transferred among all branches in the network. $S_C(0, n_B - 1)$ represents partial coordination since the hub branch (Raleigh) can send donations to the other branches, but the other branches can not send products to other locations. Formally, $B_{i0} = \emptyset$ for the hub and $B_{i0} = I \backslash i$ for all branches not equal to the hub.

4. Results

We first present the results from the forecasting model and use the experimental results to answer our first research question. We then discuss the optimization model results and interpretation of the solution results with respect to research questions 2 and 3.

4.1. Results from data preparation

Table 4 summarizes the results of the K-means clustering algorithm, which is used to build our bottom-level data sets (refer to Fig. 3). A total of 60 time series datasets are created. For example, Durham, Sandhills, and Wilmington locations have three donor frequency groups for each storage type. As mentioned in Section 3.1, creating these groupings can result in discontinuity in the data by time period. That is, consecutive months of non-zero donations may no longer exist. Table 5 summarizes the time series datasets with missing values. We replace these with zero, as indicated in our data preparation/pre-processing approach.

We also note that for two branch warehouses, our data does not begin in July 2008 for the following reasons. First, the Durham branch obtained a new warehouse, significantly increasing its capacity to receive and store food. Additionally, the New Bern branch was opened in 2010. These observations can be seen in Fig. 1. As a result, the number of data points in the bottom-level series for the Durham and New Bern Branches is smaller than the other branches.

Table 5 also provides some insight into the type of foods most frequently received every month. For example, there were no observations in the Raleigh Branch for any food types; thus, they are not listed in the table. Also note the absence of Dry goods from the Durham Branch, indicating the consistent receipt of monthly items of this particular type. We observe higher frequencies for

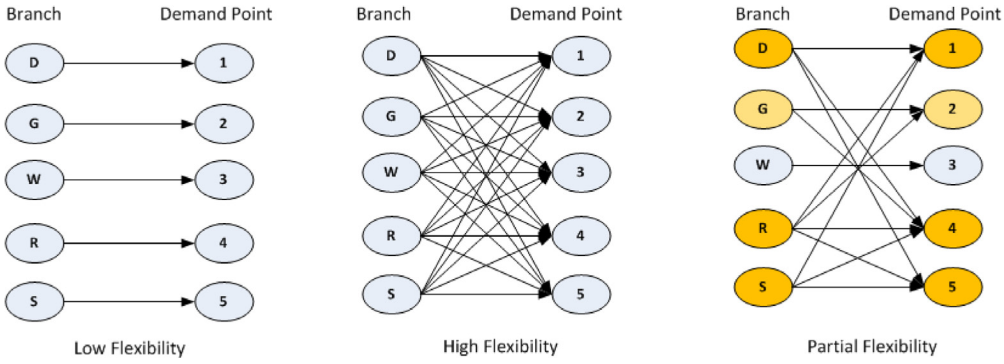


Fig. 5. Levels of supply chain flexibility.

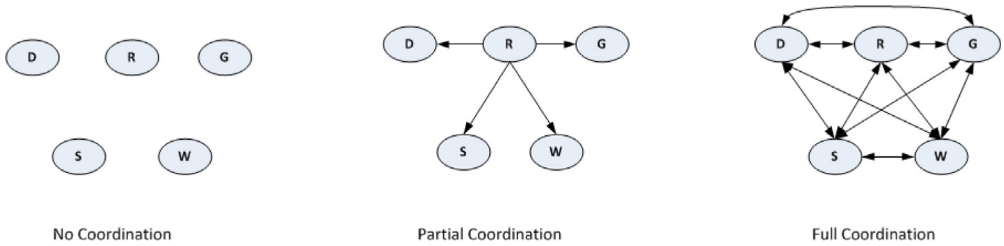


Fig. 6. Levels of supply chain coordination: $S_C(0)$, $S_C(0, n_B - 1)$, $S_C(n_B - 1)$.

Table 4
Total number of donor frequency clusters by branch and storage type.

Branch	Dry	Frozen	REF	Total
Raleigh	4	4	4	12
Durham	3	3	3	9
Sandhills	3	3	3	9
Greenville	3	3	4	10
New Bern	3	4	4	11
Wilmington	3	3	3	9
Total				60

New Bern and Wilmington, which could indicate a greater dependence on dry goods.

Lastly, by subsetting our time series into these groups, we aim to reduce the variability in the dataset and thus produce more accurate forecasts. Davis et al. (2016) notes a strong linear correlation between forecast accuracy (MAPE) and coefficient of variation. Table 10 in the Appendix summarizes the outliers removed for each branch/storage type/donor giving frequency combination and Fig. 7 illustrates the impact on the coefficient of variation for the Durham branch.

4.2. Results from forecasting model selection

The results from the time series cross-validation are presented in Table 6 for each branch. We note that the MAPE for the best model is less than 20% for every branch except Sandhills. We also evaluate the performance relative to the MAPE obtained when forecasts are not generated using a hierarchical approach. For Raleigh, Greenville, Durham, and New Bern, the MAPE under a non-hierarchical approach is 11.8%, 24.4%, 26.9%, and 15%, respectively. When compared against the best hierarchical model (shown in Table 6 with a superscript a), we obtain a percentage improvement in forecast accuracy of 4.3%, 26.5%, 48.2%, and 25.3% for Raleigh, Greenville, Durham, and New Bern branches. We also note that the ensemble model (COMP) performs best in 2 of the six cases.

Based on the time series cross-validation results, we apply the best models (along with the ensemble) to our hold-out set, which consists of fiscal year 2017–2018. We perform one-step ahead forecasts under a rolling horizon framework, the results of which are summarized in Table 7. Two of the six branches have forecast errors of less than 10% (Raleigh, New Bern). One of the branches has forecast errors above 20%. However, no branch MAPE is higher than 25% (for the best model). We note that through our experimentation, Sandhills branch time series data was consistently harder to forecast than the other branches, as evidenced by the accuracy measures.

Our results suggest that the hierarchical forecast model approach is the best way to estimate the amount of in-kind donations in a multi-warehouse food aid network (Research Question 1). Our results show that hierarchical forecast models based on donor type, food type, and location perform better than forecasts from a non-hierarchical approach, where forecasts are aggregated to the location level. The choice of which forecast model to choose is not as definitive. We suggest a model pool consisting of the forecast models considered in our study (ETS, ARIMA, MA, STL) and an ensemble model consisting of the best forecast model from each group.

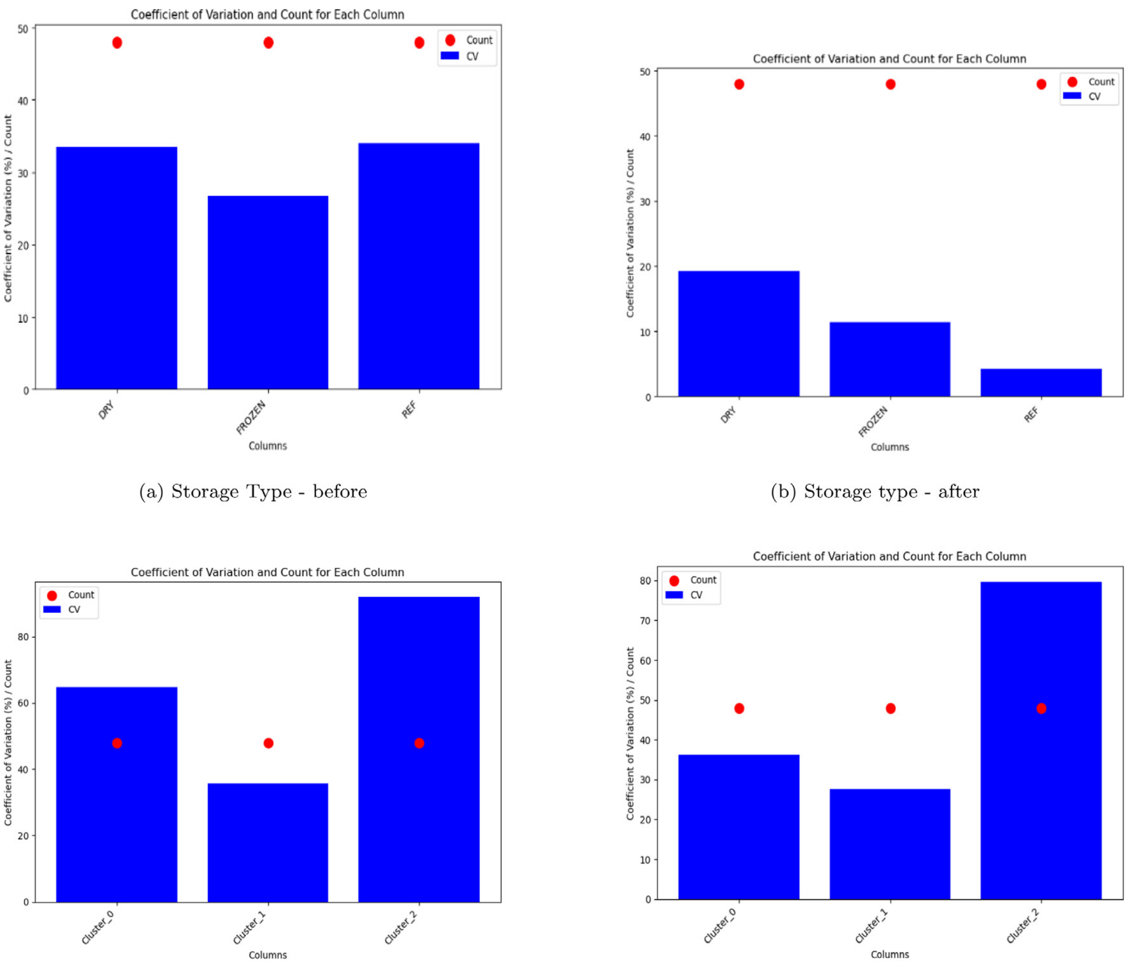
4.3. Optimization model results

We now describe the results obtained when determining equitable distribution with predictions of donated

Table 5
Frequency of missing values per branch and storage type, where the total number of data points in the series is 120 unless noted.

Branch	Storage type	Cluster 0	Cluster 1	Cluster 2	Cluster 3
Durham[a]	Frozen	0	0.1458	0	N/A
	REF	0	0	0.0208	N/A
Sandhills	Dry	0.0167	0	0	N/A
	Frozen	0.3583	0	0.0417	N/A
	REF	0	0.0833	0	N/A
Greenville[a]	Frozen	0.0083	0	0	N/A
	REF	0.0083	0.1000	0.1500	N/A
New Bern[b]	Dry	0	0.1818	0	N/A
	Frozen	0.4697	0	0	0.0606
	REF	0.01515	0.3485	0.2576	0.01515
Wilmington	Dry	0	0.0083	0.0333	N/A
	Frozen	0.175	0	0.1167	N/A
	REF	0.175	0	0.075	N/A

[a] Total number of data points in series is 48.
[b] Total number of data points in series is 66.



(a) Storage Type - before
(b) Storage type - after
(c) Donor group - before
(d) Donor group - after

Fig. 7. Graph of coefficient of variation for storage type and donor group, before and after outlier removal for the Durham Branch.

Table 6
Results from model training, ETS1 = ETS(A, N, N), ETS2 = ETS(A, M, N), ETS5 = ETS(M, N, N).

Branch	Model	MAPE	MAE (10^3)	RMSE (10^3)
Raleigh	ETS1	12.41	260.60	343.48
	ARIMA	12.99	270.16	360.55
	MA	12.50	278.84	350.32
	STL	13.32	283.67	360.72
	COMP[a]	11.29	246.68	312.22
Durham	ETS5	15.07	86.20	109.20
	ARIMA	15.17	83.40	101.74
	MA	16.52	90.19	109.60
	STL	16.99	92.85	115.45
	COMP[a]	13.94	73.87	81.26
Sandhills	ETS1	25.43	68.65	111.54
	ARIMA[a]	24.76	67.44	110.98
	MA	25.54	68.53	109.88
	STL	26.19	72.61	114.31
	COMP	30.41	76.73	113.69
Greenville	ETS2[a]	17.58	88.85	115.45
	ARIMA	18.78	99.61	128.36
	MA	18.17	100.99	137.33
	STL	17.94	96.35	126.70
	COMP	22.40	113.89	140.19
New Bern	ETS3	13.25	42.91	62.36
	ARIMA	13.96	44.51	61.91
	MA	23.51	72.23	87.02
	STL[a]	11.20	49.31	78.03
	COMP	15.61	50.22	70.97
Wilmington	ETS1	15.11	58.71	84.85
	ARIMA[a]	14.64	56.99	81.25
	MA	16.06	64.65	92.79
	STL	15.24	58.61	82.89
	COMP	14.98	58.96	83.97

[a] Best model based on minimum MAPE.

Table 7
Error statistics for branch forecasts on the validation data set using rolling horizon approach.

Branch	Model	MAPE	MAE (10^3)	RMSE (10^3)
Raleigh	ARIMA	7.35	225.56	297.45
	STL	7.30	225.50	290.13
	COMP[a]	7.01	213.8	284.67
Durham	ETS5	20.74	103.58	139.28
	STL	19.50	98.36	133.55
	COMP[a]	22.71	117.82	157.81
Sandhills	ETS1	25.32	52.09	70.60
	ARIMA[a]	24.43	52.82	72.58
	COMP	30.09	64.58	85.85
Greenville	ETS2	11.35	41.17	47.32
	STL[a]	12.61	45.55	54.41
	COMP	14.22	53.87	79.83
New Bern	ETS1	7.30	22.59	28.82
	STL[a]	8.57	24.98	28.64
	COMP	6.68	20.10	24.20
Wilmington	ETS1	10.99	57.15	76.20
	ARIMA[a]	10.45	53.22	66.93
	COMP	10.37	50.62	57.50

[a] Best model from training.

supply. We first describe how the data is prepared and then present the results.

4.4. Data preparation

Using the structure of FBCENC as our foundation, we construct a supply chain network consisting of the six branch warehouses depicted in Fig. 1. The available supply ($\tilde{y}_i$) at each branch is based on the predicted supply from the forecast model. We specifically use the forecast generated for July 2017. Demand points are represented by the 34 counties served by FBCENC (listed in Tables 11 and 12 in the Appendix). We utilize data from FBCENC fair share report and distribution history to determine the poverty population (P_j) and prior distribution quantity of food into each county over an eleven month time period (D_j). With this information, the target MPIN for each county over a rolling 12-month time frame is evaluated by multiplying the county fair share percentage by the total predicted distribution ($\sum_{j\in J} D_j + \sum_{i\in I} \tilde{y}_i$). This study yields a target MPIN value of $T = 95.52$. Fig. 6 define the supply chain coordination parameters. For the three supply chain flexibility parameters (see Fig. 5), we make the following assumptions:

Low Flexibility Each county is served by only one branch. This assignment is based on the primary branch structure of FBCENC.

Partial Flexibility We assume that some counties can be served by multiple branches. In particular, the number of counties served by the branches increases from (6, 13, 4, 5, 5, 6) to (8, 23, 14, 6, 8, 9), where the ordering in the vector corresponds to branches (D, R, G, S, W, N). We use historical distribution data into the counties to generate the assignments.

Full Flexibility Each county can be served by any branch.

The flexibility and coordination matrices are displayed in Appendix (Tables 11-15).

For the optimization model, we primarily want to understand the following: (i) Using the branch forecast, what can be stated about predicted distribution activity in the forecast month? (ii) How does the predicted distribution change as the objective function weights are changed? and (iii) How does the predicted value change as a function of supply chain coordination and flexibility? We answer these questions by examining the unweighted objective function values. In particular, the difference between the worst case over target quantity and the worst case under target quantity and the total amount of undistributed supply. In addition, we also calculate the total number of counties that have non-zero food distribution values ($m_j > 0$), the total over-target ($\sum_{j\in J} o_j^+$) and under-target ($\sum_{j\in J} o_j^-$) MPIN quantities across all counties.

4.4.1. Predicted distribution

Fig. 8 shows the unweighted equity difference corresponding to the optimal solution and specifically provides insight with respect to research question 3 (impact of supply chain structure on equity). First, the most constrained system (Low flexibility (LF) and no coordination (NC)) provides the highest level of inequity in the system. In contrast, the fully flexible and coordinated system provides a more equitable distribution solution. This is intuitive behavior. However, it should be noted that full flexibility can provide a more equitable distribution of

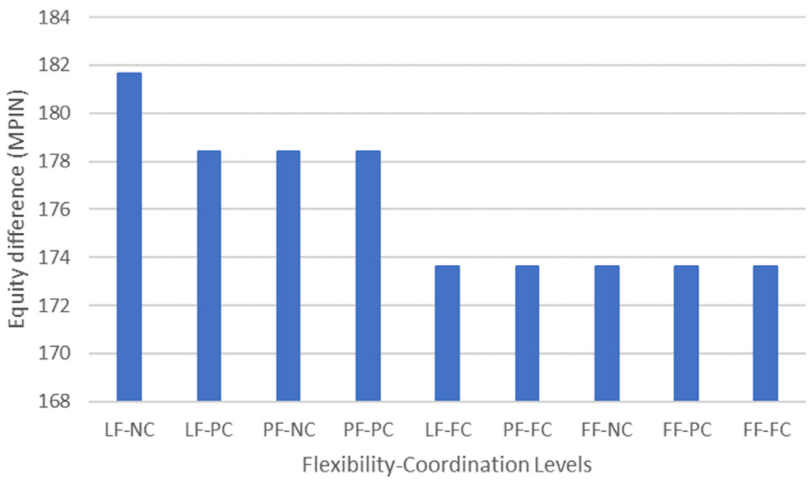


Fig. 8. Equity difference across all values of supply chain coordination and flexibility when $w_1 = w_2 = 0.5$.

Table 8
Optimization model results.

SC structure	Counties served	Total over-served (MPIN)	Total under-served (MPIN)
LF–NC	11	922.978	200.173
LF–PC	10	908.42	192.551
PF–PC	9	837.072	192.551
PF–NC	10	837.825	161.27
FF–NC[a]	7	730.75	161.27

[a] Values the same for PF–FC, FF–FC, FF–PC, LF–FC.

resources in the absence of coordination. Similarly, full coordination achieves more equitable results when there is low flexibility.

Table 8 also provides additional insight into the model behavior and is ordered by decreasing value of over-served MPIN quantities. It can be seen that more counties can be served in a less flexible or coordinated system. However, this comes at the expense of distributing more food to counties already meeting the target. Over-serving counties result from a more restrictive supply chain structure coupled with the desire to minimize waste (i.e., undistributed supply). Lastly, Fig. 9 shows that more food is primarily allocated to the counties with the highest need (i.e., the largest deviation from the target). Fig. 9 is ordered by lowest to highest MPIN based on the 11-month distribution history. So, this graph easily provides a visual of counties already under and over the target MPIN before including the supply prediction. The model prioritizes allocating donated supplies to the counties with the highest need when not restricted by the supply chain structure. The few exceptions result from the supply chain structure and the objective to have no undistributed supply. Overall, the results illustrate how predictions of in-kind donations can be used to identify geographic areas that may be over-served or under-served (research question 2) and how supply can be allocated to achieve more equitable distribution.

4.4.2. Prediction intervals

For each location specific forecast, we generate a prediction interval. Prediction intervals provide an upper and lower bound on the point forecasts within a specified probability (Hyndman & Athanasopoulos, 2023). The reader is referred to the Appendix for a more formal discussion of this calculation. We solve the optimization model to obtain the objective function value and calculate the equity differences for each case using the upper and lower bounds of the prediction intervals. This allows us to translate our point estimate of inequity (in Fig. 8) to a corresponding prediction interval estimate as seen in Fig. 10. Fig. 10 shows similar results in terms of the value of coordination and flexibility. Furthermore, as more supply becomes available, better supply allocation decisions are made, and these results improve with increasing levels of coordination.

4.4.3. Effect of weights

Fig. 11 shows the results when the weights for the objective function change. We show the results for two supply chain structures: full flexibility, full coordination, and low flexibility, full coordination. While our model contains multiple objectives, these objectives are not conflicting. In essence, as long as there is a non-zero weight for the first objective, the model will allocate all of the supply possible within the network, even if it means that some counties will be overserved. This indicates what

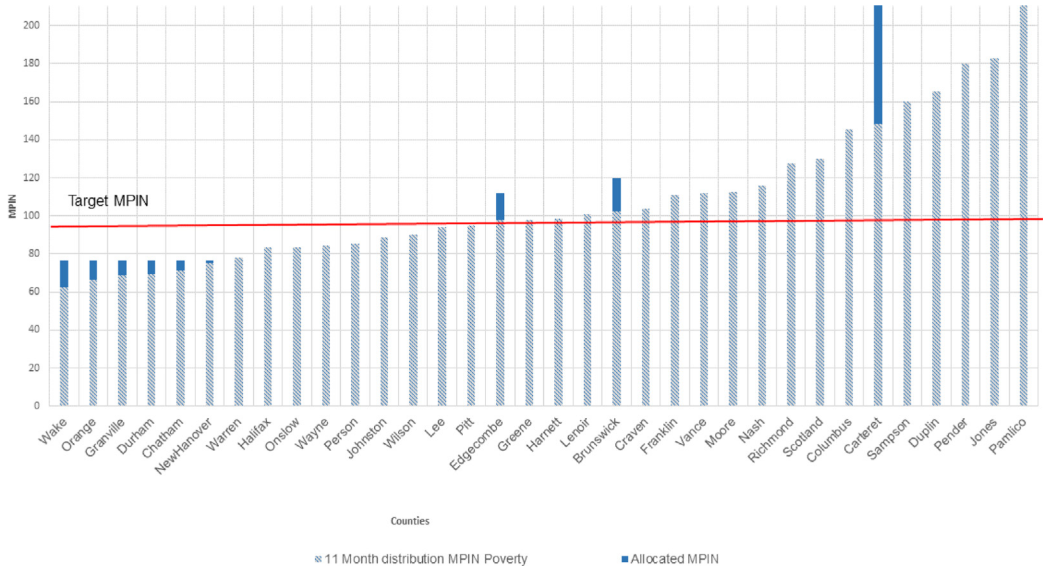


Fig. 9. MPIN allocations by county for PF-PC supply chain structure, $w_1 = w_2 = 0.5$.

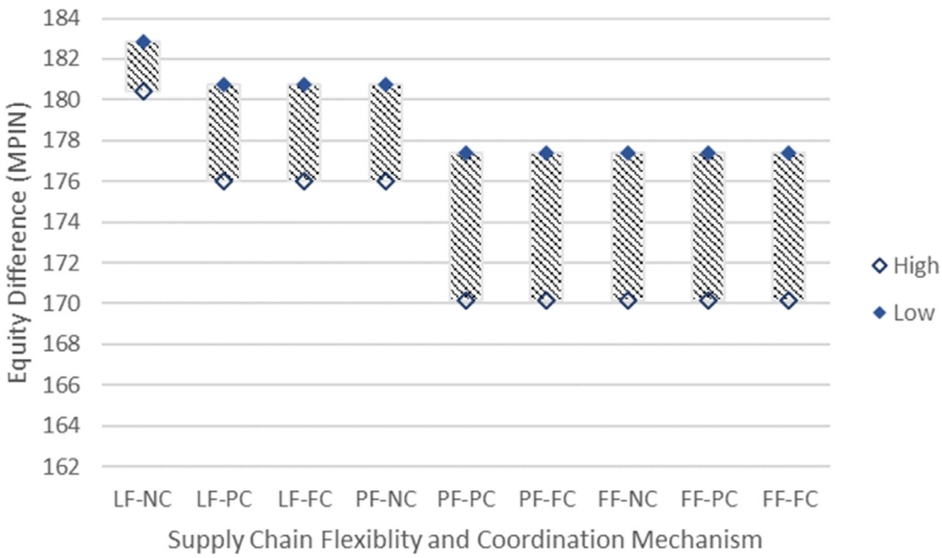


Fig. 10. Prediction Interval for Equity differences when $w_1 = w_2 = 0.5$.

happens in practice, as discarding donated or rescued food is undesirable.

5. Conclusion

This research presented an approach to predict in-kind food donations and inform optimal allocation decisions of donated supplies in a food aid network. The specific structure of the network is characterized by multiple warehouses, where each warehouse receives donated food and shares donated supplies. We briefly summarize our key findings, implications for practice, limitations, and future work.

5.1. Key findings

Our results show that the hierarchical forecasting model generally performs better than the non-hierarchical approach. The improvement in forecast accuracy averaged over the four improved branch forecasts was 26%. We also note that the highest error associated with the best models was no more than 25% in both our test and

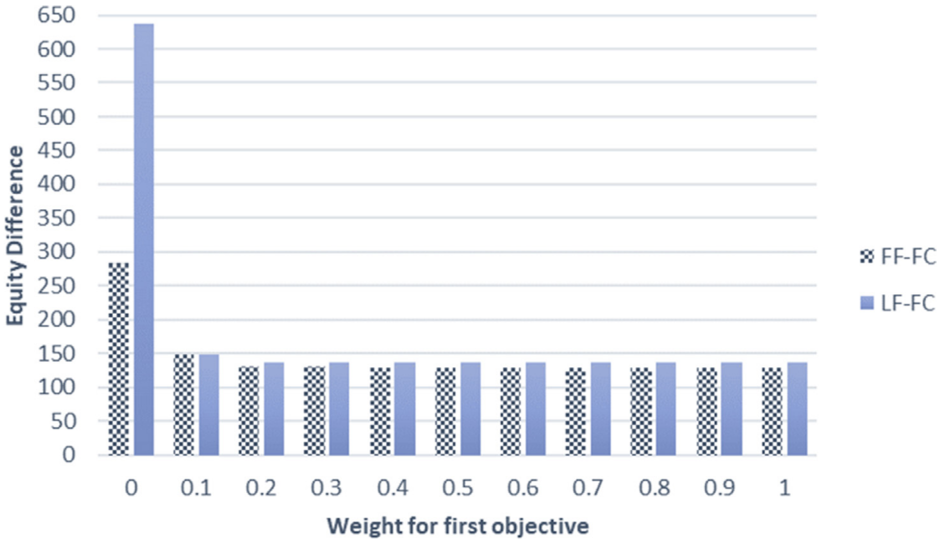


Fig. 11. Equity difference under different values for w_1.

validation data sets. While it is difficult to compare across studies, we note that similar food donation studies produced forecast errors over 50% and, in some cases, over 100% (Pérez-Rodríguez & Holguín-Veras, 2016). Also, using the location-specific forecasts, we determine how supply should be allocated within the network to best meet the county-level demand. Our approach determines which counties will be over-served or under-served and how supply should be distributed within the network to minimize the worst-case deviation from equity. We measure equity deviation by minimizing the maximum gap between the over-served and under-served MPIN quantities. In general, more supply is allocated to the most under-served counties. We also show how the level of flexibility and coordination within the distribution network can hinder or enhance the ability to allocate the food equitably. This has important implications for food aid distribution as food banks enhance their infrastructure to meet the growing need for food.

5.2. Practical implications

The operational efficiency associated with food distribution activities may be improved if effective methods for predicting donations are used. The predicted donation quantities can help drive decision-making for equitable distribution (at the aggregate and product-specific level), and supplement donated food with more healthy and nutritious food purchased using monetary donations.

While the data in our study is very specific, we have introduced a hierarchical approach that utilizes $k-$means clustering to group data into disaggregate sets for better forecasting performance. This approach can be generalizable to other organizations with similar data structures (donors giving sporadically and classifying food by how it is stored).

5.3. Limitations and future work

One limitation of our work is that we do not consider all sources of supply. In particular, we do not consider commodities received through the federal government emergency food assistance program (TEFAP). Therefore, our supply estimate used to determine equitable distribution only considers donations from non-governmental sources. Further investigation of this process into the estimate of in-kind donations is an interesting area of future research. It provides a more accurate depiction of under-served and over-served counties within a network. Also, we do not account for any disaster events in this study. In particular, North Carolina is prone to hurricanes. The time frame of our dataset does include Hurricane Matthew (2016). Simultaneously accounting for sudden-onset and slow-onset donations during forecasting is an interesting area of future work.

There are several ways that this work can be expanded. First, we note that the cost of transporting items is not directly included in the optimization model. We infer transportation feasibility through the parameterized supply chain coordination and flexibility metrics. Examining cost, equity, and waste simultaneously is an interesting area. Second, we also note that the ability of a county to receive food is determined by a number of complex operational factors, such as the existence of enough agencies to receive the food and the corresponding capacity to receive the food. Agency capacity, supply uncertainty, and resource availability are other constraints that can be explored. Third, we only explored creating hierarchical data structures based on two features: storage type and donor-giving frequency. Other features of the donor behavior could be explored, such as waste frequency and

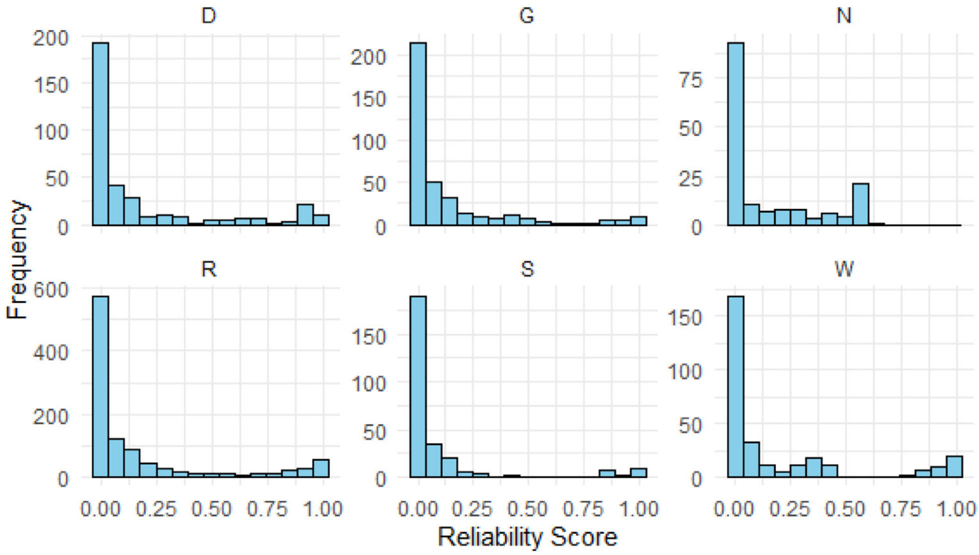


Fig. 12. Histogram of donor reliability for each branch over the time horizon of $T = 120$ months. G-Greenville, D-Durham, N-New Bern, R-Raleigh, S-Sandhills, W-Wilmington.

Table 9
Outlier range per branch.

Branch	Storage type	Outlier range
Wilmington	Dry, Frozen Ref	1.5 IQR 2.0 IQR
New Bern	Frozen, Ref Dry	1.0 IQR 1.5 IQR
Durham	Dry, Frozen, Ref	1.0 IQR
Greenville	Dry, Frozen, Ref	1.5 IQR

service score (Paul & Davis, 2021). Lastly, other forecasting techniques could be considered to improve forecast accuracy.

CRediT authorship contribution statement

Nowshin Sharmile: Methodology, Software, Writing – review & editing, Conceptualization. **Isaac A. Nuamah:** Conceptualization, Methodology, Writing – original draft. **Lauren Davis:** Conceptualization, Formal analysis, Methodology, Supervision, Writing – original draft, Writing – review & editing. **Funda Samanlioglu:** Conceptualization, Methodology, Validation, Writing – review & editing. **Steven Jiang:** Conceptualization, Validation, Writing – review & editing. **Carter Crain:** Data curation, Validation.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Lauren Davis reports financial support was provided by National Science Foundation.

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Appendix

A.1. Data preparation results

Fig. 12 shows the frequency distribution for the reliability score for the donors in each branch. A score closer to 1 indicates the donor provides in-kind donations every month.

A.2. Removing outliers

In many cases, donations from irregular entities caused a spike in donation data for a particular month. Incorporating these data could affect future predictions; therefore, we identify, remove, and replace these outliers with the median value of the series. For each series, we calculate the interquartile range (IQR) and define outliers as data points that are more than 2 IQRs from the central 50% of the data, except for those noted in Table 9. The plots showed that the Sandhills branch had very high peaks and troughs in the dataset. We decided to take a different approach. Any value smaller than (Q1-0.8*IQR) or greater than (Q3+0.8*IQR) was identified as outliers. Values smaller than (Q1-0.8*IQR) were replaced with Q1, and values greater than (Q3+0.8*IQR) were replaced with the 80th Quantile value to make the values relatively high.

Table 10
Count of outliers removed per cluster.

Branch	Storage type	Cluster 0	Cluster 1	Cluster 2	Cluster 3
Raleigh	Dry	2	1	1	1
	Frozen	6	0	2	0
	REF	2	0	0	6
Wilmington	Dry	17	8	4	NA
	Frozen	17	5	0	NA
	REF	8	1	0	NA
New Bern	Dry	0	8	3	NA
	Frozen	12	5	3	1
	REF	1	9	0	0
Durham	Dry	2	2	1	NA
	Frozen	6	6	3	NA
	REF	3	2	6	NA
Greenville	Dry	3	8	1	NA
	Frozen	11	7	1	NA
	REF	0	8	1	11
Sandhills	Dry	4	1	12	NA
	Frozen	19	9	11	NA
	REF	6	20	2	NA

Table 10 summarizes the number of outliers detected for each branch/storage type/donor frequency cluster.

A.3. Determining prediction intervals

Prediction intervals were generated in Python based on the procedure outlined in Hyndman and Athanasopoulos (2023). This consisted of four steps.

Step 1. Calculate the standard deviation of each cluster. For the first step, the standard deviation was generated automatically from the Python code for each data point while generating predictions.

Step 2. Calculate the standard deviation for each storage type Composite standard deviations were calculated when adding them up for each storage type, which is the sum of squares of each standard deviation of each forecast data point. We illustrate this below for the dry storage type.

$$\sigma_{DRY} = \sqrt{\sigma^2_{cluster0} + \sigma^2_{cluster1} + \sigma^2_{cluster2} + \sigma^2_{cluster3}} \tag{21}$$

Step 3. Calculate the standard deviation for the branch We follow the same procedure outlined in the previous step to obtain the total standard deviation for a specific branch, except we use the squared standard deviation of each storage type.

$$\sigma_{Total} = \sqrt{\sigma^2_{DRY} + \sigma^2_{FROZEN} + \sigma^2_{REF}} \tag{22}$$

Step 4. Calculate the Prediction Interval. A 95% prediction interval for a forecast for branch k at time t is calculated according to the following equation (assuming that the distribution of future observations is normal).

$$PredictionInterval = \tilde{y}_t^k \pm 1.96 * \sigma_{Total} \tag{23}$$

A.4. Experimental data

(see Tables 13–15).

Table 11
Low flexibility.

	D	R	G	S	W
BRUNSWICK	0	0	0	0	1
CARTERET	0	0	1	0	0
CHATHAM	1	0	0	0	0
COLUMBUS	0	0	0	0	1
CRAVEN	0	0	1	0	0
DUPLIN	0	1	0	0	0
DURHAM	1	0	0	0	0
EDGECOMBE	0	0	0	1	0
FRANKLIN	0	1	0	0	0
GRANVILLE	1	0	0	0	0
GREENE	0	0	1	0	0
HALIFAX	0	1	0	0	0
HARNETT	0	1	0	0	0
JOHNSTON	0	1	0	0	0
JONES	0	0	0	1	0
LEE	0	0	0	1	0
LENOIR	0	0	1	0	0
MOORE	0	0	0	1	0
NASH	0	1	0	0	0
NEWHANOVER	0	0	0	0	1
ONSLOW	0	0	0	1	0
ORANGE	1	0	0	0	0
PAMLICO	0	0	1	0	0
PENDER	0	0	0	0	1
PERSON	1	0	0	0	0
PITT	0	0	1	0	0
RICHMOND	0	0	0	1	0
SAMPSON	0	1	0	0	0
SCOTLAND	0	0	0	1	0
VANCE	1	0	0	0	0
WAKE	0	1	0	0	0
WARREN	0	1	0	0	0
WAYNE	0	1	0	0	0
WILSON	0	0	0	1	0
Total	6	10	6	8	4

A.5. Impact of disaster data

Hurricane Matthew, spanning from September 28 to October 9, 2016, left a devastating path of destruction

Table 12
Partial flexibility.

	D	R	G	S	W
BRUNSWICK	0	0	0	0	1
CARTERET	0	0	1	0	0
CHATHAM	1	1	0	0	0
COLUMBUS	0	0	0	0	1
CRAVEN	0	0	1	0	0
DUPLIN	0	1	0	0	0
DURHAM	1	1	0	1	0
EDGECOMBE	0	1	0	1	0
FRANKLIN	0	1	0	0	0
GRANVILLE	1	0	0	0	0
GREENE	0	0	1	0	0
HALIFAX	0	1	0	0	0
HARNETT	0	1	0	0	0
JOHNSTON	0	1	0	0	0
JONES	0	0	0	1	0
LEE	0	0	0	1	0
LENOIR	0	0	1	0	0
MOORE	0	0	0	1	0
NASH	0	1	0	0	0
NEWHANOVER	0	0	0	0	1
ONSLOW	0	0	1	1	0
ORANGE	1	0	0	0	0
PAMLICO	0	0	1	0	0
PENDER	0	0	0	0	1
PERSON	1	0	0	0	0
PITT	0	0	1	0	0
RICHMOND	0	0	0	1	0
SAMPSON	0	1	0	0	0
SCOTLAND	0	0	0	1	0
VANCE	1	1	0	0	0
WAKE	0	1	0	0	0
WARREN	0	1	0	0	0
WAYNE	0	1	0	0	0
WILSON	0	1	0	1	0
Total	6	15	7	9	4

Table 13
No coordination.

	D	R	G	S	W	N
D	1	0	0	0	0	0
R	0	1	0	0	0	0
G	0	0	1	0	0	0
S	0	0	0	1	0	0
W	0	0	0	0	1	0
N	0	0	0	0	0	1

Table 14
Partial coordination.

	D	R	G	S	W	N
D	1	0	0	0	0	0
R	1	1	1	1	1	1
G	0	0	1	0	0	0
S	0	0	0	1	0	0
W	0	0	0	0	1	0
N	0	0	0	0	0	1

across the Caribbean and southeastern United States, claiming over 1000 lives and causing billions of dollars in damages. Its fierce winds and torrential rains triggered widespread flooding, displacing thousands and leaving communities in ruins.

Foodbanks received donations from various donors during the last quarter of 2016 to help those in need. These donation items are coded as Disaster "DR". A total of 271 entries fell under this category. However, these are high-volume donations. To get better predictions, we removed those one-time donations from FY2016-17 from the donation data.

Table 15
Summary of disaster relief items by month.

Month	Count % of disaster data	Weight % of disaster data
Jul-16	0.0%	0.0%
Aug-16	0.0%	0.0%
Sep-16	0.0%	0.0%
Oct-16	4.5%	22.0%
Nov-16	1.7%	17.4%
Dec-16	0.4%	8.1%
Jan-17	0.0%	0.0%
Feb-17	0.0%	0.0%
Mar-17	0.0%	0.0%
Apr-17	0.0%	0.0%
May17	0.0%	0.0%
Jun-17	0.0%	0.0%

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