HYPERCONNECTED FRESH SUPPLY CHAINS: LOGISTICS & MARKET EXPANSION FRAMEWORKS

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HYPERCONNECTED FRESH SUPPLY CHAINS: LOGISTICS & MARKET EXPANSION FRAMEWORKS

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To my late undergraduate research advisor, Dr. Andrew Friedman, who built me into the researcher I am today.

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SUMMARY

In this dissertation we take a trans-disciplinary approach, notably using Operations Research, Geographic Information Systems and Strategic Management to build hybrid frameworks. By using such techniques in unison, we aim to create robust frameworks that consider a wide range of factors.

This dissertation focuses on hyperconnected fresh supply chains, particularly focusing on local food supply chains with additional exploration into quick service restaurants and fresh cut flowers. Local food systems are becoming increasingly important as consumers are shifting towards traceability and sustainability of their food. Additionally, during COVID-19 we saw the negative effects of depending on a global food supply chain, as many countries limited imports and exports during the pandemic. We build market expansion and logistics frameworks to manage local food systems and strengthen their infrastructure.

In local food supply chains, though sustainability is considered, perishability is not typically a concern as the time from farm-to-fork usually spans 24-48 hours. However, outside of local systems, fresh supply chains must consider both perishability and sustainability. We propose a new framework that allows companies to assess their supply chains from a big picture perspective to find improvements to better their sustainability.

In Chapter 1, we provide background information on fresh supply chain systems and introduce each of the chapters. In Chapter 2, we propose a market deployment framework which outlines a company's dynamic expansion plan. We apply our framework to a case study of a platform which enables local food supply chains by connecting farmers directly to restaurants. In Chapter 3, we provide a Hybrid OR & GIS methodological framework to the Dynamic (Mobile) Hub Location Problem in the context of a small-scale local food supply chain network. In Chapter 4, we address the increasing corporate pressure to be environmentally sustainable through the creation of a framework which allows companies

to assess and improve the sustainability within their supply chain. we apply our framework to case studies concerning fresh cut flowers and quick service restaurants. Lastly, Chapter 5 summarizes our contributions to fresh supply chain frameworks and identifies potential areas for future research.

CHAPTER 1
INTRODUCTION AND BACKGROUND

1.1 Background

Fresh supply chains have been brought to light in the recent COVID-19 pandemic. Food was being dumped at the farm, but there were shortages in the grocery stores [1]. This was largely due to the fact that so much of the world relies on global food supply chains. Global food supply chains allow for consumers to have variety all year long as seasonal items can be produced in opposite hemispheres during off seasons. This is a major benefit of Global supply chains. However, food supply chains often must have temperature controlled transportation which is energy intensive and releases a large amount of CO_2 into the atmosphere [2]. In fact, food refrigeration accounts for 15% of global fossil fuel consumption and 40% of greenhouse gas effects [3]. There are also large amounts of food wasted, in fact 30-40% [4] is lost within the supply chain and 40% of those losses are occurring post-harvest [5].

One solution to this problem is the use of Local Supply Chains. Researchers argue whether the emissions are in fact less in Local Food supply chains rather than Global Supply Chains due to economies of scale [6]. However, there are clear benefits to local supply chains. For one, refrigeration is not needed, or greatly reduced as food generally travels from ground-to-fork within 24-48 hours [7]. This eliminates the fossil fuel consumption needed for refrigeration. Also, there is little to no waste as local supply chains are often on demand, such that a strawberry is not picked unless there is a customer already assigned to it. Additionally, local supply chains are better integrated into the communities in which they live, making diversion of any remaining goods easier. These goods can be diverted to food terminals, farmers markets and food banks relatively easily within a local system[8]. However, local supply chains often lack proper infrastructure and their logistics systems can be improved. In this dissertation, we build market expansion and logistics frameworks to manage local food systems and strengthen their infrastructure.

We also acknowledge that Global Supply Chains are not being eliminated anytime soon. They are still incredibly important and help increase the variety of diets worldwide. We also propose a new framework that allows companies to assess their national and global fresh supply chains from a big picture perspective to find improvements to better their sustainability.

1.2 Introduction

This thesis contributes novel frameworks that utilize transdisciplinary approaches to Fresh Supply Chain and Logistics Problems via Operations Research, GIS and Strategic Management. These fresh supply chain frameworks help build market deployment roadmaps, sustainable logistics strategies and assign hub location in local supply chains. Our study helps to provide solution approaches that are directly implementable in Industry.

In Chapter 2, we propose a market deployment framework which outlines a company's dynamic expansion plan. We build a complementary solution approach that is made up of Executive Factors, Market Ranking, Optimization and Heuristic Models with Dynamic Capabilities. This framework results in a series of alternative solution roadmaps that identify which markets should be deployed in each time phase over a given time horizon. We apply our framework to a case study of a farm-to-table platform which enables local food supply chains by connecting farmers directly to restaurants.

In Chapter 3, we provide a Hybrid OR & GIS methodological framework to the Dynamic (Mobile) Hub Location Problem in the context of a small-scale local food supply chain network. In our hybrid approach, we formulate our network as a p-hub median problem alongside the use of Kernel Density Analysis for hub placement in the network in the case of p = 1. We evaluate our hub effectiveness within a local food supply network through a comparison between historical distribution flows (without a mobile hub), expected stationary hub routes and expected mobile hub routes (both via TSP Heuristics utilizing real road distance).

In Chapter 4, we address the increasing corporate pressure to be environmentally sustainable. Fresh supply chains face special considerations with decay and loss of quality in perishable products that can occur in transit. We provide a framework that both suppliers and purchasers can utilize to improve the sustainability of their supply chain. We employ customer segmentation, decay & quality modeling, and life cycle assessment (LCA) to help companies rethink their logistics strategies to better align with environmentally sustainable practice. In this chapter, we apply our framework to case studies concerning fresh cut flowers and quick service restaurants.

Lastly, Chapter 5 summarizes our contributions to fresh supply chain frameworks and identifies potential areas for future research.

CHAPTER 2

STRATEGIC MARKET DEPLOYMENT PLANNING: FARM-TO-TABLE PLATFORMS

This chapter introduces a data-driven market deployment planning methodology towards applicability in the context of farm-to-table logistics platforms. Our framework contains a mix of qualitative and quantitative approaches, including semi-structured interviews, optimization, heuristics, dynamic planning, clustering, executive factors, and weighted linear combination, to create a market deployment process. Our methodology produces alternative roadmaps that can be directly used by companies to plan their expansion.

A portion of work presented in this chapter has been published in the *Proceedings of the Institute of Industrial and Systems Engineers Annual Conference* under the following reference:

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2.1 Introduction

In a technology driven era, start-ups have gained more momentum in the marketplace, particularly user based platforms. As startups develop, they need to plan growing their user base through expansion [9]. We propose a novel data-driven market deployment planning methodology for guiding budding start-up platforms to plan their expansion. Particularly, we examine farm-to-table logistics platforms whose expansion must consider both the downstream side of markets, such as urban agglomerations with restaurants, institutions, and households demanding fresh and local food, and their upstream side consisting of farms producing and selling fresh and local food.

Food supply chains have gained traction moving towards sustainability and transparency. Consumers are demanding more information from restaurants [10]. Where did the food come from? Are the products genetically modified? What is the carbon footprint of my food [10]? In turn, restaurants have increased responsibility for the raw supplies they purchase [11]. One way to shift supply chains towards sustainability is through smaller local supply chains. Local supply chains are generally known to be sustainable, notably helping to reduce emissions by eliminating long-distance transport and minimizing ”food miles” [7]. Local food supply chains also bring more money into rural communities, helping producers and disrupting the large scale supply chains controlled by giant food distributors [12].

We apply our planning process to the food supply chains within the restaurant sector. Our use case focuses on Farm’d, a start-up logistics platform, which connects farmers to chefs allowing for direct shipment of goods without middlemen. Through enabling the expansion of Farm’d, we create local fresh supply chains countrywide. These local supply chains reduce the cost of transporting food to restaurants, enabling a higher profit margin for both farmers and restaurants. By keeping distribution local, carbon footprints are reduced through less emissions and use of fewer resources. Combining these benefits, we help to create a more sustainable fresh supply chain.

In entirety, we used a mix of qualitative and quantitative approaches including semi-structured interviews, optimization, heuristics, dynamic planning, clustering, executive factors, and weighted linear combination to create a market deployment process. To our knowledge there are no current approaches for market selection that use all of these tools in combination and this kind of strategic market deployment has not been studied for farm-to-table platforms. We provide a framework that can be directly followed in industry and applied by companies for their own expansion.

2.2 Literature Review

2.2.1 Semi-Structured Interviews

Semi-Structured interviews are a common research technique to gather qualitative data. They have been used in both operations management and food studies and ”are well suited to generate in-depth insights” [13]. Semi-structured interviews consist of a series of interviews, generally in groups, focusing on open ended questions to gain information and insights through discussion. Hendry et al, gain insights on how local food supply chains prepare for and respond to threats and opportunities stemming from constitutional change, building resilience through semi-structured interviews [14]. Hill used semi-structured interviews to study the use of electronic data interchange for supply chain coordination in the food industry [15]. Teller et al. conducted semi-structured interviews with food waste experts to gain insight on the relationship between retail store operations and food waste [13]. We use semi-structured interviews to help determine Executive Factors.

2.2.2 Market Deployment

Once a company has established itself successfully in its first market, there comes a time when its leaders must decide how to grow it. Often, this is done through market selection and expansion. By selecting geo-markets carefully for stability and increased market potential, firms can increase their likelihood of success [16]. Following the outline in Fish and Ruby [17], international market selection is broken down into three processes: (1) market screening, (2) market identification, and (3) market selection [18, 19]. Market screening reduces the set of potential markets by eliminating candidates that do not fit certain criteria. Market identification pinpoints markets that best fit the company’s objectives. Market selection picks the final candidates to be used in expansion. Anderson used the approaches of market share estimation, market grouping and market ranking to assess different markets [19]. Using this combination of quantitative approaches can provide the decision makers with more comprehensive results to use in decision making processes [19].

2.2.3 Market Grouping/Clustering

Market grouping uses clustering to bunch markets for deployment. It has previously been used by Kimiagari in a hybrid modeling approach to market deployment planning for natural disaster relief [9]. Market grouping has also been used by Papadopoulos as a quantitative market approach for potential market assessment [20]. In the context of farm-to-table platforms, it makes sense to base groupings on ”megaregions,” as coined by the Regional Plan Association [21]. Megaregions are are clustered networks of American cities, which are currently estimated to contain a total population exceeding 237 million [21]. Megaregions share some or all of the following factors [21]:

1. Environmental systems and topography
2. Infrastructure systems
3. Economic linkages
4. Settlement and land use patterns
5. Culture and history

There are 11 megaregions identified by the Regional Plan Association including the Arizona Sun Corridor, Cascadia, Florida, Front Range, Great Lakes, Gulf Coast, Northeast, Northern California, Piedmont Atlantic, Southern California and Texas Triangle. These megaregions can be seen in Figure 2.1.

2.2.4 Executive Factors and Market Ranking

Executive factors are defined by Kimigiari as influencing factors that determine market demand [9]. They arise from statistical data and can be used for assessing market attractiveness. Other quantitative methods for market selection have also used executive factors

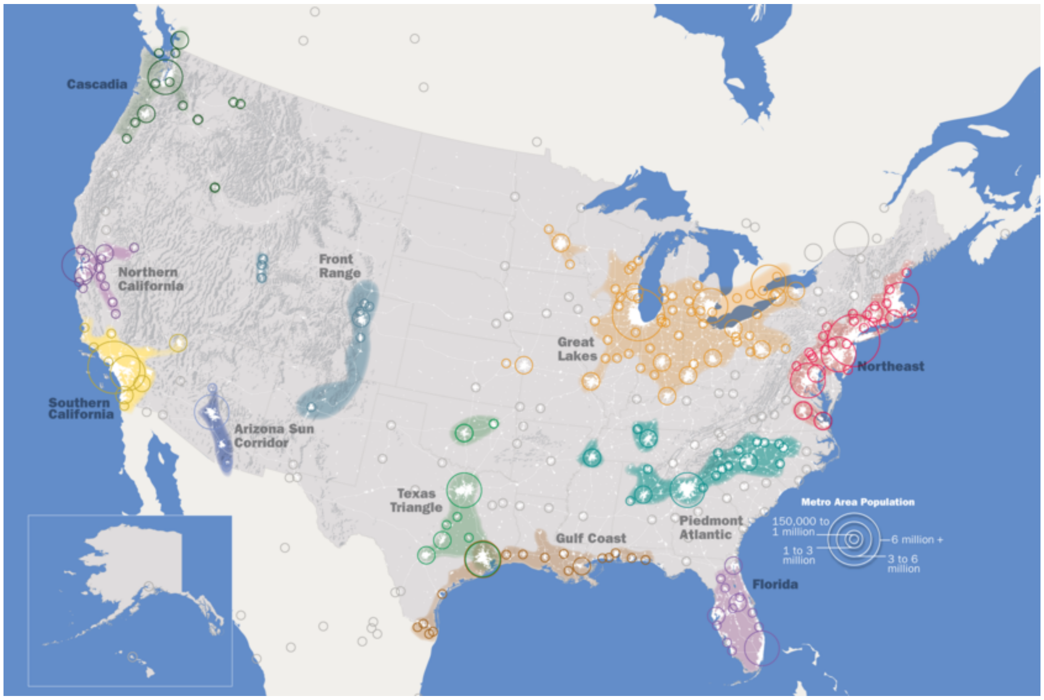

Figure 2.1: US Megaregions as defined by the Regional Plan Association
Source: Regional Plan Association

including Zschocke et al., Papadoupolous and Denis and Golsefid et al [22, 20, 23]. Papadopoulous used executive factors to help determine market rankings for optimal market expansion [20]. However, current literature does not provide details on the collection of Executive Factors, most seem to come from the author's individual research efforts rather than a systematic method. We propose an organized system to gather and assess Executive Factors through semi-structured interviews with experts as described in 2.2.1 and use weighted linear combination to ascertain the final rankings.

2.2.5 Weighted Linear Combination

Albino states the relevance for of the use of spatial aspects in supply chains, particularly at the local level due to an emphasis on the relationship between energy and environmental aspects with economic aspects [24]. Weighted Linear Combination (WLC) is a spatial technique [25]. It is a type of suitability analysis which is used for problems involving multi-attribute decision making (MADM). Every attribute is considered a criterion and carries a weight based upon importance, the results are multi-attribute spatial features with total scores [25]. WLC is commonly used for location intelligence, for example, Mahini and Gholamalifard use WLC to select landfill locations [26]. WLC use has also been expanded for selection of logistics hub locations in the Czech Republic by Ruda and in Iran by Shahparvari et al. [27, 28]. We explore using Executive Factors in combination with Weighted Linear Combination for Market Rankings.

2.2.6 Local Food Supply Chains

As consumers are demanding more information from restaurants [10]: Where did the food come from? Are the products genetically modified? What is the carbon footprint of my food [10]? In turn, restaurants have increased responsibility for the raw supplies they purchase [29]. One way to shift supply chains towards sustainability is through smaller local supply chains. Local supply chains are generally known to be sustainable, notably helping to reduce emissions by eliminating long-distance transport and minimizing ”food miles” [7, 12]. They also increase transparency as routes are shorter and it is easier to track product all the way from origin to destination. Local food supply chains also bring more money into rural communities, helping producers and disrupting the large scale supply chains controlled by giant food distributors [7]. They are known to give fairer prices to customers, a reduced environmental impact, and greater traceability [6]. They can also bring tourism which can bring economic benefits to the communities [30].

Recently there has also been a shift towards global food security concerns calling for improved traceability, and decreased food poverty [31]. Global supply chains also face risk from political, environmental and health disruptions [31]. Also, in the current case of COVID-19, infrastructure was broken down for large-scale food supply chains. It has become harder to source food globally due to health and safety restrictions. The World Economic Forum advised consumers for the “post-COVID need” to support “local food systems with shorter, fairer and cleaner supply chains that address local priorities.” [32].

2.2.7 Optimization and Heuristic Solution Methods

Optimization has been historically used to aid in market selection. Bhutta, Chang and Chen use linear programming, Ou and Kuo use fuzzy analysis, Zschocke uses game theory and Golsefid and Marchi use hybrid modeling [33, 34, 35, 36, 22, 23, 37]. The complexity and solution algorithms associated with optimization can be challenging, but if models are correctly formulated, optimization can be be a strong tool to aid in Market Selection. Heuristic methods, may not solve to optimality, but can capture some factors that can be difficult to build into an optimization model.

2.2.8 Dynamic Capabilities

Dynamic Capabilities enable the creation and implementation of effective business models [38]. Teece defines dynamic capabilities as a firm's ability to integrate, build and reconfigure internal competencies to address, or in some cases, bring about change in the business environment [39]. Over time, a market deployment plan must adapt as the business environment changes. Shane and Delmar stated that a key issue with previous market deployment models is that they do not consider planning across a time horizon [40]. We address this by building a dynamic model that accounts for continuous potential change in growth over time and fluctuating markets.

2.3 Case Study Context

The businesses providing the marketplace and logistics platforms enabling food supply chains between farms and restaurants, such as the Atlanta-based startup, Farm'd, whose case is outlined in this paper, have ambition to profitably enable direct local fresh supply chains in multiple markets. They have the goal of spreading to multiple markets across a specific time window.

Under stringent venture capital investment and cash flow constraints, such businesses have to smartly plan their deployment beyond their original startup market [9]. At this phase of their development, Farm'd did not have the in-house talent to plan their own expansion, as would other startups in this phase of infancy. This paper introduces a data-driven methodology, which takes in a desired time frame and list of goal markets and produces instructions, or "roadmaps" as coined by Kimiagari, for where to deploy in which time frame [9]. We call this methodology a market deployment process. Specifically, this process uses two distinct solution approaches to produce a series of alternative roadmaps consisting of sets of markets targeted for deployment at each phase of development of the business. Our process allows for Farm'd and other growing businesses to generate feasible market deployment roadmaps to meet their growth, profit and risk management goals.

The first step in creating the deployment model is to determine strategic intents of the company at hand. In this case, the goal of the startup was to expand to the 66 most populous metropolitan statistical areas (MSA's) of the U.S.A. over a 4-year planning horizon. An MSA has a central core of people with neighboring communities that are strongly integrated with the core [41]. For example, Atlanta-Sandy Springs-Roswell is an MSA where Atlanta is the central hub and Sandy Springs and Roswell are neighboring communities. In each year of the planning horizon, the startup is to deploy into a set of cities. Market penetration is defined as the percentage of the available market that a company has captured. In the first year, a deployed city will have low market penetration that will increase with time as the company acquires more customers.

The market deployment planning process produces multiple alternative roadmaps. A roadmap outlines the cities that will be deployed in each time period and are assumed to remain active in the time periods after deployment. Below, in Table 2.1, is a sample roadmap that includes 8 cities over 4 years. In Year 4, New York is planned to have a higher market penetration than Boston since its market will have been active for a longer period of time.

Table 2.1: Sample deployment roadmap

Year 1	Year 2	Year 3	Year 4
New York, Charlotte	Tuscon, Houston	Boston, Chicago	Kansas City, St. Louis

2.4 Methodology

We use a mix of qualitative and quantitative approaches to build our model. We start with semi-structured interviews to learn about what is important to successful markets which house F2T platforms. In this project, we combined qualitative approaches with data driven quantitative approaches to build a framework for each of these processes. For example, in market screening we use quantitative approaches in order to remain objective and to pre-process a large amount of potential markets.A summary of the methodology can be seen in the figure below:

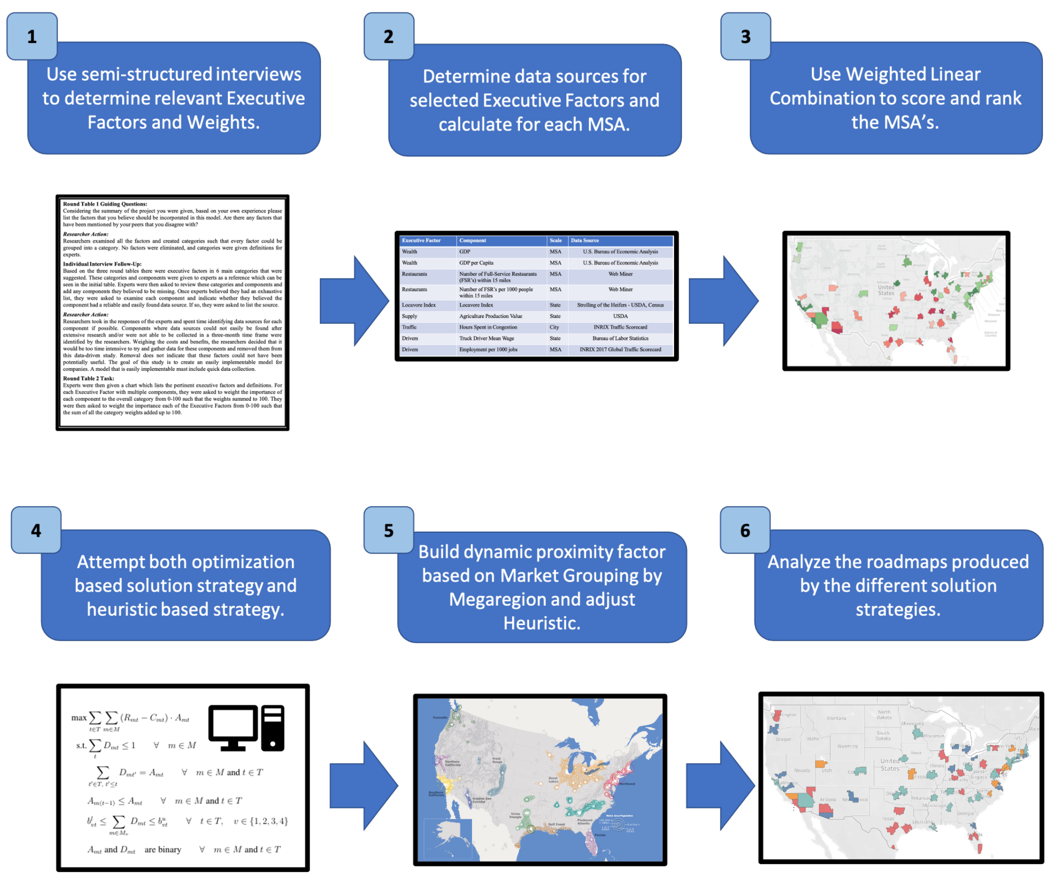

Figure 2.2: Outline of Methodology for production of market deployment roadmaps

2.4.1 Semi-Structured Interviews

In order to collect data to determine executive factors and their weights we conducted a series of semi-structured interviews with subject matter experts (SME's). There were 2 main stages of interviewing: the first stage included open ended discussions to gather data, the second stage was dedicated to refine the factor candidates and later assign appropriate factor weights. In the first stage, the interviewees were each invited to a round table discussion. The questions seen in Table 2.2 were used to start the discussion but we allowed for the interviewees to direct the flow of the conversation. There were 3 round table discussions in the first phase, and each round table brought up the same factors of influence, with minor deviations in details.

Since independent round tables often identify the same important factors, this can help validate and triangulate the data. After the round tables, individual interviews were scheduled for follow up. They were provided Table 2.3 to look at the summary of factors identified.

The semi-structured interviews ended with one final round table with as many representatives from each of the original three round tables as possible. These SME's were tasked with assigning weights to the executive factors that they had originally identified as can be seen in Table 2.4.

2.4.2 Weighted Linear Combination

Next we use Weighted Linear Combination or WLC. When facing a problem involving multi-attribute decision making, WLC can be used. Every attribute that is considered is called a criterion. Each criterion has an assigned weight based on its importance. This process results in multi-attribute spatial features with final scores [25]. We use a combination of the Executive Factors and weights found in the semi-structured interviews to score and rank the MSA's. An MSA with a rank of one is the most desirable MSA, and an MSA with a rank of 66 is the least desired MSA.

Round Table 1 Guiding Questions:
Considering the summary of the project you were given, based on your own experience please list the factors that you believe should be incorporated in this model. Are there any factors that have been mentioned by your peers that you disagree with?

Researcher Action:
Researchers examined all the factors and created categories such that every factor could be grouped into a category. No factors were eliminated, and categories were given definitions for experts.

Individual Interview Follow-Up:
Based on the three round tables there were executive factors in 6 main categories that were suggested. These categories and components were given to experts as a reference which can be seen in the initial table. Experts were then asked to review these categories and components and add any components they believed to be missing. Once experts believed they had an exhaustive list, they were asked to examine each component and indicate whether they believed the component had a reliable and easily found data source. If so, they were asked to list the source.

Researcher Action:
Researchers took in the responses of the experts and spent time identifying data sources for each component if possible. Components where data sources could not easily be found after extensive research and/or were not able to be collected in a three-month time frame were identified by the researchers. Weighing the costs and benefits, the researchers decided that it would be too time intensive to try and gather data for these components and removed them from this data-driven study. Removal does not indicate that these factors could not have been potentially useful. The goal of this study is to create an easily implementable model for companies. A model that is easily implementable must include quick data collection.

Round Table 2 Task:
Experts were then given a chart which lists the pertinent executive factors and definitions. For each Executive Factor with multiple components, they were asked to weight the importance of each component to the overall category from 0-100 such that the weights summed to 100. They were then asked to weight the importance each of the Executive Factors from 0-100 such that the sum of all the category weights added up to 100.

Table 2.2: Semi-Structured Interview Outline

In our application, we conduct WLC based on weights and Executive factors selected during the Semi-Structured Interviews. For each MSA calculate the score:

$$\text{score} = \sum_{i=1}^{n} E_i * w_i \qquad \text{s.t.} \qquad \sum_{i=1}^{n} w_i = 1 \tag{2.1}$$

E_i is the score of an MSA for the ith executive factor, n is the total number of Executive Factors. All values E_i are all normalized to hold a value between 0 and 100 and the sum of all weights w_i is equal to 1.

Table 2.3: Results from Round Table Discussions

Exec Factor 1	Exec Factor 2	Exec Factor 3
Definition of Executive Factor 1	Definition of Executive Factor 2	Definition of Executive Factor 3
Component 1.1	Component 2.1	Component 3.1
Component 1.2		Component 3.2

Table 2.4: Finalized Executive factors, components and data sources

Executive Factor	Component	Scale Examples	Data Source Examples
Exec Factor 1	Component 1.1	MSA	Census
Exec Factor 1	Component 1.2	State	USDA
Exec Factor 2	Component 2.1	City	Bureau of Labor Statistics
Exec Factor 3	Component 3.1	MSA	Web Miner
Exec Factor 3	Component 3.2	MSA	USDA

In the case an Executive Factor E_i is made up of more than one component:

$$E_i = \sum_{j=1}^{m} C_{i,j} * w_{i,j} \qquad \text{s.t.} \qquad \sum_{j=1}^{m} w_{i,j} = 1 \tag{2.2}$$

Such that C_j is the score of the jth component, m is the total number of components making up E_i, and w_j is the weight of component j. The sum of component weights for each Executive Factor must add to 1. Using Equation 2.1 and Equation 2.2 should result in a a final score between 0 and 100 for each MSA. A score of 100 indicates a location best suited for a market where as a score of 0 represents the worst. The MSA's can then be ranked using these scores. We save these rankings are they are used for both the heuristic and optimization model. A table of the variables in Equation 2.1 and Equation 2.2 are seen below in Table 2.5:

2.4.3 External Factors

There were some key factors that were not directly put into the ranking method as executive factors. They were saved for the market selection step since most were hard to quantify

Table 2.5: WLC Criterion

Executive Factor	Component	Variable	Weight	Scale Examples	Data Source Examples
Exec Factor 1	Component 1.1	$C_{1,1}$	$w_{1,1}$	MSA	Census
Exec Factor 1	Component 1.2	$C_{1,2}$	$w_{1,2}$	State	USDA
Exec Factor 2	Component 2.1	E_2	w_2	City	Bureau of Labor Statistics
Exec Factor 3	Component 3.1	$C_{3,1}$	$w_{3,1}$	MSA	Web Miner
Exec Factor 3	Component 3.2	$C_{3,2}$	$w_{3,2}$	MSA	USDA

and scenario based. Thus, knowledgeable decisions were made based on our preliminary ranking in combination with the following external factors. These factors were worked into the optimization model and/or the heuristic as a constraint or multiplier.

Megaregions

From discussions during the Semi-Structured Interviews, it became clear that market deployment roadmapping should exploit the overall configuration of the MSA's across the U.S.A. into 12 megaregions, as defined in America2050 as shown in Figure 2.1 [41]. Once the platform was deployed in one city of a megaregion, it would be easier to deploy into other cities in that megaregion due to the connectivity through the interstate system as well as a base of suppliers that could serve neighboring markets. Also, once deployment in a megaregion's cities was launched, it was similarly easier to deploy in cities of neighboring megaregions. To counter the above, the longer the venture waited before it penetrated and built critical mass in an MSA and a megaregion, the more it opened the door to competition. This factor is captured in the second version of the heuristic through an adjustable multiplier.

Population

Population was not used in the rankings because it would artificially skew our results in favor of large cities. It would have been inconceivable for the executive team of the farm-to-chef platform to launch the deployment in a large city such as New York early in the market deployment roadmap, due to both capital constraints and minimal deployment maturity. Targeted MSA's were thus grouped in four categories in terms of population size where M represents million: $>$ 10 M (Tier 1), 5-10 M (Tier 2), 1-5 M (Tier 3), and 500 K to 1 M (Tier 4) [42]. Depictions of these tiers can be seen in Figure 2.3 and Table 2.6.

Table 2.6: Definition of Population Tiers by MSA

Category	Definition	Examples
Tier 1	>10 M	New York, Los Angeles
Tier 2	5 – 10 M	Chicago, Dallas, Philadelphia, Houston, Washington DC, Miami, Atlanta
Tier 3	1 – 5 M	Boston, San Francisco, Detroit, Phoenix, Seattle, Minneapolis, San Diego, St. Louis, Tampa, Baltimore, etc
Tier 4	500k – 1M	Tulsa, Fresno, Honolulu, Bridgeport, Worcester, Omaha, Albuquerque, Greenville, Bakersfield, etc
Tier 5	100k – 500k	N/A

This allowed for the generation of roadmaps assuming various levels of the venture's capacity in which they could concurrently deploy in multiple cities of diverse population size within the same year. This capacity was generally increasing with venture maturation. The heuristic and optimization model take this factor in to consideration through capacity constraints. For example, a constraint could enforce that no Tier 1 or 2 cities be picked in the first time phase and a maximum of 12 MSA's are chosen in the first time phase. Similar constraints were generated for each time phase. Alternative roadmaps can have differing constraints to test several scenarios.

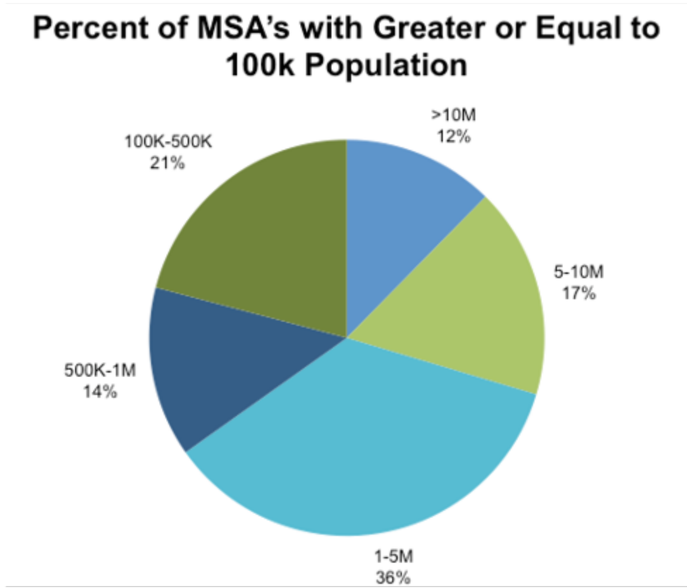

Figure 2.3: Percent of MSA's in Different Tiers

2.4.4 Cost and Revenue Equations

We generate cost and revenue equations based on the important components of the company at hand. In order to build these equations, we took what we learned in the Semi-Structured interviews and followed up to make sure our formulations aligned with the company profit model.

2.4.5 Solution Approaches

We choose to do two complementary solution approaches. One solution requires the formulation of an optimization model, the other is a heuristic model based on the ranking we created in the previous section. We then expand upon the initial Heuristic to include a proximity factor that considers previous deployments. In both approaches we use the same constraints and evaluate the models using the same Cost and Revenue Functions.

2.5 Application of Methodology

2.5.1 Semi-Structured Interviews

In order to collect data to determine pertinent market ranking factors and their weights, we conducted a series of semi-structured interviews with subject matter experts (SME's). The 12 SME's selected for interviews have different expertise, but each is relevant to market deployment of farm-to-table platform. The SME's include a Food Sourcing Manager, a Logistics Practitioner, a Business Strategy Consultant, a Farmer, a Restaurant Owner, a Marketing Manager, a Food Data Analyst, a Platform CEO and Academics in the fields of marketing and supply chain.

Since the all of the independent round tables identified the same important factors, this can help validate and triangulate the data. After the round tables, individual interviews were scheduled for follow up. They were provided Table 2.7 to look at the summary of factors identified.

Table 2.7: Results from Round Table Discussions: Factors and Definitions

Wealth	Restaurants	Type of People	Suppliers	Traffic	Drivers
How wealthy is a given Region? Will they have money to spend at Restaurants?	Are there a lot or restaurants in the Area? Is there a high density of restaurants?	Do people like to eat local food? Are there initiatives to support local food in the region?	Are there farms in the area? Are there the right types of farms?	How much traffic is present?	How much does it cost to hire drivers? Are there drivers available?
GDP	Number of Restaurants	Farmers Markets	Agriculture production Value	Traffic Measure	Truck Driver Wage
GDP per Capita	Density of Restaurants	People who like to eat Locally		Congestion Measure	Available Truck Drivers

The semi-structured interviews ended with one final round table with representatives from each of the original three round tables (not everyone could attend due to scheduling). These 6 SME's were tasked with assigning weights to the executive factors that they had originally identified as can be seen in Table 2.8.

Table 2.8: Executive Factors, Components, Scale and Data Source

Executive Factor	Component	Scale	Data Source
Wealth	GDP	MSA	U.S. Bureau of Economic Analysis
Wealth	GDP per Capita	MSA	U.S. Bureau of Economic Analysis
Restaurants	Number of Full-Service Restaurants (FSR's) within 15 miles	MSA	Web Miner
Restaurants	Number of FSR's per 1000 people within 15 miles	MSA	Web Miner
Locavore Index	Locavore Index	State	Strolling of the Heifers - USDA, Census
Supply	Agriculture Production Value	State	USDA
Traffic	Hours Spent in Congestion	City	INRIX Traffic Scorecard
Drivers	Truck Driver Mean Wage	State	Bureau of Labor Statistics
Drivers	Employment per 1000 jobs	MSA	INRIX 2017 Global Traffic Scorecard

2.5.2 Definition of Executive Factors

Restaurants

Since the platform provides matches farmers to restaurants, it is important that there are enough restaurants in the market. To measure this, we calculated the number of full service restaurants (FSR) and number of FSR's per capita within 15 miles of a MSA center. These factors were combined into one group so that concentration and pure volume are both considered. This data was captured through use of the Web Miner. The Web Miner pulls restaurant location information from Google maps for the most recent restaurant data. This data was not available by MSA but by city. For an MSA with multiple cities, the total number of restaurants was calculated as the sum of restaurants within 15 miles of individual cities. In the Atlanta-Sandy Springs-Roswell MSA example, the total number of restaurants was calculated by adding together the FSR's within 15 miles of Atlanta's MSA center plus the FSR's within 15 miles of Sandy Spring's MSA center plus the number of FSR's within Roswell's MSA center and then the overlap was subtracted from that total.

Wealth

We were not only interested in the amount of restaurants, but the success of these restaurants. As GDP increases the standard of living for that population also increases. With more disposable income, consumer spending on FSR's also increases. It has been shown that there is a statistically significant positive correlation between GDP and sales of FSR's [43]. The more sales a FSR has, the more supply they must purchase, which creates an increased demand for the platform, thus in our ranking we use the factors GDP and GDP/capita for each MSA retrieved from the U.S. Bureau of Economic Analysis [44]. Once again, we combined two similar factors into one group so that concentration and pure volume are both considered.

Locavore Index

Since this platform focuses on local supply chains, we wanted to try to quantify the desire for local meat and produce in a given market as presented in the semi-structured interviews. To do this we made use of the "Locavore Index" by state. The 2018 Locavore Index was researched and compiled by Strolling of the Heifers, a non-profit food advocacy group [45]. Most of the raw data came from the USDA and Census. The index was calculated as the weighted average ranking in all of the component categories. The weighting is as follows and can be seen in Table 3 farmers markets per 100,000 people (15%); Consumer Supported Agriculture (CSA's) per 100,000 people (15%); Farm to School (product of participation rate and budget percentage) (10%); Food Hubs per 100,000 people (5%); direct sales per capita (20%); USDA local food grants per capita (25%); and hospitals sourcing food locally (10%).

Agriculture Production Value

We not only needed to measure the consumer market, but also the market supply. To measure this we used the USDA's dataset, "Agriculture Production Value by State" [46].

Table 2.9: Locavore Index Components

Components	Explanation	Weight
Farmers Markets	Cooperative efforts to market locally produced food in a central location	0.15
CSA's	Consumer Supported Agriculture	0.15
Farm-To-School	Schools buy and feature locally produced farm-fresh foods	0.10
Food Hubs	Facilities that handle aggregation, distribution of foods from a group of farms	0.05
Direct Sales	Direct to the public food sales revenue at farms	0.20
SC Grants	Local food program promotion, grants, specialty crop block grants, etc.	0.25
LF Hospitals	Hospitals that have pledged to source food locally whenever possible	0.1

The initial data set included dozens of entries per state that tracked and measured several metrics that were not pertinent to this project, like cattle death rate. Thus, we pruned the metrics that were not useful. We also eliminated commodities that are not edible, such as cotton. The remaining commodities mainly fell into the following categories: cattle, hogs, chickens, food fish, milk, vegetable total, etc. Lastly, we subtracted any exports as this project focused on local supply chains. The MSA's were then ranked based on their state's agricultural production value of these categories. If an MSA has a city in more than one state, the state of the central hub city is selected. Also, since a state can have more than one MSA, we allow for ties in this category. For example, Dallas-Fort Worth-Arlington and Houston-The Woodlands-Sugar Land are both ranked 9th in agriculture production value.

Logistics (Drivers)

Logistics is also an important factor in opening a new market. The platform provides logistics services to connect delivery drivers to farms and restaurants. Therefore, truck driver availability and affordability is critical to the platform. We measured this through data gathered from the Bureau of Labor Statistics [47]. We use average truck driver salary per hour data to help estimate the affordability of logistics in an MSA. We also used the number of people employed as truck drivers per 1000 jobs in each MSA to estimate the availability of truck drivers.

Traffic

A driver's environment is also significant. To capture the conditions of an MSA's transportation system we used INRIX's traffic scorecard [48]. The INRIX 2017 Global Traffic Scorecard provides an evaluation of urban travel and traffic health for over a thousand cities around the world. The analysis was based on the average number of hours a driver spends in traffic in a year, and INRIX congestion index, the percentage of time spent in congestion during peak hours, etc. This project focused on number of hours spent in traffic to evaluate a MSA's transportation system. If an MSA had multiple cities, the one with largest population would be selected to determine the hours spent in traffic.

2.5.3 Weighted Linear Combination

Using the Executive Factors and weights we obtained from the Semi-Structured Interviews we get Table 2.10 below:

Table 2.10: Final Executive Factors, Components and associated Weights

Executive Factor	Component	Variable	Weight	Scale	Data Source
Wealth	GDP	$C_{1,1}$	$w_{1,1} = 50\%$	MSA	U.S. Bureau of Economic Analysis
Wealth	GDP per Capita	$C_{1,2}$	$w_{1,2} = 50\%$	MSA	U.S. Bureau of Economic Analysis
Wealth	Combined	E_1	$w_1 = 10\%$	-	-
Restaurants	Number of Full-Service Restaurants (FSR's) within 15 miles	$C_{2,1}$	$w_{2,1} = 50\%$	MSA	Web Miner
Restaurants	Number of FSR's per 1000 people within 15 miles	$C_{2,1}$	$w_{2,2} = 50\%$	MSA	Web Miner
Restaurants	Combined	E_2	$w_2 = 20\%$	-	-
Locavore Index	Locavore Index	E_3	$w_3 = 30\%$	State	Strolling of the Heifers - USDA, Census
Supply	Agriculture Production Value	E_4	$w_4 = 20\%$	State	USDA
Traffic	Hours Spent in Congestion	E_5	$w_5 = 10\%$	City	INRIX Traffic Scorecard
Drivers	Truck Driver Mean Wage	$C_{6,1}$	$w_{6,1} = 50\%$	State	Bureau of Labor Statistics
Drivers	Employment per 1000 jobs	$C_{6,2}$	$w_{6,2} = 50\%$	MSA	INRIX 2017 Global Traffic Scorecard
Drivers	Combined	E_6	$w_6 = 10\%$	-	-

We apply these weights to Equation 2.1 and Equation 2.2 for each MSA resulting in a score. We then rank them based on the score. The original ranking can be seen in Table 2.11.

Table 2.11: Original Rankings of MSA's

Original ranking	MSA	msa	Tier
1	SJS	San Jose-Sunnyvale-Santa Clara, CA MSA	3
2	MIL	Milwaukee-Waukesha-West Allis, WI MSA	3
3	SFO	San Francisco-Oakland-Hayward, CA MSA	3
4	OMH	Omaha-Council Bluffs, NE-IA MSA	4
5	PHI	Philadelphia-Camden-Wilmington, PA-NJ-DE-MD MSA	2
6	GRS	Grand Rapids-Wyoming, MI MSA	3
7	LAX	Los Angeles-Long Beach-Anaheim, CA MSA	1
7	BLT	Baltimore-Columbia-Towson, MD MSA	3
9	FRE	Fresno, CA MSA	4
10	DET	Detroit-Warren-Dearborn, MI MSA	3

2.5.4 Cost and Revenue Equations

To estimate the success of each roadmap for the optimization model, the following revenue and cost estimation models were used. These are all pre-computed. First, in Equation 2.3, the restaurant market penetration rate is based on time since the platform has been deployed in MSA m and the anticipated growth rate. Then in Equation 2.4, revenue is calculated by estimating the average amount of revenue each restaurant would spend on food in the platform and multiplying that by the current restaurant market penetration rate. This is then multiplied by the rate which the platform charges. Note that the percent food share, F_{mt} and the speed of growth factor, g_{mt}, are different for each MSA and are based on Executive Factor scores for the Locavore Index, Restaurants, and Supply. The value for average percent of a restaurants revenue spent on food is largely similar across the industry and the value of p was gathered through the Semi-structured interviews.

$r_m =$ restaurant revenue per state $\cdot \frac{\text{GDP of MSA } m}{\text{GDP of corresponding state}}$

$A_{mt} =$ is MSA m is deployed at time t? 0 - no, 1 - yes

$p =$ avg. percent of a restaurant's revenue spent on food

R_{mt} = Total revenue in MSA m at time t

P^R_{mt} = percent market penetration of restaurants in MSA M at time t

z = the percentage cut of revenue for farms

F_{mt} = percent food share, how much of a Restaurant's food cost is spent on the platform in MSA m at time t

$g_{mt} = [1.5, 2, 2.5]$ speed of growth factor for MSA m at time t, three options for speed: slow, medium and fast

$$P^R_{mt} = \frac{g_{mt}}{100} \cdot \sum_t A_{mt} \tag{2.3}$$

$$R_{mt} = r_m \cdot p \cdot F_{mt} \cdot P^R_{mt} \cdot (1 - z) \tag{2.4}$$

To calculate cost, we estimate the market penetration of the farms (Equation 2.5) and restaurants based on time since the platform has been deployed in MSA m and the anticipated growth rate. We add together the delivery costs based on the average number of drops per farm and per restaurant over the course of a year. Acquisition costs are also added in each period to account for the new farms and restaurants acquired. Drop and stop costs are different for each MSA based on Executive Factor scores in Traffic and Drivers. An additional fixed cost associated with the initial deployment of a MSA is also added based on the Executive Factor of Wealth and external factor of population. This total cost can be seen in Equation 2.6.

T^R_m = total number of restaurants in MSA m

T^F_m = total number of farms in MSA m

f_m = fixed cost to deploy in MSA m (Sales force, marketing costs)

s^F_m = cost per Farm stop in MSA m

P^F_{mt} = percent market penetration of farms in MSA m at time t

s_m^R = cost per Restaurant drop in MSA m

a_{mt}^R = acquisition cost for a restaurant in MSA m at time t

a_{mt}^F = acquisition cost for a farm in MSA m at time t

D_{mt}^F = average number of stops per farm/year

D_{mt}^R = average number of drops per restaurant/year

C_{mt} = total cost of MSA m at time t

$$P_{mt}^F = \sqrt{\frac{g_{mt} - 0.5}{100}} \cdot \sum_t A_{mt} \tag{2.5}$$

$$C_{mt} = s_m^R(T_m^R \cdot P_{mt}^R \cdot D_{mt}^R) + s_m^F(T_m^F \cdot P_{mt}^F \cdot D_{mt}^F) + a_{mt}^F \cdot T_m^F(P_{mt}^F - P_{m(t-1)}^F) + a_{mt}^R \cdot T_m^R(P_{mt}^R - P_{m(t-1)}^R) + f_m \tag{2.6}$$

Now that we have calculated the cost and revenue components, we calculate the estimated induced profit of the platform at time t:

$$\text{Expected Induced Profit at time } t = \sum_m R_{mt} - C_{mt} \tag{2.7}$$

2.5.5 Solution Approaches

We choose to do two complementary solution approaches which are both dynamic. One solution requires the formulation of an optimization model, the other is a heuristic model based on the ranking. We then expand upon the initial Heuristic to include a proximity factor that considers previous deployments. In both approaches we use the same constraints and evaluate the models using the same Cost and Revenue Functions.

Optimization Model

Decision Variables:

A_{mt} = whether a MSA m is actively deployed at time t, 1 if currently active, 0 otherwise

D_{mt} = whether MSA m is FIRST deployed at time t, 1 if first deployed in this time phase, 0 otherwise

Parameters:

$M = M_1 \cup M_2 \cup M_3 \cup M_4$ where M is the set of all MSA's and M_v is a set of all MSA's in tier v

b^l_{vt} = lower bound of number of deployed MSA's in tier v at time t

b^u_{vt} = upper bound of number of deployed cities in tier v at time t

$$\max \sum_{t\in T}\sum_{m\in M}(R_{mt} - C_{mt}) \cdot A_{mt} \tag{2.8a}$$

$$\text{s.t.} \sum_{t} D_{mt} \leq 1 \qquad \forall \quad m \in M \tag{2.8b}$$

$$\sum_{t'\in T,\ t'\leq t} D_{mt'} = A_{mt} \qquad \forall \quad m \in M \text{ and } t \in T \tag{2.8c}$$

$$A_{m(t-1)} \leq A_{mt} \qquad \forall \quad m \in M \text{ and } t \in T \tag{2.8d}$$

$$b^l_{vt} \leq \sum_{m\in M_v} D_{mt} \leq b^u_{vt} \qquad \forall \quad t \in T, \quad v \in \{1,2,3,4\} \tag{2.8e}$$

$$A_{mt} \text{ and } D_{mt} \quad \text{are binary} \qquad \forall \quad m \in M \text{ and } t \in T \tag{2.8f}$$

Above in objective (2.8a) we optimize for profit by subtracting cost from revenue and multiplying it by an indicator variable which tells us whether a MSA m is deployed in time t. Constraint (2.8b) ensures that a MSA can only start deployment in one time phase. Constraint (2.8c) ensures that a MSA cannot be actively deployed before an initial deployment is made by $D_{mt'}$. Constraint (2.8d) ensures that if a MSA is active it indeed stays active and does not shut down. Constraint (2.8e) ensures that an appropriate amount of cities from each tier are deployed in each time phase. (Each MSA is assigned to a tier based on its population.) This is to prevent too much capital being spent in the first few time periods, and to prevent taking on large cities before a solid reputation is built.

We solve the optimization model through the use of CPLEX within Python. Due to the pre-processing, the optimization model solves very quickly, in less than one minute.

Original Heuristic Model

In the Original Heuristic Model we are using the rankings as input, and setting population constraints based on tiers. In each time phase we take our ranked list of MSA's, starting with Rank 1, and see if it fits the constraints. If it does, we deploy in that time phase, if not we go to the next Ranked MSA and check constraints. We repeat until we have either filled all possible positions set by the constraints or we have iterated through the entire list of MSA's. This heuristic is solved via Python and solves in less than one minute. An outline can be seen in Figure 2.4

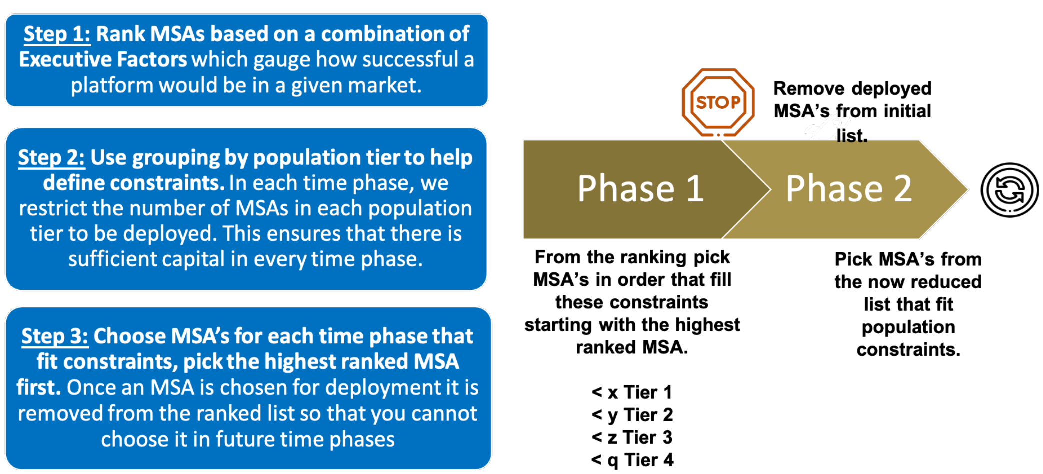

Figure 2.4: Outline for Original Heuristic

Heuristic Model with Proximity Factor

In the Heuristic Model with Proximity Factor we follow the same logic, however we rerank at the end of every time phase. We take the list of MSA's that were deployed in the first time phase and make note of their respective megaregions. Now we take the list of remaining MSA's that have not been deployed. We take their initial Executive factor total score and multiply it by a proximity factor IF an MSA has been deployed in the same megaregion previously. We use this new score to determine the rankings and the process is repeated. This heuristic is solved via Python and solves in less than one minute. An outline can be seen in Figure 2.5.

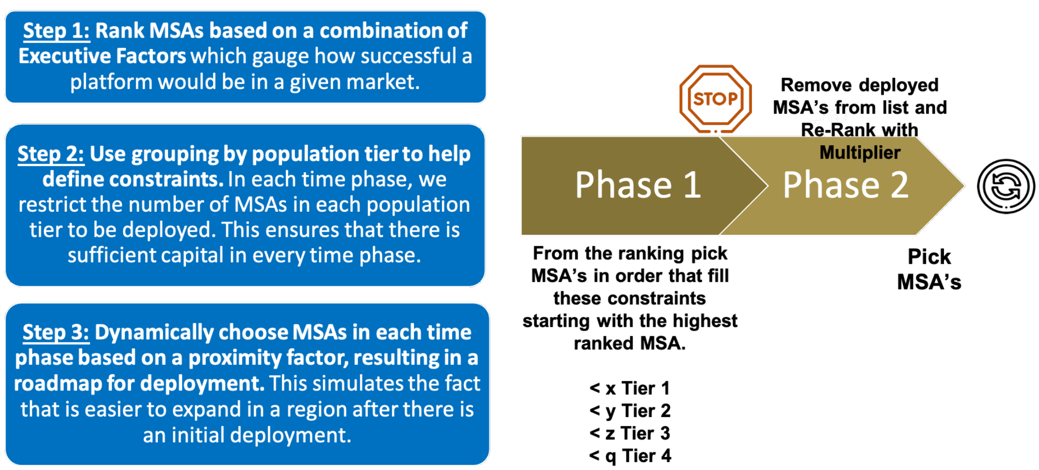

Figure 2.5: Outline for Heuristic with Proximity Multiplier

2.6 Results

There are three main categories of results to compare: the output of the optimization model, the initial output of the heuristic and the output of the heuristic with an added proximity factor. These three outputs can be seen as Market Deployment Roadmaps in Figure 2.6, Figure 2.7, and Figure 2.8.

2.6.1 Roadmap generated by the Optimization Model

The roadmap created from the optimization model, Figure 2.6, values slow growth with only one MSA pursued in the first time phase. Notably, the Phase 1 opening is an MSA that is not categorized within a megaregion. The second time phase shows moderate growth, spread across the country, with concentrations in the Northeast and California. The 3rd time phase hosts the majority of market openings. The 4th time phase is much smaller and only hosts 7 openings. This method chooses to exclude certain MSA's that are not profitable resulting in a roadmap that only features 45 of the original 66 MSAs.

2.6.2 Roadmap generated by Initial Heuristic

This roadmap, Figure 2.7, generally follows a more hyperconnected deployment, with the majority of openings occurring in the 4th time phase. In the first two time phases, MSA's in different megaregions are deployed across the country. In the third and fourth time phases there is expansion within each of the clustered megaregions and some reach into new megaregions. Note that there is no Phase 1 deployment into the Gulf Coast, Texas Triangle, Southern California Megaregions. There is also no Phase 1 deployment into the Piedmont Atlantic Region, however this megaregion already has the ”Phase 0” deployment of the original starting MSA of Atlanta.

2.6.3 Roadmap Generated by Heuristic Model with a 0.5 Proximity Factor

This roadmap, Figure 2.8, also features a hyperconnected deployment by megaregion, with the majority of openings happening within the 4th time phase. In the first two time phases, MSA's in different megaregions are deployed across the country. In the third and fourth time phases there is expansion within each of the clustered megaregions and some reach into new megaregions. Note that there is no Phase 1 deployment into the Florida, Gulf Coast, Southern California and Cascadia Megaregions. There is also no Phase 1 deployment into the Piedmont Atlantic Region, however this megaregion already has the ”Phase

0” deployment of the original starting MSA of Atlanta.

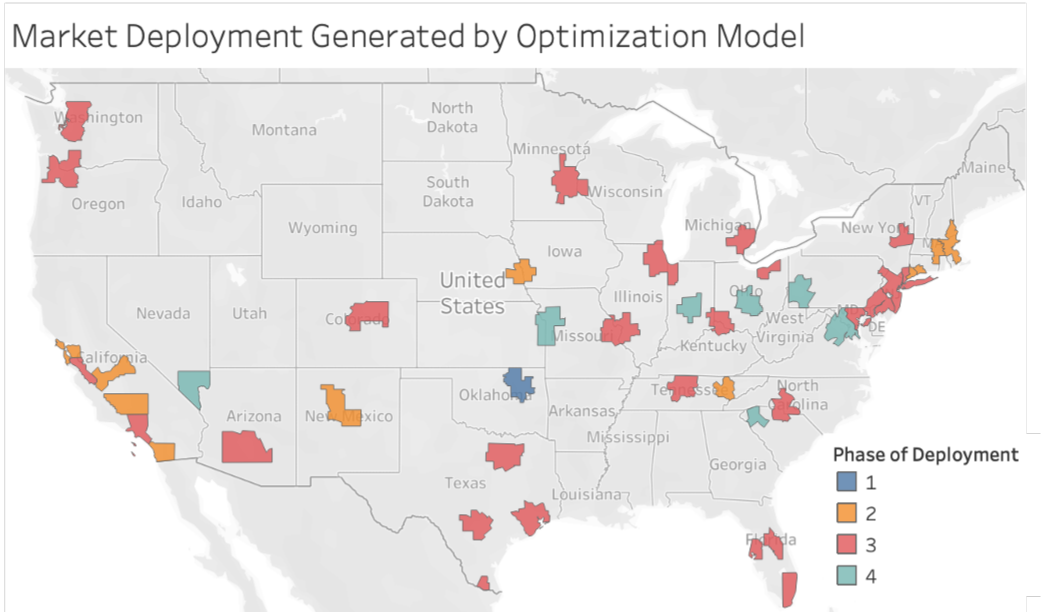

Figure 2.6: Roadmap for deployment generated by Original Optimization Model where some MSA’s were not selected.

2.6.4 Comparison of Roadmaps in the Northeast Megaregion

In Figure 2.9 we can see the roadmaps produced by each of the models within the Northeast Megaregion. We can clearly see which MSA’s were not chosen in the Optimization model and can also see the differences in phases of deployment for each of the MSA’s.

2.6.5 Sensitivity Analysis of Proximity Factor on Profit

We conducted a sensitivity analysis on the Proximity Factor used in the third model, looking at the expected profit as related to the magnitude of the factor. Since the proximity factor is not included within the Cost and Revenue equations, due to complexity, it follows that there is no association between magnitude of Proximity Factor and expected profit as seen in Figure 2.10.

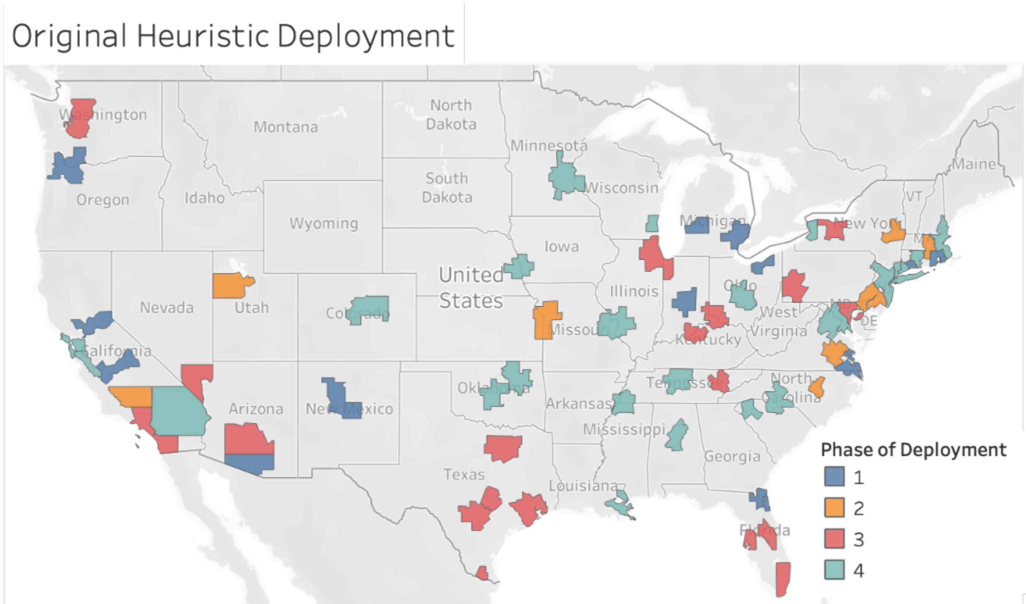

Figure 2.7: Roadmap for deployment generated by the initial Heuristic Model

2.6.6 Comparison of Expected Profit

In Table 2.12 we display the expected profits for each roadmap as generated by the same Revenue and Cost Equations. Since we saw that Optimization model did not pick MSA's as they were not profitable, we wanted to see the impact of removing those MSA's from the Heuristic inputs. As seen in the table, it drastically improves the expected profit. However, we must take into account that we only consider the first four time phases, it is possible that these non-profitable MSA's become profitable in future phases.

Table 2.12: Expected Profits resulting from Roadmaps

Model	Expected Profit (in Millions of US Dollars)	Number of MSA's Selected
Optimization Model	111.667	45
Original Heuristic Model	63.789	66
Heuristic Model with 0.5 Proximity Factor	63.507	66
Original Heuristic Model with Non-Profitable MSA's Removed	96.553	45
Heuristic Model with 0.5 Proximity Factor with Non-Profitable MSA's Removed	94.375	45

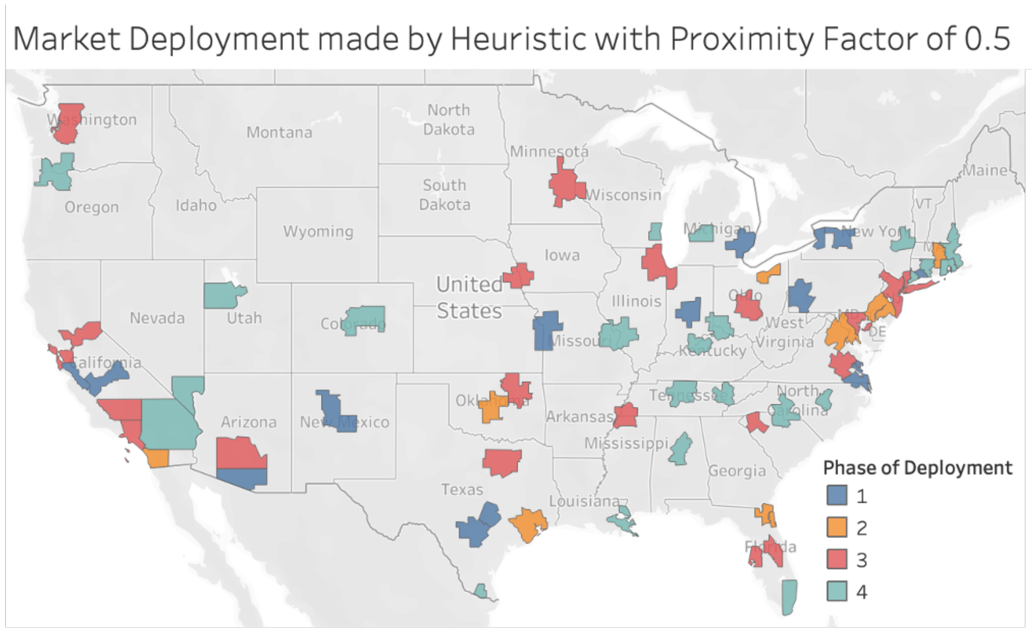

Figure 2.8: Roadmap for time-phased deployment generated by the Heuristic Model with a Proximity Factor of 0.5

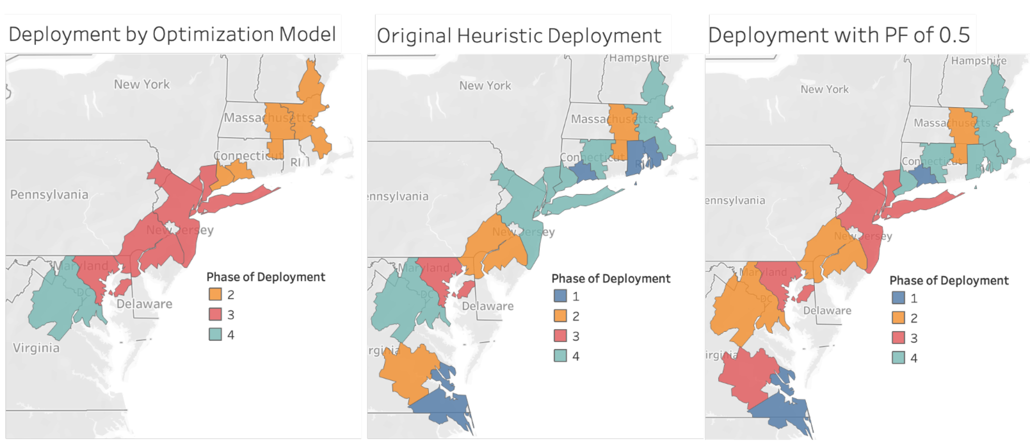

Figure 2.9: Roadmaps from each Methodology for the Northeast Megaregion

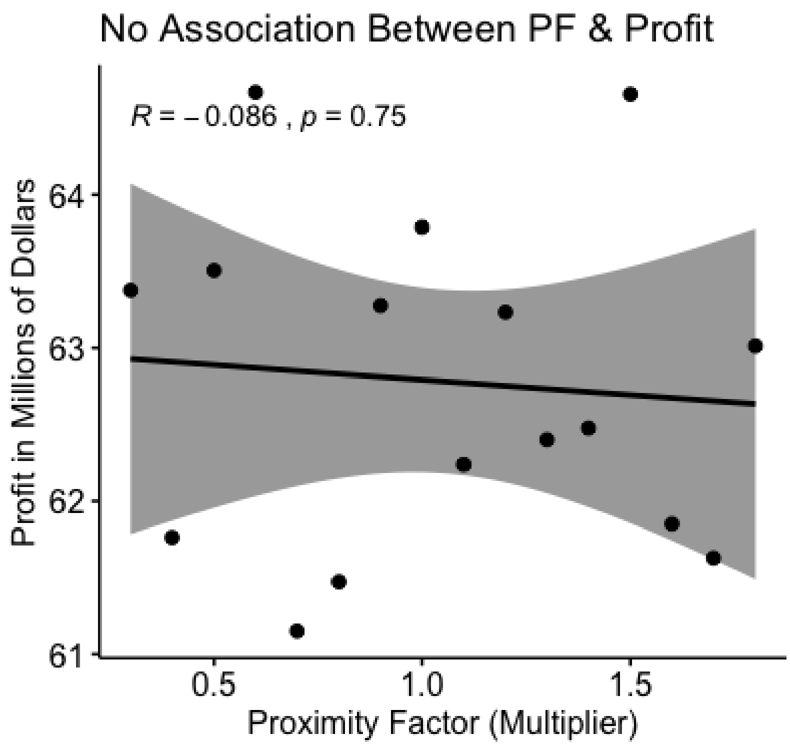

Figure 2.10: When adjusting the Heuristic with different PF's we see no association between PF and Profit

2.7 Discussion of Results

Between the two different solution methodologies, there are two distinct patterns. The optimization methodology leads to a map that generally forms in clusters starting at the second time phase. In most cases, MSA's that are generally close together begin deployment in the same time phase. However, in the two roadmaps generated by the Heuristic (Initial, and with Proximity Factor 0.5) we see more of a hyperconnected network. Once an MSA is deployed in a given Megaregion we see steady deployments in that region growing in each phase. There are fewer clusters of MSA's in the same region all deploying in the same time phase. Specifically, once we add in a Proximity Factor to the Heuristic Model we see the removal of the third time phase cluster within the MSA's in the state of Texas. This is expected as the proximity factor aids the model in creating more growth spread over time.

Another interesting feature is the difference in profits as seen in Table 2.12. Though the Heuristic with the Proximity Factor achieves a lower profit margin, we must consider that the cost and revenue equations do not capture the cost benefits of proximity. This fact is proven in Figure 2.10. The proximity of deployed MSA's give potential for shared suppliers, better reputation and connection through interstate which can impact profit. These benefits can be hard to capture in Cost and Revenue Equations which is why we pursued a complementary solution approach. It allowed us to generate roadmap solutions that were focused on different aspects. This portfolio of roadmaps gives decision makers more options and information so that they can make informed decisions for their own companies.

2.8 Conclusion

In this chapter, we have introduced a data driven market deployment planning methodology for marketplace and logistics platform startups in the farm-to-table industry that combines qualitative and quantitative approaches. We applied our methodology of ranking and selection and have shown the profitability through the use case of a farm-to-chef platform startup. Our results show that our methodologies are profitable and that each roadmap has different benefits. Semi-structured interviews, optimization, dynamic planning, clustering, executive factors, scenario-based analysis and weighed linear combination were used to create a novel profitable market deployment process. To our knowledge, there are no current approaches for market selection that use all of these tools in combination. By combining qualitative and quantitative methods we were able to create a new holistic approach to provide a better framework for new business platforms looking to expand.

In this use case, our process can enable local food supply chains that are sustainable. This helps grow local economies, reduce carbon footprints and support underpaid farmers. This model was also deployed by the F2T Atlanta based platform and one of the roadmaps created was selected for their own expansion. The generalized decision making process we presented can be modified to aid other businesses in creating their market deployment strategies in many fields.

In this research we did not consider the differentiation in available products in different regions and seasons. This was not considered since the current customers of the platform define their menus around what products are in season in their local area. However, as the platform expands, the customer base may change and may be more particular about the products they require. Future research could incorporate product differentiation seasonality into the model, considering the origins of products (meat, produce, dairy). The research could also extend to cases where there is demand for fresh food grown in farms not necessarily in the same market, and downstream growth in a market's demand depends on multi-category food supply offering from farms.

In a different stream, future work could examine resiliency in supply chain networks that can be generated through Market Deployment Frameworks. The company should be able to use the generated frameworks to expand over time with confidence. Supply chain collaboration, supplier selection and supply chain network design all play a part in generating supply chain resilience [49]. Resiliency of local food systems have garnered attention in other fields [50, 51] but limited work from an operations and supply chain management perspective [52]. In future work, we hope to expand into the further study of product segmentation among suppliers and the impact it has on supply chain resiliency.

CHAPTER 3

REDUCING TRANSPORT MILES THROUGH THE USE OF MOBILE HUBS: A CASE STUDY IN LOCAL FOOD SUPPLY CHAINS

This chapter examines the use of mobile hubs in local food supply chains and proposes a combined operations research and spatial methodology for mobile hub suitability and location analysis, specifically using using kernel density, the p-hub median problem and weighted linear combination.

The work presented in this chapter has been published in the *Proceedings of the 54th Hawaii International Conference on System Sciences* under the following reference:

- I.T. Sanders and B. Montreuil, ”Reducing Transport Miles Through the Use of Mobile Hubs: A Case Study in Local Food Supply Chains,” *Proceedings of the 54th Hawaii International Conference on System Sciences* (HICSS-54 2021). ISBN 978-0-9981331-4-0.

3.1 Introduction

Food supply chains have gained traction moving towards sustainability and transparency. Consumers are demanding more information from restaurants. Where did the food come from? [10] Are the products genetically modified? What is the carbon footprint of my food? In turn, restaurants have increased responsibility for the raw supplies they purchase [11]. One way to shift towards sustainability and transparency is through local food supply chains. They are generally known to be sustainable, notably helping to reduce emissions by eliminating long-distance transport and minimizing ”food miles” [7]. Local food supply chains also bring more money into rural communities, helping producers and disrupting the large-scale supply chains controlled by giant food distributors [12].

Local food supply chains have not gone unnoticed by the business world. There has been an increased presence of marketplace and logistics platforms enabling direct connection between farms and restaurants. However, these startups often do not have the time or capital to invest in logistics infrastructure which leads to non optimized routing.

A lack of logistics infrastructure is not unique to local food supply chains. It is present in many supply chain and logistics systems. For example, infrastructure can be destroyed by disaster [53]. In other cases, a lack of infrastructure investment and planning can threaten supply chain efficiency [54]. Local community interest and involvement in neighborhood logistics has blossomed. Government and industry have begun to consider local needs in resource allocation and decision-making processes [28]. This interest has pushed companies to consider ventures within local supply chains.

Also, in the current case of COVID-19, infrastructure was broken down for large-scale food supply chains. It has become harder to source food globally due to health and safety restrictions. The World Economic Forum advised consumers for the "post-COVID need" to support "local food systems with shorter, fairer and cleaner supply chains that address local priorities." [32]

Logistics are essential to these supply chains and directly affect supply chain performance [55]. The use of logistics centers as inter modal distribution hubs has become increasingly popular. These logistics centers often serve multiple purposes including but not limited to: distribution, consolidation, storage, infrastructure nodes, materials handling and customs checkpoints [56].

Particularly in food supply chains, food hubs have grown in prominence. As defined by the USDA, a food hub is "a business or organization that actively manages the aggregation, distribution and marketing of source-identified food products, primarily from local and regional producers to strengthen their ability to satisfy wholesale, retail and institutional demand" [8]. These hubs serve as a meeting points and points of sale for both producers and consumers. Local food supply chains stand to benefit from the use of a hub that is made up of characteristics drawn from both logistics and food hubs. However, local food supply chain hubs do not need as many features as traditional logistics and food hubs. Simplicity is key. This study aims combine attributes of logistics hubs and food hubs in order to define important characteristics needed for a mobile food logistics hub.

In this case, we examine a Farm-to-Table (F2T) platform which owns no physical assets and secures the services of drivers who own their own vehicles. The drivers are paid via a daily salary, which is formulated considering the number of stops, volume of goods, and are paid a bonus if they are able to deliver all their goods on time. Since the drivers own their vehicles, they are self-incentivized to take the most efficient routes.

Currently, the F2T platform does not use any hubs. The hired drivers travel directly from supply points (farms) to demand points (restaurants). There is no systematic organization to the assignment of drivers to routes or stops and it is done manually by an analyst at the company. Since most restaurants order goods from multiple farms, some products (that have the same destination) may be delivered by different drivers. This has led to several restaurants receiving multiple deliveries in one day which is inconvenient for the restaurants. For each delivery, the restaurant employees must spend some time greeting the driver and providing oversight and direction. The clients also expect to get deliveries by 3pm to allow adequate preparation for their dinner customers. Unfortunately, the F2T platform was seeing late delivery instances in up to 27% of its restaurant clients.

We explore integrating mobile hubs into such a F2T logistics network to help solve some of the unique requirements of a logistics system for a local food supply chain. A mobile hub in this case, is a movable, refrigerated trailer cooled at a food safe temperature that can be picked up by a pickup truck and moved on command. The mobile hub will be manned by one driver who will serve as security and organize the products by customer/planned route. This driver owns the vehicle and is paid at approximately the same rate as a delivery driver. Examples of mobile hubs can be seen in Figure 3.1. In this initial exploration, we study a mobile hub with the ability to be moved from day to day but not within a day. Drivers will pick up products from supply points (farms) and bring them to the mobile hub. There will then be a secondary set of delivery drivers. These drivers pick up the products necessary for their customers/planned route from the hub, and deliver the products from the hub to the end destinations (restaurants).

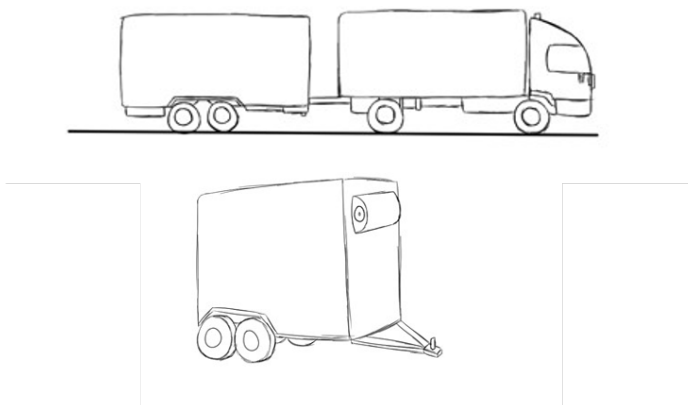

Figure 3.1: Mobile hubs of different sizes

Unlike large food distribution systems, in local food supply chains, customer deliveries are not on a regular schedule and vary by day. Therefore, a stationary hub may not be best. Due to the fluctuating nature of the daily customers, this study aims to test the feasibility of mobile hubs. To ensure success of such a mobile hub, location is of the utmost importance. The hubs must be placed strategically for accessibility, transportation efficiency and service coverage. These hubs serve as both consolidation and distribution points for delivery drivers that can change location based on daily demand.

The work that has been done in hub location has focused on large scale supply chains often with large geographical areas, thousands of customers, and thousands of suppliers. These papers must consider several hubs to cover the intended customer coverage area. They often must make several assumptions and estimations for simplicity of calculation due to the size of the system. However, in local supply chains customer coverage is much smaller. Local supply chains are often defined by consumers and policy makers to only cover a radius of 100 - 400 miles [57]. Due to the small number of suppliers and customers, we are able to consider exact road distance in most circumstances whereas most hub location solutions use route length estimation variants. We also consider details such as service constraints (on time delivery) and congestion in a large scale metropolitan area which have not been considered by many in literature.

Previous research efforts in hub location focus on solely using OR efforts or solely using GIS efforts, there are very few combined approaches. We are able to create a novel combined framework that uses both OR and GIS techniques to effectively identify potential mobile hub locations. We make use of integer programming formulations, kernel density and weighted linear combination to select mobile hub locations. We strengthen our contribution by considering real transportation costs and service measures in addition to evaluating our results through a comparison to historical route data. We answer Campbell and O'Kelley's call for research "directed at more realistic problem variants" and their call for the study of environmental implications of flow consolidation [58]. We also build on the small set of papers that address dynamic (mobile) hub location and the set that address small networks.

The paper is structured as follows: 3.2 reviews literature in hub location and kernel density. Section 3.3 presents the case study context. Section 3.4 introduces the methodologies for hub location selection in a condensed form. Section 3.5 expands upon 3.4 and provides the details of the methodology. Section 3.6 provides the application of the Methodology to the case study. Section 3.7 displays the results and Section 3.8 provides a discussion of said results. Section 3.9 presents conclusions of the study and presents areas for future research.

3.2 Literature Review

There are two equally regarded main tracks of hub location research as outlined by Campbell and O'Kelly in their literature review of the past 25 years of hub location research

[58]. One track approaches Hub Location Problems with an Operations Research (OR) lens, focusing on robust mathematical formulations, including effective cuts and strong lower bounds often highlighting computation times. While providing computational insights, these OR style approaches often do not explore the interpretation of the impacts on real-life logistical results. The second track approaches hub location problems with a Geographic Information Systems (GIS) lens. These studies focus on spatial analysis and often involve the use of real-life data and study the societal impact of their logistics and transportation strategies. Campbell and O'Kelly argue that both of these lenses are "vital and have contributed to the the impressive progress" made in Hub Location Research [58].

However, the efforts within these lenses are often siloed and there is little interdisciplinary work done to make use of both OR and GIS in a combined approach for hub location research. We hope to expand on this sparse literature by presenting a hybrid methodology that combines established hub location techniques from both OR and GIS with a practical implementation.

3.2.1 Hub Location Definition

Hub location problems share several key characteristics as outlined by Campbell and O'Kelly [58]. Our problem has each of these distinguishing features and can therefore be categorized as a Hub Location Problem.

1. Demand assigned via flows between OD pairs and not individual points.

2. Flows can go through hubs.

3. Hubs are facilities to be placed.

4. There is some benefit (or requirement) of routing flows through hubs.

5. There is an objective who's outcome is dependent on the placement of the hub facilities and their associated routing of flows.

3.2.2 Operations Research Approaches to the Hub Location Problem

One of the earliest facility location models that could be categorized as Hub Location Research was formulation of the P-Median Location Problem (PMLP) by Hakimi [59]. In this problem, Hakimi defined origin-destination (OD) flows within ”a communication network such as a telephone interconnecting system ...[where] all traffic flows (messages) within the network must arrive at the center S before they are processed and then sent to their proper destination” [59]. Here, S serves as a hub within the network as it fits the definition we presented in the previous section. The problem searches for the location of p hubs which minimize the average distance between the hubs and each customer. Soon after, Goldman was able to extend node optimality of Hakimi's models [60]. Two decades later, Campbell defined a hub location analogue to the the the PMLP as the p-hub median problem (PHMP) [61]. In this work, Campbell defines the PHMP: Given a set of demands, locate p-hub facilities at candidate sites to minimize the total transportation cost to serve the demand [61]. Several other works have applied and/or built upon Hakimi and Campbell's work including Groothedde et al., Marin et al., and Daskin and Maass. [62, 63, 64]. There have also been many other MIP formulations studied [65, 66, 67]. In our work, we apply the Integer Programming formulation by Campbell with the parameters set to fit our case study [61].

Another line of modeling done within Operations Research for the hub location problem is continuous approximation modeling for many-to-many networks. In such models, demand is handled as continuous over a planar service region. In solutions, origins and destinations can be allocated to multiple hub locations. Daganzo has done a majority of the work in this field and an overview of the method is seen in [68]. Continuous approximation as applied to logistics systems can be seen in work by [69, 70]. Though this method can provide near optimal solutions, it is built for larger instances and performs better in larger cases rather than smaller instances [70]. This has been demonstrated in [71, 72, 73]. Since our case study involves a small instance, we choose to use an Integer Programming formulation (in combination with Kernel Density), as described in the previous paragraph, as opposed to a continuous approximation approach.

3.2.3 Geographic Information Systems Approaches to the Hub Location Problem

GIS has seen more varied approaches including gravity models and spatial interaction models [58]. A popular type of GIS model used is a weighted linear combination (WLC) [25]. It is a type of suitability analysis which is used for problems involving multi-attribute decision making (MADM). Every attribute is considered a criterion and carries a weight based upon importance, the results are multi-attribute spatial features with total scores [25]. WLC is commonly used for location intelligence, for example, Mahini and Gholamalifard use Weighted Linear Combination (WLC) to select landfill locations [26]. WLC use has also been expanded for selection of logistics hub locations in the Czech Republic by Ruda and in Iran by Shahparvari et al. [27, 28].

Shahparvari et al. discuss five main Spatio-structural criteria that are important in WLC for logistics hub location: Transportation Infrastructures, Geophysical Conditions, Socio-Economic Infrastructures, Environmental Limits and Geo-political Conditions [28]. Transportation Infrastructures is defined as access to a transportation network, in our case, interstates and roads. Geophysical Conditions are defined as areas that have suitable land surface and landform. Socio-Economic Infrastructures focus on the ability to access skilled manpower. Environmental limits encompass vegetation cover, soil types, and temperature. Geo-Political Conditions consider proximity to political boundaries [28]. Some of these criteria do not apply to local system mobile hubs (Environmental Limits, Geo-Political Conditions, and Socio-economic Infrastructures), but some may prove useful and should be considered (Transportation Infrastructures and Geophysical Conditions) as seen in the following paragraphs.

Local food is defined as food purchased within 275 miles or the same State where it was produced by the Food Safety Modernization Act, enacted in January 2011 [57]. Geo-political conditions, or the proximity to political boundaries, are negligible here as a small geographic area is highly likely to have uniform conditions. Environmental limits, such as vegetation cover, and soil types are also insignificant as mobile hubs do not need to be built and will remain on asphalt. As a mobile hub is a one-man operation and there is not a need for a large number of skilled workers. Socio-economic infrastructures such as access to skilled workers, therefore, are also inconsequential.

The last two criteria, Geophysical Conditions and Transportation Infrastructures are important to a mobile hub. The mobile hub's main goal follows the same goal as the logistics hub location problem: to pick a site that offers the greatest customer coverage while offering the lowest possible transportation cost [74]. Access to transportation infrastructure, in this case, highways and interstates, are especially important, thus showing the importance of Transportation Infrastructures [56, 75]. Geophysical conditions usually pertain to topography and disaster risk [76]. However, for this case, it concerns the availability of a flat parking space for the mobile hub. This is not a given commodity at every location since many restaurants are located in extremely urban areas without nearby parking.

Beyond WLC, we also see systematic descriptive and explanatory models to capture flow in works like Olsson and Fotheringham [77, 78]. There has also been work done connecting the spatial interaction framework with the location allocation model [79]. Notably, GIS methodologies often provide a degree of accuracy that can't be captured in a MIP model [26]. Historical routes with actual road-traveled distances can be used, rather than rough approximations. Albino states the relevance for of the use of spatial aspects in supply chains, particularly at the local level due to an emphasis on the relationship between energy and environmental aspects with economic aspects [24].

3.2.4 Dynamic (Mobile) Hubs

There has been little research done on Dynamic hub location, where the hub is changing locations over time and the majority of work has been done through OR approaches.

Gelareh and Nickel studied public transport hub networks that do not require a fully interconnected set of hubs and include multiple time periods and operating and closing costs of hubs [80]. Contreras et al. used branch and bound in addition to a Lagrangean relaxation to solve multi period uncapacitated multiple allocation hub location problems where the hubs were fully interconnected [81]. Faugere et al. study mobile hubs in the context of parcel delivery [82]. They show that mobile hubs are valuable when demand is consistent and are even more valuable when demand is variable. The flexibility offered by mobile hubs allow for network adjustments based on variations in demand patterns. Faugere et al. also show the positive impact of mobile hubs on environmental sustainability of the systems [82]. However, all of these models consider multiple hubs in large logistics systems. To our knowledge, there is no literature on the application of Mobile Hubs in small instances, such as local supply chain networks.

3.2.5 Kernel Density

Kernel Density is a commonly used GIS technique which aggregates sample points into geographic units, often known as rasters, to model spatial occurrences. This aggregation of points into a raster is known as a smoother density estimator. The first paper that dealt with such a probability density estimation with a general kernel estimator was Rosenblatt [83]. A Kernel Density Estimator, helps visualize an unknown probability density function for a series of topological sample points in order to predict future points.There are several variations of the Kernel Density Estimator, one of the most commonly used in GIS is quartic kernel function described by Silverman [84]. Kernel Density has seen numerous applications. For example, when using a naive Bayes classifier to estimate the class-conditional densities of data, it can improve prediction accuracy [85]. Kernel density has also been used to build effective hot spot maps, most notably in analyzing crime density for the purpose of community planning [86]. It has also been used in public planning efforts to predict fire incidents and ambulance demand [87, 88].

3.2.6 Combined Approaches

In literature, we see a lack of combined approaches that consider both OR and GIS. However, there are two new papers that show promise in using a combined method. Belu et al. propose a spatial model for optimal placement of logistics hubs in a predefined economic area, through the use of linear programming [89]. They consider variables such as the point coordinates, served population, number of served townships and average delivery time. More recently, Rodriguez et al. demonstrate the usefulness of a combined approach by combining a simulation-optimization approach with a spatio-temporal arrival process for facility location and vehicle assignment for firefighters [90]. They combine a Kernel Density Estimator and a Markov-Mixture of Erlangs of Common Order model.

3.2.7 Review

Although there has been over 25 years of work done on Hub Location problems, there are improvements to be made. Most work has either been done solely within OR or solely within GIS. Even though ”both aspects are vital and have contributed to the impressive progress in the field,” there has been little combined work [58]. Kernel Density has long been used in other applications but has only been recently applied to hub location problems [90]. There is also a call for more research to be directed at more realistic problem variants especially ones that include transportation costs and service measures [58]. In existing application papers, there is very little research done on small instances or in local supply chains. Campbell and O'Kelly also call for more work done on Dynamic Hub Location and the incorporation of environmental assessment into hub location problems, especially considering flow consolidation [58]. In this work we address these limitations by creating a hybrid OR and GIS model that utilizes Kernel Density. We apply our methodology to a real case study concerning hub location within a local food supply chain system considering transportation costs, service measures and the environmental impact of consolidation.

This implementation demonstrates the impact of the solution approach within the intricacies of local food supply chains. Specifically, we utilize the OR approaches of a MIP formulation of the p-hub median problem and TSP heuristics, complemented with the GIS methods of Kernel Density, Suitability Analysis and Network Analysis.

Most solution approaches to hub location problems depend on Euclidean distance [58], by using a GIS solver we are able to utilize real road distance, providing a degree of accuracy not previously achieved. This is possible due to natural small size of instances for a local supply chain system.

3.3 Case Study Context

We explore the location analysis of a mobile hub within a logistics system for a startup Farm-to-Table (F2T) platform that enables local food supply chains. We particularly look at an Atlanta based F2T platform that connects suppliers (farms), directly to customers (restaurants), surpassing middlemen. The F2T platform secures the services of drivers to deliver between suppliers and customers on a contract basis. This platform induces logistics that must consider both the downstream side of markets, such as urban agglomerations with restaurants, institutions, and households demanding fresh and local food, and their upstream side consisting of farms producing and selling fresh and local food. There are four main types of orders in the system: subscription type (where orders are known well in advance), orders with a week advance notice, orders with one-day advance notice, and same-day orders. The majority of orders are not same-day orders, so routes can be planned daily and in advance. Unlike large food distributors, the customer list (for farms and restaurants) is not the same each day. The restaurants and farms are all located in the state of Georgia, since this is a local food supply chain. A map of the restaurants and farms can be seen in Figure 3.2.

In this particular case, we are looking at a system where the platform has no physical assets and secures the services of drivers who own their own vehicles. The drivers are paid via a daily salary, which is formulated considering the number of stops, volume of

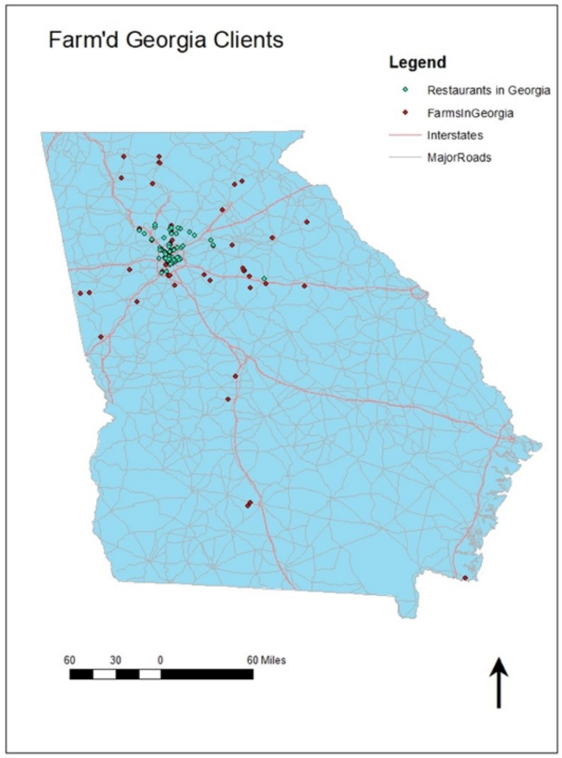

Figure 3.2: Farm-to-Table Farms and Restaurants

goods, and are paid a bonus if they are able to deliver all their goods on time. Roughly, each hired driver is given the same number of stops per day. Since the drivers own their vehicles, they are self-incentivized to take the most efficient routes because they are responsible for their own gas, mileage to their vehicle and the time at which their workday ends. The combination of these factors imply that the drivers are motivated to maintain efficiency and timeliness for their routes. They are therefore aligned with the overall goal of using mobile hubs to reduce the time and length of routes.

Currently the F2T platform does not use any hubs. The hired drivers travel directly from supply points (farms) to demand points (restaurants). There is no systematic organization to the assignment of drivers to routes or stops and it is done manually by an analyst at the company. A typical logistics timeline for a F2T can be seen in Figure 3.3 and an approximation of routing can be seen in Figure 3.4.

Since most restaurants order goods from multiple farms, some products (that have the

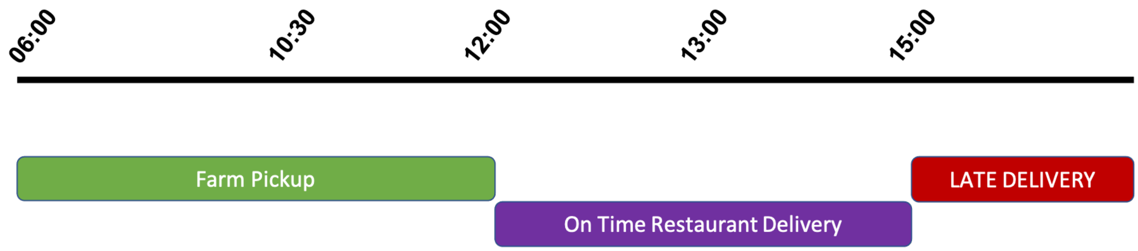

Figure 3.3: Sample timeline with no hub

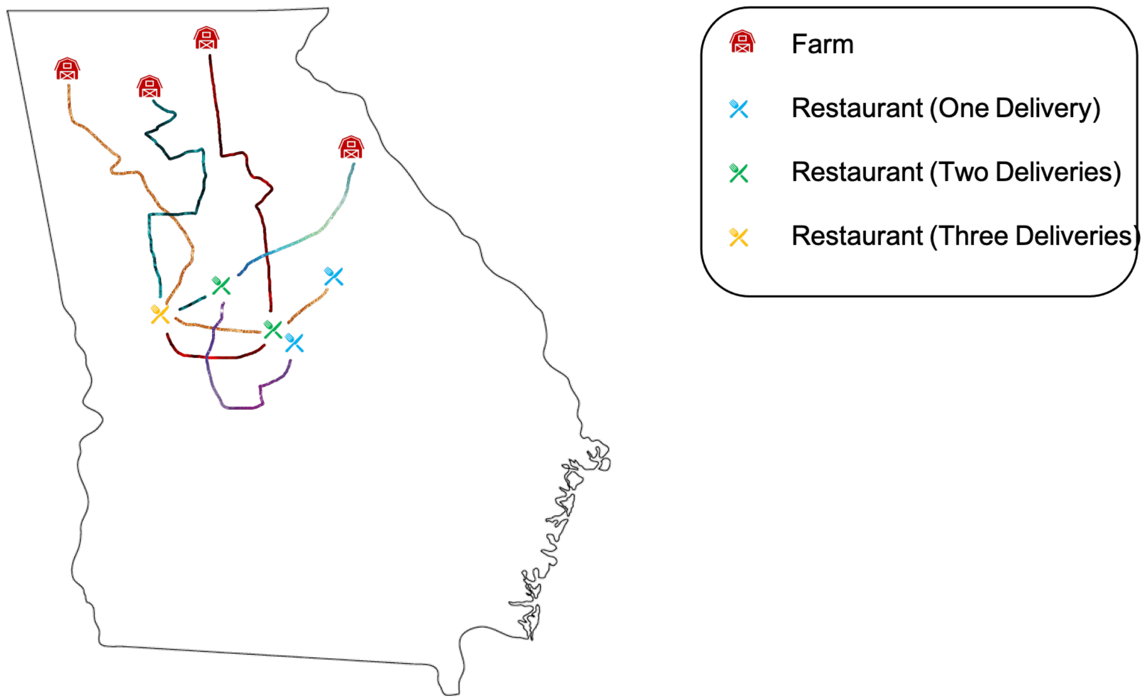

Figure 3.4: Sample map and routes including farms and restaurants but no hub

same destination) may be delivered by different drivers. This has led to several restaurants receiving multiple deliveries in one day which is inconvenient for the restaurants. This can be seen in Figure 3.4, where restaurants in green and yellow are receiving more than one delivery each day. For each delivery, the restaurant employees must spend some time greeting the driver and providing oversight and direction. As confirmed by the structured interviews in Chapter 2, one delivery is highly preferred for restaurant clients. The clients also expect to get deliveries by 3pm to allow adequate preparation for their dinner customers. Unfortunately, the F2T platform was seeing late delivery instances in up to 27% of its restaurant clients.

We explore integrating mobile hubs into a F2T logistics network to help solve some of the unique requirements of a logistics system for a local food supply chain. A mobile hub in this case, is a movable, refrigerated trailer cooled at a food safe temperature that can be picked up by a pickup truck and moved on command. A picture of such a hub can be seen in Figure 3.1. The mobile hub will be manned by one driver who will serve as security and organize the products by customer/planned route. This driver owns the vehicle and is paid at approximately the same rate as a delivery driver. In this initial exploration, we study a mobile hub with the ability to be moved from day to day but not within a day. Drivers will pick up products from supply points (farms) and bring them to the mobile hub. There will then be a secondary set of delivery drivers. These drivers pick up the products necessary for their customers/planned route from the hub, and deliver the products from the hub to the end destinations (restaurants). A visualization of this can be seen in Figure 3.5

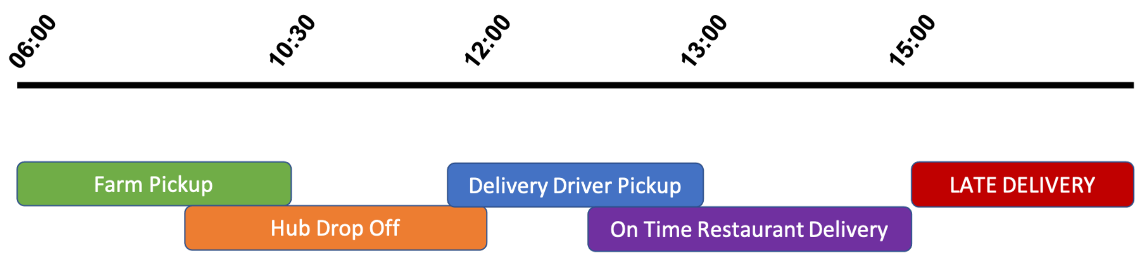

Figure 3.5: Logistics Daily timeline with hub

The mobile hub addresses the problem of multiple deliveries through consolidation. That is, all of the supply (products from the different farms) will be brought to the mobile hub such that a driver can pick up all of the ordered products for a restaurant and make a single delivery to each customer. This can be seen in Figure 3.6 where we add a hub and there are no longer restaurants with multiple deliveries in one day like in Figure 3.4. We address the second problem, of late deliveries, by improving routing. First, we require supply points (farms) to have goods ready for pickup at a set time allowing for consolidation at the hub before 12 pm. Second, we hire several hub-to-demand point drivers with a limited number of stops to ensure on time delivery. Also, since the mobile hub can be moved from one location to another on different days with no additional cost, this could help address the fluctuating nature of the daily customers. If more customers are concentrated south of the city one day, the hub could be located in the south. Conversely, if more customers are concentrated north of the city, the hub could be located in the north.

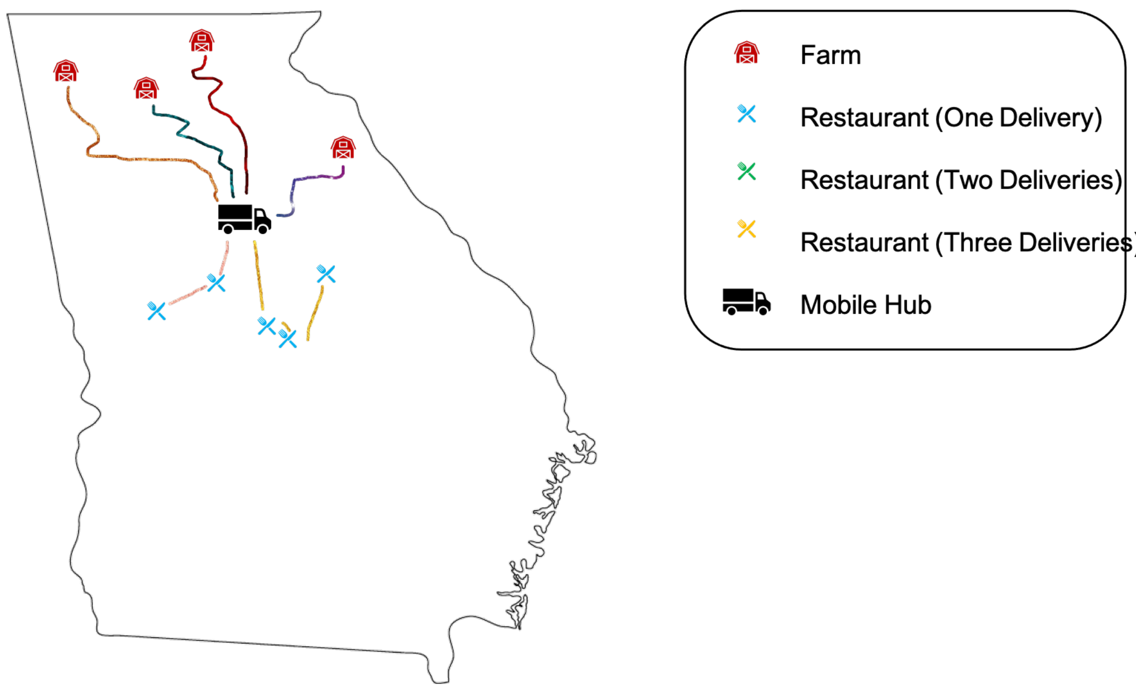

Figure 3.6: Sample network with farms, restaurants and a hub

In this analysis, we limit the potential hub locations to existing F2T restaurant customers. This was done because existing customers demonstrated interest and could be granted a discount on their purchases in exchange for participation. Permission to park the hub at these restaurants was granted with minimal effort, whereas, parking in non-customer locations would likely involve permits and bureaucracy.

To summarize, in this problem, there is a large pool of on-demand carriers, with time windows for both pickups at farms and for deliveries at restaurants. The set of customers is not consistent on a day to day basis and fluctuates. We also have strict service requirements and penalties for late delivery. Each restaurant order can contain multiple products from multiple farms, with potential transport incompatibilities between purchased products, calling for consolidation. We also study the environmental impact of consolidation implementation. We explore the use of a mobile hub that can serve as a consolidation and distribution point and be relocated as necessary from day to day to fit these constraints.

This idea of a mobile hub aligns with the idea of Hyperconnectivity which stems from the Physical Internet (PI) and aims to improve the economic, environmental, societal efficiency and sustainability of the way physical objects are moved, deployed, realized, supplied, designed, and used. PI is a global hyperconnected logistics system that enables asset sharing and consolidation across numerous parties and modes. Hyperconnectivity allows for efficient and seamless information, transaction, and material flow across stakeholders throughout the supply chain [91].

3.4 Methodology Summary

We present two alternative methodologies. The Methodology for Selection of Mobile Hub Location(s) presents our hybrid methodology for selecting a Mobile Hub throughout the week. In a non-traditional manner, we use the P-hub median model to narrow down the candidate hubs instead of using it as the final selection model. In our results we hope to show that the model can be used for this purpose, in combination with other techniques, to provide efficient results.

A summary visual representation can be seen in Figure 3.7, further details are seen in the following section. To demonstrate that this application is effective, we use Stationary Hub Algorithm to select the stationary hub for comparison. Stationary Hub Algorithm uses a more traditional application of the P-hub median model such that it selects the one hub that minimizes the distance traveled from the hub to the demand points.

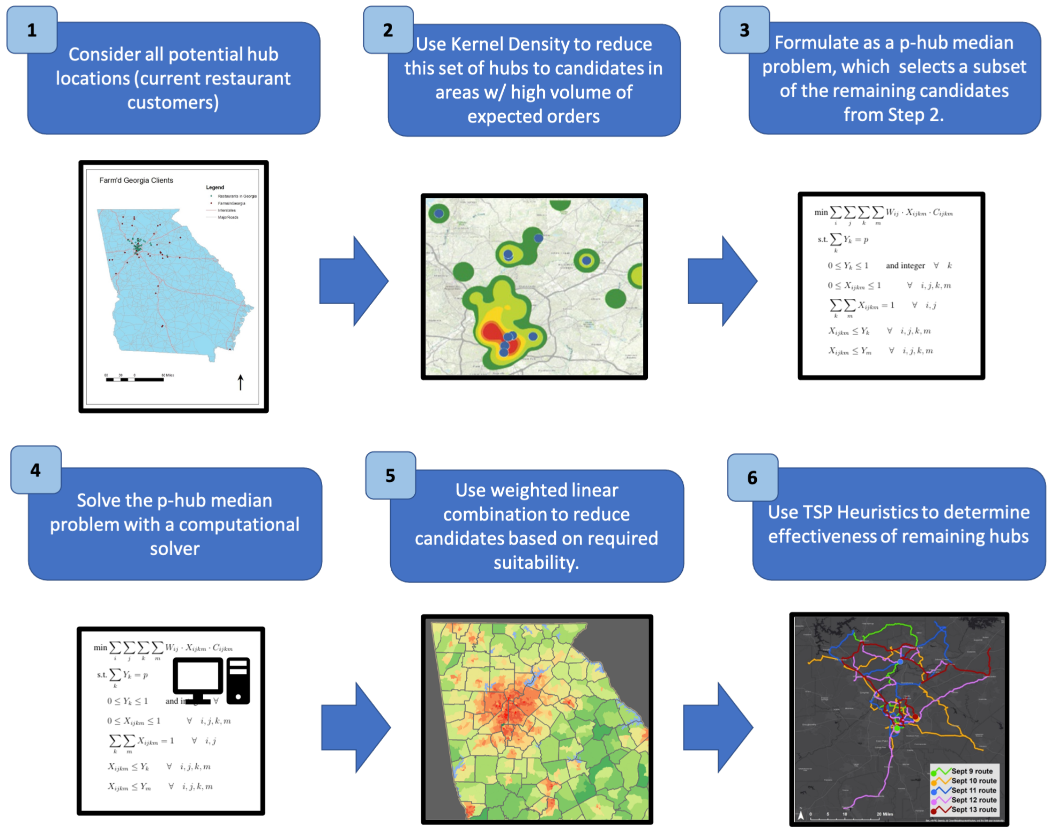

Figure 3.7: Outline of Methodology for Mobile Hub Location

3.4.1 Methodology for Selection of Mobile Hub Location(s)

1. Consider all potential hub locations which are current restaurant customers. We only consider current customers to eliminate the need to deal with applying for parking permits or other documentation.

2. Use kernel density on historical data to identify customer hot spots. Identify all demand points that fall within a predetermined range of the centroids of the hot spots. These serve as the new set of candidate hubs. This helps drastically reduce the number of candidate hubs to be used in p-hub median problem (next step) to be solved in a reasonable amount of time (minutes or hours vs. days).

3. Formulate the problem as a p-hub median discrete facility location problem. We do this to identify the remaining hubs that minimize the total transportation cost.

4. Solve the p-hub median problem using a computational solver for a predetermined number of hubs, p.

5. Use a Weighted Linear Combination to further reduce the number of candidates based on required suitability. Here, we address some important variables like availability of parking. To collect this data at an earlier stage (with many more candidates) would have been extremely time consuming. Therefore, it is done later in the process when there are fewer candidates for which to collect data.

6. Use TSP heuristics to determine the effectiveness of each of the remaining candidate hubs.

3.4.2 Methodology for Selection of One stationary Hub

In the secondary methodology we propose a shorter methodology. We use a more traditional application of the P-hub median model such that we set p = 1 and select the one hub that minimizes the distance traveled from the hub to the demand points. We then evaluate it using TSP heuristics. For the detailed algorithm, please see Section 3.6.6.

3.5 Methodology

3.5.1 Kernel Density (Steps 1 and 2 of Mobile Hub Methodology)

Kernel Density is a method that estimates the probability density function of a random variable. In this case, we are studying demand points, which are (x,y) geographic coordinates (restaurant orders/deliveries). We are making inferences about future points based on a data sample. Since we are looking at geographic data demand points, we aggregate by a grid, or raster. The generic kernel density estimator can be written as follows in Equation 3.1:

$$\hat{f}(x;H) = \frac{1}{n \cdot h} \sum_{i=1}^{n} K(\frac{x - X_i}{h}) \tag{3.1}$$

Here, $\hat{f}$ is the smoothed probability mass for a data point X_i in a geographic area (determined by the kernel), and K is the kernel estimator [84]. The function arguments are x which is the unobserved demand point, and H which is commonly called the bandwidth estimator, window width or smoothing parameter, based on author preference. This bandwidth estimator determines the smoothness of the kernel. Lastly, to make sure that the probability mass $\hat{f}$ remains 1, we divide by n [84, 90]. There are several types of kernel functions, including but not limited to Uniform, Triangular Epanechnikov, Quartic, Triweight , Gaussian and Cosinus as seen in the Table 3.1 [90].

Table 3.1: Popular forms of Kernel Density Estimators

Kernel	K(u)
Uniform	$\frac{1}{2}I(\mid u \mid\leq 1)$
Triangle	$(1-\mid u \mid)\ \ I(\mid u \mid\leq 1)$
Epanechnikov	$\frac{3}{4}(1-u^2)I(\mid u \mid\leq 1)$
Quartic	$\frac{15}{16}(1-u^2)^2I(\mid u \mid\leq 1)$
Triweight	$\frac{35}{32}(1-u^2)^3I(\mid u \mid\leq 1)$
Gaussian	$\frac{1}{\sqrt{2\pi}}exp(-\frac{1}{2}u^2)$
Cosinus	$\frac{\pi}{4}cos(\frac{\pi}{2}u)I(\mid u \mid\leq 1)$

Source: https://homepages.inf.ed.ac.uk/rbf/CVonline/LOCAL$_{C}OPIES/AV0405/MISHRA/kde.html$

Quartic Kernel Functions are most commonly used in GIS, and are the form that we use. In order to calculate the bandwidth, we use an adapted version of Silverman's Rule built for two dimensions [84].

We use kernel density to identify customer hot spots, or areas where total number of demand points are expected to be high. We then identify demand points which fall within these high frequency regions. The original data set had hundreds of hub candidate locations. Using kernel density, we can lessen the number of hub candidates such that computation time to solve the P-hub Median problem is reduced. Since we use real route data to solve the p-hub median, it is important to have a relatively small number of points such that solving can be down within an hour.

3.5.2 The P-hub Median Problem

The p-hub median problem is defined by Campbell: Given a set of demands (OD pair flows), locate p-hub facilities at candidate sites to minimize the total transportation cost to serve demand. The total transportation cost is the demand weighted sum of costs for serving all OD pairs [58]. To protect the interests of the F2T platform that was used for this study, we do not exactly define the transportation cost here. However, generally, the transportation costs are the rate in which the hired drivers are paid. The drivers are paid via a daily salary, which is formulated considering the number of stops, volume of goods, and are paid a bonus if they are able to deliver all their goods on time. The bonus is not included in the cost equation used in the formulation. The basic formulation of the p-hub median problem can be seen below as defined by Campbell [61]:

Decision Variables:

X_{ijkm} = Fraction of flow from location (origin) i to location (destination) j is routed via hubs at locations k and m in that order

Y_k = 1 if location k is a hub 0 otherwise

Z_{ik} = 1 if location i is allocated to the hub at location k and 0 otherwise

Parameters:

W_{ij} = Flow from location i to location j

C_{ij} = Standard cost per unit from location i to location j

$C_{ijkm} = c_{ik} + c_{mj} + \alpha c_{km}$

$$\min \sum_i \sum_j \sum_k \sum_m W_{ij} \cdot X_{ijkm} \cdot C_{ijkm} \tag{3.2a}$$

$$\text{s.t.} \sum_k Y_k = p \tag{3.2b}$$

$$0 \leq Y_k \leq 1 \qquad \text{and integer} \quad \forall \quad k \tag{3.2c}$$

$$0 \leq X_{ijkm} \leq 1 \qquad \forall \quad i, j, k, m \tag{3.2d}$$

$$\sum_k \sum_m X_{ijkm} = 1 \qquad \forall \quad i, j \tag{3.2e}$$

$$X_{ijkm} \leq Y_k \qquad \forall \quad i, j, k, m \tag{3.2f}$$

$$X_{ijkm} \leq Y_m \qquad \forall \quad i, j, k, m \tag{3.2g}$$

The objective function adds together all of the transportation costs over all OD pairs. Constraint 3.2b establishes exactly p hubs. Constraint 3.2c restricts Y_k to be 0 or 1. Constraint 3.2d limits the range of X_{ijkm}. Constraint 3.2e ensures that the flow for every OD pair is routed via a hub pair. Constraints 3.2f and 3.2g assure that flows are routed via hub locations [61].

In this step, we further reduce the number of hubs by selecting p hubs that minimize the transportation cost. We acknowledge that this is not a traditional application of the p-hub median problem, as it is usually used for final hub selection. However, we hope to show that it can be a powerful tool for hub reduction in our combined methodology.

3.5.3 Weighted Linear Combination

The next technique we use is called Weighted Linear Combination or WLC. When facing a problem involving multi-attribute decision making, WLC can be used. Every attribute that is considered is called a criterion. Each criterion has an assigned weight based on its importance. This process results in multi-attribute spatial features with final scores. The higher the score, the more suitable the area [25]. We are using WLC to help reduce the number of hub candidates and select the best hub locations.

We focus on three attributes, Geophysical Conditions, Transportation Infrastructures and Population Density are important to a mobile hub. The mobile hub's main goal follows the same goal as the logistics hub location problem: to pick a site that offers the greatest customer coverage while offering the lowest possible transportation cost [74]. Access to transportation infrastructure, in this case, highways and interstates, are especially important, thus showing the importance of Transportation Infrastructures [56, 75]. Geophysical conditions in this case, concerns the availability of a flat parking space for the mobile hub. This is not a given commodity at every location since many restaurants are located in extremely urban areas without nearby parking. Population density is important to capture the foot traffic and vehicle congestion in an area. For ease of access to the mobile hub for delivery drivers, we want areas of lower density. Areas of higher density may make it hard for transfers between drivers to take place. Population density has previously been shown as a useful attribute by Merchan, Snoeck and Winkenbach to discriminate areas of interest for local road networks [92].

In our application, we conduct WLC based on distance to interstate, availability of parking and population density. For all rasters with centroid coordinates (x, y) :

$$\text{score} = I_{(x,y)} * w_i + P_{(x,y)} * w_p + D_{(x,y)} * w_d \tag{3.3}$$

I, P, and D values are all normalized to hold a value between 0 and 100 and the sum of $w_i + w_p + w_d = 1$ resulting in a a final score between 0 and 100. A score of 100 indicates a location best suited for a hub where as a score of 0 represents the worst. A table of the variables in Equation 3.3 are seen below in Table 3.2:

Table 3.2: WLC Criterion

Type of Attribute	Attribute	Variable	Weight
Transportation Infrastructure	Distance to Interstate	I	w_i
Geophysical Conditions	Available Parking	P	w_p
Social Conditions	Population Density	D	w_d

3.6 Application of Methodology

3.6.1 Mapping Potential Hub Locations

In order to test our methodology, we apply it to the our Farm-to-Table case study. Following Step 1 of the Methodology section, as discussed in the case study, we choose to only use current restaurant customers as potential hub locations. This allows us to avoid applying for parking permits and any other bureaucracy that may pop up in other locations. A map of these candidate locations can be seen in Figure 3.2.

3.6.2 Kernel Density

Following step 2 of the methodology, next, we conducted Kernel Density Analysis. ArcMap version 10.7.1 (ESRI) was used to geocode 123,556 destinations that received deliveries between Oct 15, 2018 and Nov 18, 2019. We calculated the bandwidth using a formula adapted from Silverman's Rule of thumb as seen below [84, 93]:

$$\text{bandwidth} = 0.9 * \min(SD, \sqrt{\frac{1}{D_m * ln(2)}}) * n^{-0.2} \tag{3.4}$$

Here, SD is the standard distance, a statistic which measures the degree to which features are dispersed around a geometric mean center, D_m is the median distance (weighted) from the mean center and n is the number of points in the sample. This resulted in a bandwidth of $.05$ decimal degrees. We then input this value into a quartic kernel density estimator, which is commonly used in GIS, adapted from Equation 3.1.

The kernel density map seen in the Figure 3.8 was colored according to the Jenks natural breaks classification. The distribution and density of destinations were mapped for the full set of data obtained, as well as each of the distinct weekdays for a singular week during the year. we were able to identify 41 feasible hub locations. The 41 candidate hubs were plotted on top of the kernel density map for each weekday of a singular week. The results from the kernel density analysis indicated that for every day of the week, the estimated concentration of the restaurants that required deliveries were in the central region of Atlanta.

3.6.3 Formulation as p-hub median problem

Next, following Step 3 of the Methodology, we created a formulation of the p-hub median problem. We use the basic formulation defined in 3.2 of the Methodology section, and adjust the parameters to fit our case study. We set p=10 to reduce the number of candidate hubs (input 42 hubs). The total transportation cost is the demand weighted sum of costs for serving all OD pairs. To protect the interests of the F2T platform that was used for this study, we do not exactly define the transportation cost here. However, generally the transportation costs are the rate in which the hired drivers are paid. The drivers are paid via a daily salary, which is formulated considering the number of stops, volume of goods, and are paid a bonus if they are able to deliver all their goods on time. The bonus is not included in the cost equation used in the formulation. Following step 4 of the methodology, we solved our formulation through the use of the Network Analyst solver within ArcMap version 10.7.1 (ESRI). It solved this case within one hour.

Figure 3.8 depicts the 10 candidate hubs overlaid on the Kernel Density Map. Most hubs are located in Downtown and Midtown Atlanta with some in restaurant heavy suburbs such as Roswell. The ten candidate consolidation hubs are illustrated as blue circles on kernel density maps which estimate density of deliveries for each day of the week between Monday, September 9, 2019 & Friday, September 13, 2019, and for all deliveries recorded between Oct 15, 2018 & Nov 18, 2019. Locations with the highest estimated density are in highlighted in red, and areas with lowest estimated density are Dark Green.

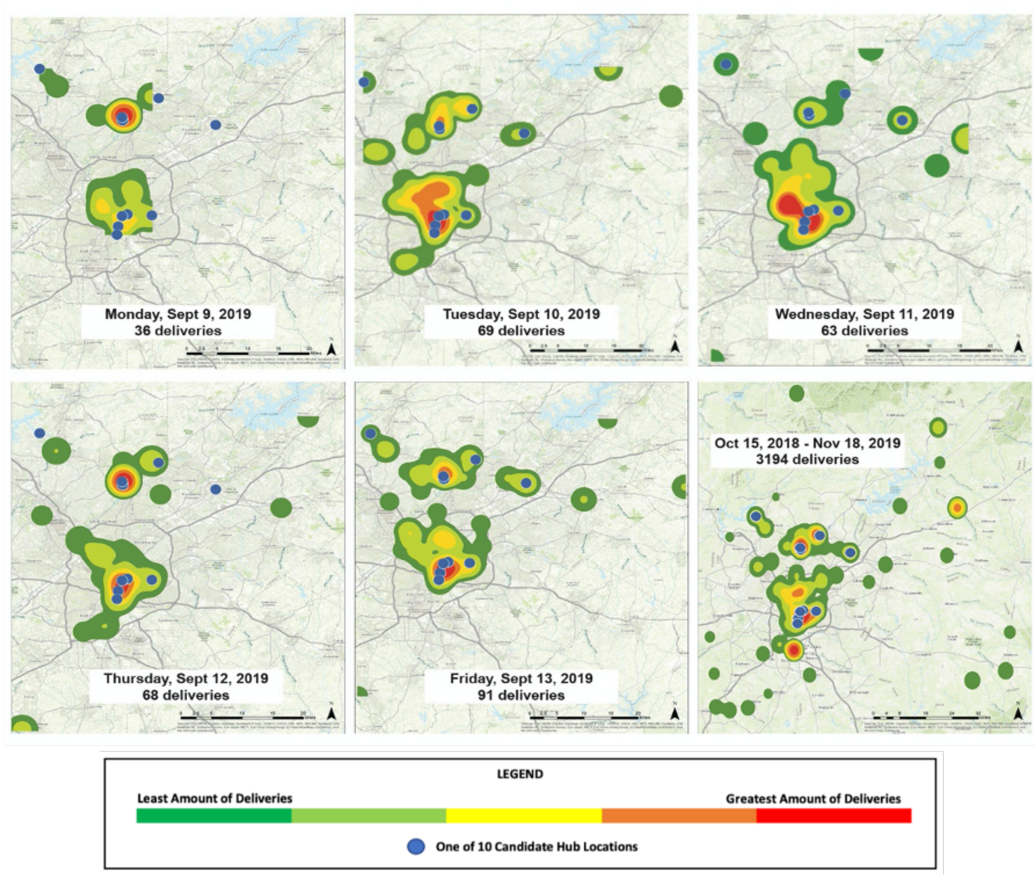

Figure 3.8: Kernel Density of Deliveries over a year with hub candidates

3.6.4 Weighted Linear Combination (WLC)

Next, following Step 5 of the Methodology, we use weighted linear combination to further reduce the number of candidate hubs. We gathered the weights for each of these criterion shown in Table 3.3 during our semi-structured interviews discussed in Chapter 2 and associated data sources are listed in Table 3.3.

Table 3.3: WLC Criterion with weights

Type of Attribute	Attribute	Variable	Weight	Data Source
Transportation Infrastructure	Distance to Interstate	*I*	w_i =.3	U.S. Roads Dataset
Geophysical Conditions	Available Parking	*P*	w_p = .4	Data Collection by Authors
Social Conditions	Population Density	*D*	w_d = .3	U.S. Census Bureau

These weights served as input into Equation 3.3. The category scores I, P, and D are calculated by taking data from the sources listed in Table 3.3 and normalizing the data to a value between 0-100. This equation results in a score from 0-100 for every raster. We solve this using the weighted overlay tool within ArcMap version 10.7.1 (ESRI) where each criterion is its own feature layer. After which, we identify the four hub location candidates with the highest WLC scores. These candidates are considered the finalists and are then evaluated using TSP heuristics.

3.6.5 TSP Heuristics

Now, in order to complete the last step (6) of the Methodology, we must calculate proposed routes for each of the hubs and sum the distances to assess which hub(s) result in the least distance traveled. Here we are presented with the vehicle routing problem (VRP), that is, given multiple vehicles and multiple delivery locations, what is the optimal assignment of routes in order to deliver to all customers efficiently. This a generalization of the Traveling Salesman Problem (TSP), that is, given multiple delivery locations and one vehicle what is the optimal route such that the vehicle starts and ends at the origin point and reaches all delivery locations [94].

For the purpose of the study, we simplify the presented VRP with a variation of the TSP where a return to the origin is not needed. This is done because we face a complex problem with strict service requirements, and we are dealing with a dense metropolitan area. VRP's often fail in large city networks, therefore we use a TSP heuristic. TSP's have also been historically successfully used in hub location problems to find routes among nodes assigned to a given hub [95].

We assume that route of the hub (origin) to delivery locations is covered by one driver for all the buyers of the day. We use this generalization to simplify the problem because the VRP is very computationally complex and has been shown to be very difficult to solve whereas solving the TSP is considerably easier in most cases [94]. We solve for a variation of TSP which does not require the driver to return to the origin therefore solving for the route such that the driver starts at the hub and delivers to all customers. In order to simulate having multiple drivers, we added a small 5-mile buffer to the total distance for each driver that would have been assigned that day. That is - on each day we have the same number of drivers that the company used when they were not using mobile hubs to serve as a fair comparison. For example, if in the historical data 4 drivers were used on May 1st, 4 drivers would have to be used (from hub to restaurant) in the mobile hub analysis. The buffer for each of the drivers is to account for the small distance from the hub to the driver's first stop (hub – restaurant) that falls along that long TSP route.

To solve this TSP heuristic, we use the New Route Analysis function within ArcMap version 10.7.1 (ESRI) was used to generate hub-to-restaurant routes for the remaining candidate hubs, for a randomly selected week of historical data. To efficiently execute this, the stops were allowed to reorder with hub location preserved as the starting point. The New Route Analysis function is effectively solving the variation of the TSP where return to origin in not required as discussed earlier. Next, farm-to-hub distances were calculated using closest facility analysis for each day of the week. Here, it is assumed that farm-to-hub distances for each day are being covered by a separate driver (from each farm) to the hub in this initial exploration to ensure pickup within the correct time horizon. The farm-to-hub distance was added to the hub-to-restaurant distance for a final distance total for each hub. The distances for the final candidate hubs can be seen in the Results section.

The final hub selections were made by selecting the daily hub that resulted in the least distance traveled based on that day's customers. Using this technique, one hub (roaming) was selected for each day of the week for the final selection. In order to calculate the efficiency of these hubs, we compare the distance traveled by drivers with and without hubs by using historical routing data collected by the F2T.

3.6.6 Stationary Hub Algorithm

To build a comparison between the above Mobile Hub and a Stationary Hub, we create an Stationary Hub Location Selection algorithm that utilizes kernel density and the p-hub median problem to determine the location of one stationary hub. This algorithm can be seen below:

Algorithm - First follow steps 1-4.

1. Consider all potential hub locations (current restaurant customers), as analogous to Step 1 of the Mobile Hub Methodology.

2. Use kernel density on historical data to identify customer hot spots. Identify all demand points that fall within a predetermined range of the centroid of the hot spots. These serve as the candidate hubs. This is analogous to Steps 2 in the Mobile Hub Methodology. We do this to reduce the candidates that serve as input into the P-hub Median problem.

3. Formulate the problem as a p-hub median discrete facility location problem. Analogous to Step 3 of the Mobile Hub Methodology.

4. Solve the p-hub median problem using a computational solver for a predetermined number p = 1. Analogous to Step 4 of the Mobile Hub Methodology.

If selected hub does not satisfy all suitability constraints as given in step 5 of Methodology for Selection of Mobile Hub Location(s) (Here we give the minimum thresholds that the top 4 hubs reached in each of the 3 criterion):

1. Remove selected hub from candidates.

2. Repeat Step 4 of the algorithm

Else:

Use TSP heuristics to determine the effectiveness of the selected Mobile Hub.

END

At the conclusion of the run of this algorithm, we are left with one mobile hub and its assigned drivers and routes.

3.6.7 Comparison of Methodologies

At this stage, we selected our final hub candidates for each methodology and evaluated them based on historical sample data over several days. We compared historical routes that had no hubs, to routes made using (3.4.1) Methodology for Selection of One stationary Hub, to routes made using (3.4.2) Methodology for Selection of Mobile Hub locations. Routes generated using 3.4.1 and 3.4.2 were created using TSP heuristics.

3.7 Results

We tested our methodology on one random week from the year. Through our methodology we were able to select hub locations and compare real and estimated route distances. Table 3.4 shows the selections of mobile hubs throughout the sample week where the underlined numbers indicate the chosen hub for that day. These hubs are selected by the least distance traveled for that particular day. Hubs 2 and 4 were chosen twice, Hub 3 once and Hub 1 chosen zero times. Table 3.5 shows the associated estimated distances for each day with the selected stationary hub location. This hub is the same as Hub 2 in Table 3.4. Table 3.6 shows the historical distances traveled throughout the selected week via the F2T.

Table 3.7 displays information from both Historical routes and Estimated Mobile

Hub Routes. First, it displays historical information: the number of drivers needed, the number of restaurants served, the number of farm pickups, volume of orders, and historical distance. Next, it shows the estimated distances for deliveries using the mobile hub. To calculate the total distance, we add together the total distance traveled from the individual farms-to-hub, the distance traveled from the hub-to-restaurants, and the driver-to-hub distance (which we added to the TSP variant value in order to better estimate the VRP value). This chart shows the demand variability from day to day, as well as comparison of miles traveled, which varied.

Table 3.8 depicts the change in the number of stops and the change in distance from the historical distance traveled to the calculated estimated distance traveled with the use of a hub. Every day a hub is used, there is a reduction in the number of stops. In all but one day, Thursday, there is a reduction in the amount of distance traveled with an average reduction of 7.46% and a range from -17.4% to +2.2%.

Table 3.9 Shows the comparison between route distances of each methodology and includes the Driver-to-hub buffer. When compared to the historical routes, the stationary hub shows a 0.5% increase in road distance, the mobile hub shows a 5.4% decrease in total distance traveled.

Table 3.10 displays the percentage of deliveries that were late historically, and then expected in both the mobile hub and stationary hub scenarios. We see that there is a significant drop in late deliveries with the stationary hub and then no late deliveries with the mobile hub.

In Figure 3.9, the optimal hub for each day of the week is shown by a colored dot along with their associated route. This map shows the routes before they are broken down into separate drivers by the heuristic. This shows that two candidate hubs were able to serve as hubs on multiple days. Deliveries on Mon, Sept 9 & Thurs, Sept 12 and Tues, Sept 10 & Fri, Sept 13 share the same hubs. Figure 3.10 shows the hub location and associated rout with Sept 11th. Wednesday had more stops than any other day throughout this sample week.

Table 3.4: Estimated Delivery distance in Miles for Mobile Hub Candidates without Buffer

Estimated Delivery Distance in Miles for Mobile Hub Candidates (No Buffer)					
	Monday	**Tuesday**	**Wednesday**	**Thursday**	**Friday**
Hub 1	540	912	1297	962	703
Hub 2	491	905	1340	945	716
Hub 3	523	899	1153	951	688
Hub 4	567	871	1248	957	669

Table 3.5: Estimated Delivery distance in Miles for Stationary Hub Candidate without Buffer

Estimated Delivery Distance in Miles for Stationary Hub Candidate (No Buffer)					
	Monday	**Tuesday**	**Wednesday**	**Thursday**	**Friday**
Hub 2	491	905	1340	945	716

Table 3.6: Historical route distances

Historical Delivery Distance in Miles with No Hub					
	Monday	**Tuesday**	**Wednesday**	**Thursday**	**Friday**
Historical	576	917	1354	959	743

Table 3.7: Comparison of Historical Routes to Estimated Mobile Hub Routes

Day	**Drivers**	**# of Rest.**	**# of Farms**	**# of Orders**	**Historical Farm-Direct-to-Restaurant Distance (miles)**	**Estimated Distances for Deliveries Using Consolidation Hubs (miles)**			
						Hub-to-Restaurant	**Farm-to-Hub**	**Farm-to-Hub-to-Restaurant**	**Driver-to-Hub**
MON	5	23	6	31	576	86.84	404.2	491.04	25
TUES	6	48	7	67	917	158.44	712.4	870.84	30
WED	7	41	10	58	1354	209.13	943.8	1152.93	35
THUR	7	59	9	75	959	190.03	755.3	945.33	35
FRI	10	42	7	115	743	132.53	536.9	669.43	50

Table 3.8: Change in Number of Stops and Distances between Historical Routes and Mobile Hub Estimated Routes

Change in Number of Stops and Distances between Historical and Mobile Hub Estimations				
	Change in Stops	Percentage Difference in Stops	Change in Distance (Miles)	Percentage Difference in Distance
Monday	-3	-9.7%	-59.96	-10.4%
Tuesday	-14	-20.9%	-16.16	-1.8%
Wednesday	-8	-13.8%	-236.07	-17.4%
Thursday	-7	-8.8%	+21.33	+2.2%
Friday	-4	-3.5%	-73.57	-9.9%

Table 3.9: Comparison of Route Distances (including buffer) between the three methodologies

Comparison of Route Distances Including Driver-to-Hub Buffer when Applicable						
	Monday	Tuesday	Wednesday	Thursday	Friday	Total Dist
Historical	576	917	1354	959	743	4549
Stationary Hub	516	935	1375	980	766	4572
Mobile Hub	516	901	1188	980	719	4304

Table 3.10: Comparison of Late Deliveries between the three methodologies

Comparison of Late Deliveries						
	Monday	Tuesday	Wednesday	Thursday	Friday	Average
Historical	0 %	27%	19%	5%	12%	12.6%
Stationary Hub	0 %	5%	10%	0 %	3%	3.6%
Mobile Hub	0 %	0 %	0 %	0 %	0 %	0%

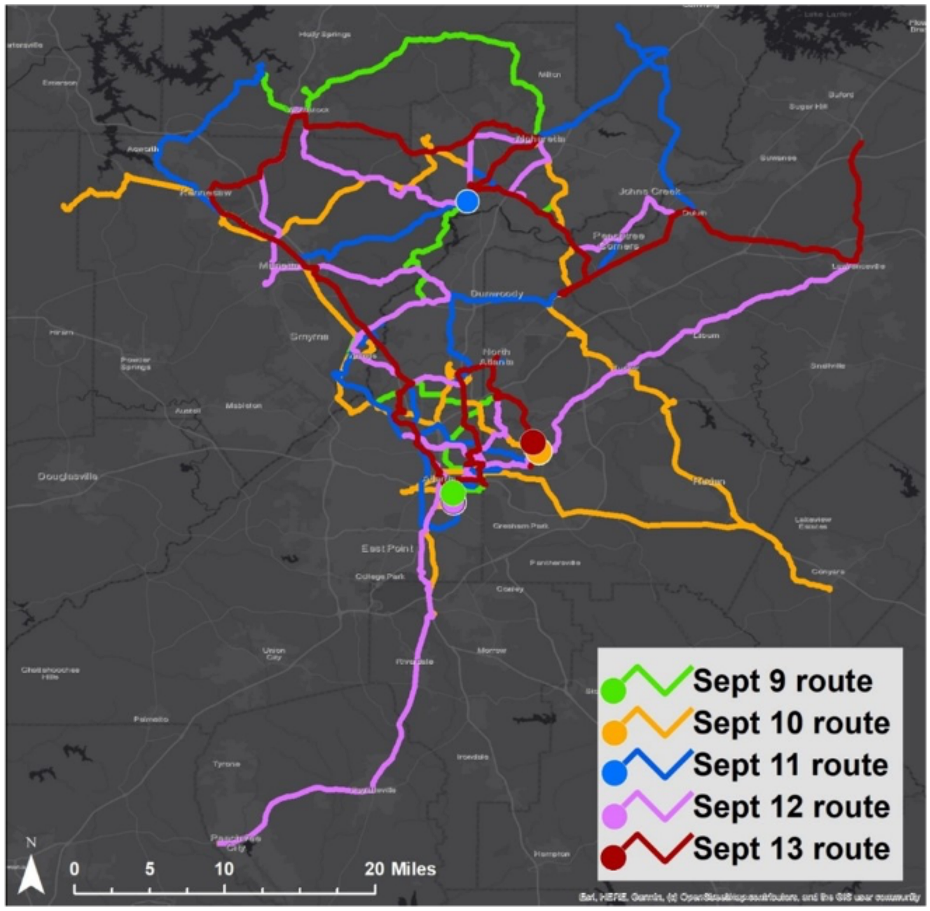

Figure 3.9: Change in Number of Stops and Distances between Historical Routes and Mobile Hub Estimated Routes

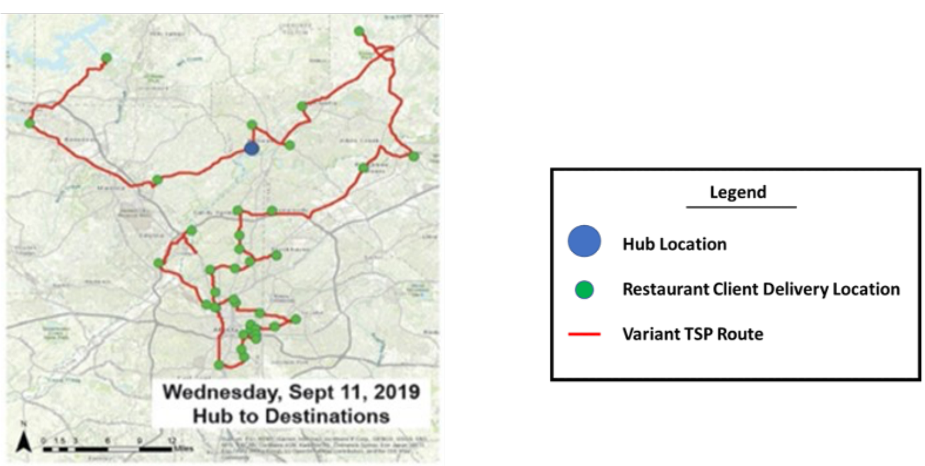

Figure 3.10: Change in Number of Stops and Distances between Historical Routes and Mobile Hub Estimated Routes

3.8 Discussion of Results

When selecting one hub location from the final four options for each of the five days, both Monday and Thursday had the same location for a hub (Client 1) and Tuesday and Friday had the same ideal location for a hub (Client 2). This may indicate that since a lot of the restaurants are clustered near each other, there is a very likely chance that the same hubs will be utilized on a frequent basis. This is ideal for drivers when they pick up products from the hub location because they would essentially be alternating between a few locations regularly, although the days may change.

Demand varies on different days of the week and the routes become more efficient when the hubs can move based on demand. This can be seen in the different distances traveled for all hubs in Table 3.5. This indicates that consolidation was not the only factor in reducing the mileage. Each hub provides consolidation, but the location of each hub is different, indicating that there is importance to the location of the hub, demonstrating the added value of having a mobile rather than stationary hub. When using the stationary hub, shown in Table 3.5, there is actually a slight increase in mileage. However, though there was in increase in mileage there was a drastic decrease in the percentage of late deliveries as seen in Table 3.10.

Table 3.8 indicates that there is a reduction in stops in all cases since we are consolidating orders such that no restaurant receives more than one shipment a day. There are the same number of stops in both the Mobile Hub scenario and the Stationary Hub scenario. The consolidation seen when using a hub drastically reduces the time drivers spend unloading, as a single drop off typically takes between 5-10 minutes. This also helps cut down on the distance traveled in the mobile hub scenario. We notice that in almost all cases distance is reduced when adding the mobile hub. In the case where distance is not reduced, we hypothesize this is due to wide farm-spread for that day.

These preliminary results indicate mobile hub use could serve as a valid way to reduce mileage and stops. Mobile hubs also provide a more sustainable system as emissions are directly related to distance traveled. A reduction in mileage will result in a reduction in emissions. Reducing the number of stops can also provide a reduction in emissions as vehicles often need to be kept running even when a delivery is being made. The hub system is also more cost-effective as the overall number of stops is reduced, lessening the number of drivers needed to be hired.

We also demonstrate that there is a clear difference between the use of a stationary hub and the use of a mobile hub. In our experiment we see that mobile hubs lead to fewer miles traveled, and fewer late deliveries, in comparison to a stationary hub. Also, in the case study, a mobile hub does not cost any more than a stationary hub. Our results show clear benefits to not only using a hub, but clear benefits to using a mobile hub.

3.9 Conclusion

Though we used a small sample size for testing, we believe our results are important for small local supply chains. We have addressed the call in literature for the use of "more realistic transportation costs and service measures" in more realistic problem variants by using a case study where service (on time delivery) is consistently measured and incredibly important [58]. We also expand on the growing field of dynamic hub location solution approaches using a hybrid OR and GIS model. Through our analysis we have shown that using a mobile hub can reduce miles traveled, number of stops on a route, and the percentage of late deliveries. This is not only good for the F2T company, but also for the environment; transportation accounts for 28.9% of the US's Greenhouse gas emissions [96]. Any reduction in transportation helps reduce such emissions. We have also shown how to incorporate the use of real routing data into hub location analysis.

We have demonstrated how to use a hybrid methodology for hub location selection, in the case of a local supply chain with a small network where traditional approaches may not be as strong. We are also able to build a model that focuses on real distance traveled and makes fewer estimations and assumptions than is usually done in literature for larger supply chains. We understand that there are limitations to this study. We do make assumptions in the estimation of hub routes. Future research could study the feasibility of creating a VRP heuristic for such routing.

In further research, we hope to show the statistical significance of these reductions through t-testing on a larger set of days with a cost analysis of the hubs used. Mobile hubs could change the way local supply chains operate. Instead of warehouses with large footprints, mobile hubs only take up a spot in a parking lot. They are especially useful in supply chains where demand is not constant and origin-destination pairs are variable. The number and location of mobile hubs are flexible, such that they can be assigned on the day of delivery and could even move throughout the day based on changing demand. Additional research could also investigate the impact of time sensitivity, such as accounting for preferred and detrimental delivery times at client locations, as well as synchronicity impacts of arrival and departure times at the hub on overall performance.

This work can also be expanded beyond our F2T case study, notably in other local supply chains where there a lack of literature. Mobile hubs could also be used in local disaster relief. Relief supplies often come from many different areas and need to be distributed to various locations daily. In this example, there is also a fluctuating nature in the customers and their locations, which makes it a candidate for mobile hub use. Another application could also be for food waste. Many restaurants have leftover food at the end of the day. We could use this model to deliver leftover food to homeless shelters, schools or those in need. Our research shows that there is potential in this area of study, and we hope more work is done in the future.

CHAPTER 4
SUSTAINABLE SUPPLY CHAIN DESIGN FRAMEWORKS FOR FRESH PRODUCTS

4.1 Introduction

As consumers are shifting towards sustainability, companies are facing increased pressure to be sustainable themselves. According to Harvard Business Review ”Business leaders need to start treating carbon emissions as costly, because they are or soon will be, and companies need to assess and reduce their vulnerability to climate-related environmental and economic shocks” [97]. Companies often do not know where to start to improve sustainability efforts. We create a framework that can be carried out by analysts at a company in a short time span (on the order of a month). This short timeframe is cheaper for the company and provides a good first effort to show validity before a company invests in a more substantial sustainability effort. In this chapter, we provide an introductory conceptual framework for integrated use of Customer Segmentation and Life Cycle Assessments to help shape fresh supply chain and logistics design. This framework can help identify weaknesses within the supply chain and pinpoint improvements that can be made for a shift toward more sustainable practices.

We focus our efforts on two main fresh industries, the quick service restaurant industry and the fresh cut flower industry. Though seemingly different, both industries deal with perishable goods and are facing pressure to increase sustainability. An EY report shows that 81% of consumers feel strongly that organizations should help improve the environment. Within the Quick Service Restaurant Industry, Heikke Cosse of Aegon Asset Management stated ”global fast-food brands need to take concrete action to manage supply-chain emissions and water impacts... firms that fail to meet this challenge face regulatory and reputational risks that put their long term financial sustainability under threat" [98]. These industries are also interestingly tied together through the growing market for edible flowers which crosses the boundaries of both food and horticulture [99].

Creating a true sustainable system may need reorganization at a base level and rethinking of practices that have been done for decades. We propose a three-prong system to examine the state of a company's supply chain and identify improvements that can be made to increase sustainability through: the creation or adaptation of a perishability or decay model, customer segmentation analysis for logistics, and Life Cycle Assessment (LCA) Calculations.

We then provide two case studies to test different aspects of the three prong system. The first is Incorporating Decay and Customer Segmentation into Logistics Decisions in the Fresh Cut Flower Industry. The second is Conducting Customer Segmentation and LCA to Fries for a QSR.

4.2 Literature Review

4.2.1 Life Cycle Assessments

Life Cycle Assessments, or LCA, is a standardized methodology for investigating the environmental impact of a product, process or system [100] by objectively identifying and measuring inputs and outputs of energy and material usage and the associated environmental impacts such that efforts can be made to reduce the impact [101]. LCA's have been used to assess and measure impact in many fields including but not limited to wine [102], potatoes [103], fruits [104], edible flowers [99] and cut flowers [105]. Literature studying applications LCA's for supply chain management (SCM) is limited [106, 107]. Blass calls for increased interaction between LCA and SCM [107]. We hope to demonstrate how to effectively use LCA in Supply Chain Design for sustainability.

Most Life Cycle Assessments use lengthy data collection, interviews and time spent in the field. This is perfect for in depth analysis and provides a great deal of accuracy. However, not all companies have resources, or want to use the resources, to conduct an in depth LCA. However, there is incredible value in conducting rough estimate LCA's to identifies weak points in the supply chain. These rough LCA's may include a data from a variety of public sources that serve as estimations for the actual supply chain data. We propose the use of rough LCA's in combination with other strategies to help companies quickly identify areas of improvement for better sustainability.

4.2.2 Food Quality

Food quality is a feature that can describe value and or safety of a food product. Shelf life is a common measure of food quality, indicating how long food can remain on the shelf until spoiled. Most often food quality declines over time. Food quality is an important factor to measure in transit because the cost of low quality food. Poor quality food can lead to food-borne illness. Food borne illnesses annually cost the population of the U.S. alone over 50 billion dollars [108]. Food borne illness is often caused by food not being stored at the right temperature. Quality of food is largely impacted by the temperature in which it is stored. The impact of changes in temperature on food can be estimated through exponential functions as shown in [109, 110, 111, 112]. However, temperature control of food is very expensive. Temperature control requires a lot of energy and therefore releases a large amount of CO_2 emissions [2]. Food refrigeration contributes to 15% of global fossil fuel consumption and 40% of greenhouse effects [3]. When moving towards sustainability, it is important to consider the use of refrigeration and whether it is being done efficiently.

4.2.3 Flower Quality

Cut flower quality is equivalently an important feature in flower supply chains. However, unless they edible, low cut flower quality does not pose the same risk as low quality food. Cut flower quality is often measured by shelf life or vase life. Different authors provide different definitions of these terms. In this chapter, shelf life refers to the lifetime of a flower once it is cut on a farm to the time it wilts. We define vase life to be the lifetime a flower has once it reaches its end customer and sits in a vase with water. There have been several studies that study the reasons for reduced shelf life [113, 114, 115] and some that study the impact of transportation on shelf life [116, 117, 118]. However, unlike the many studies that build functions for food to estimate shelf life [109, 110, 111, 112], there are no models present in literature to estimate shelf life or vase life of cut flowers. This may be due to the fact that flower quality does not impact human health. There also have not been many papers concerning fresh cut flower transit in the last 10 years. We propose a simple cut flower decay model built from data in [119] and validate it using data drawn from [116]. The methodology to build this model can be duplicated for other products.

4.2.4 Transportation Planning for Perishable Goods

Transportation planning for perishable goods is a well studied field, and focuses mainly on optimization of delivery routes, and delivery time. Many incorporate food quality into their models. Rijgersberg builds a simulation model concerning the safety and distribution of iceberg lettuce [120]. Dabbene solved a perishable distribution planning model through a heuristic approach [121, 122]. Others expand to include factors like harvest time, horizontal collaboration, and temperature respectively [123, 124, 125]. However, there were few articles which considered customer segmentation as a factor to be considered in Transportation Planning, and we hope to show its importance.

4.2.5 Customer Segmentation

Customer Segmentation is widely studied in marketing. Customers often have different valuations towards the same kind of products with same quality [126]. Herbon studies a customers sensitivity to freshness and age of a perishable product relative to price [127, 128]. Chew studies dynamic pricing for perishable products that have multi period lifetimes [129]. However, this sensitivity to Customer Segmentation is largely only studied at the pricing and inventory level, not at the transportation level. We seek to show a framework for how customer segmentation can influence transportation modeling.

4.2.6 Summary

There is currently a lack of literature that addresses supply chain sustainability from a big picture perspective and incorporates LCA, customer segmentation and perishability models. We answer Blass's call for increased interaction between LCA and SCM [107] through the creation of a supply chain assessment framework that can be quickly used by companies to address potential improvements for sustainability in supply chain design.

4.3 Methodology

An outline of the Methodology we used for assessment can be seen in Figure 4.1 below:

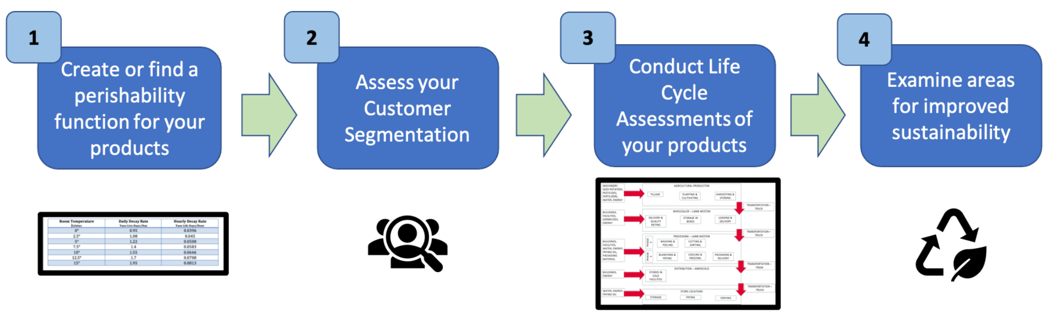

Figure 4.1: Outline of Sustainable Supply Chain Design Framework

4.3.1 Step 1: Create or find a perishability function for your products

30-40% of food is wasted in the United States [4] and 40% of those losses occur post harvest [5]. Therefore, it is important to understand the perishability rate and shelf life of products. Both of these components can help set constraints for transportation. Perishability is largely dependent on temperature [126], which is important to consider when different modes of transportation have different environments. Here, it is possible that you are shipping goods too quickly and the added cost does pay off in the end. These are considerations that must be weighed. You can find such perishability/decay models in literature or create your own as we do in the Cut Flower Case Study in Section 4.5.1.

4.3.2 Step 2: Assess Customer Segmentation

Customers often have different valuations towards the same kind of products with same quality [126]. Can you determine the different buckets your customers can be grouped into? You can determine Customer Segments by discussing with your marketing department and/or combing over past sales receipts. For example, if you are a fruit seller you may notice that the jam company that buys your fruit does not require it to be as fresh as the customer who uses the fruit in decorative pieces like a fruit arrangement. In fact, a strawberry with a 7 day shelf life is not worth any more than one with a 2 day shelf life to the jam seller but holds a great deal of difference to the fruit arranger. Does your supply chain network capture this difference? How can you change your network to capture this? Perhaps use the cheaper shipping vendor for the Jam customer as shelf life is not as important of a factor. Are there new customer segments you have not addressed that could help reduce product waste? These are the questions one must consider when looking at customer segmentation for logistics. We assess customer segmentation in the fresh cut flower case study.

4.3.3 Step 3: Conduct Life Cycle Assessments of products

According to Carnegie Mellon, an LCA is a ”way to investigate, estimate, and evaluate the environmental burdens caused by a material, product, process, or service throughout its life span.” By conducting LCA’s you can help evaluate both where the most money is being spent and where you are generating the most emissions. It can help easily identify where sustainability improvements can be made. Conducting a Life Cycle Assessment does not have to include a several month long process. Life Cycle Assessments can be as simple or as complicated as the user desires. Most literature focuses on creating LCA’s that are very detailed and very accurate, however, this can be time and cost prohibitive. Simple LCA’s can be done by using public data in combination with one or two interviews with those in the field. We explore the creation of such an LCA in the Quick Service Restaurant case study.

4.3.4 Step 4: Examine areas for improved sustainability

In this last step, take what you have learned from the previous steps and identify some improvements that can be made in your supply chain framework. Based on your situation, you can go for low cost improvements or you could go for high impact improvements. The steps we provided allow the user to see their big picture supply chain network. It can give you enough information to determine which approach to take. For example, perhaps the life cycle assessment was very useful, this could indicate that maybe you should expand the assessments to other products or conduct a more detailed and accurate assessment.

4.4 Case Study: Applying LCA in a Quick Service Restaurant Environment

In this case study, we address how to conduct a rough LCA calculation of a Quick Service Restaurant product. Particularly we are looking at fries at a Quick Service Restaurant.

4.4.1 Introduction

Quick Service Restaurants (QSRs) have begun to react to consumer pressure through the creation of climate strategies. These climate strategies often include initiatives to track food transit and understand the impact of different meals and ingredients. For example, Chipotle recently announced the release of their Real Foodprint initiative [130]. Chipotle's Real Foodprint "measures your impact on the planet, one ingredient at a time." Now, in a customer's app receipt they can see "the positive impact [they're] making on the planet by choosing Chipotle's real, responsibly sourced ingredients versus conventional ones," in categories like water, carbon emissions, antibiotics, and soil health. Other QSR's are more direct in their initiatives. For example, Panera Bread partnered with Cool Food to disclose the exact amount of carbon emissions for many of their menu items [131].

However, many QSR's have yet to create a climate strategy. One of these restaurants is the QSR we examine in this case study. Though climate strategies can be daunting, a simple way to start is through a Life cycle assessment (LCA) calculation of a menu item. An LCA is a "way to investigate, estimate, and evaluate the environmental burdens caused by a material, product, process, or service throughout its life span" [Carnegie Mellon]. Carnegie Mellon defines environmental burdens to be "the materials and energy resources required to create the product, as well as the wastes and emissions generated during the process." In this paper, we explore an initial LCA calculation for the QSR's fries.

4.4.2 Problem Statement

What are the total estimated CO2 emissions for this QSR's fries, from the farm to the hands of the end consumer?

We address this question through a process based LCA calculation of the entire fry supply chain by utilizing data from existing literature and reliable web sources.

Boundary of Analysis

Some assumptions and decisions were made in order to complete the LCA calculation in a reasonable time frame. First, we choose to focus on carbon emissions and have limited discussion on other wastes. This strategy was chosen in order to provide a definitive measurable output that can be compared to other QSR's disclosures. We only consider processes that contribute 5% or more to the overall supply chain, which was generally approximated based on available data. Next, we choose to do our calculation for a local Atlanta QSR restaurant location with the assumption that the potatoes are being sourced from Idaho. We also approximate distances traveled to the nearest 25 miles for ease of calculation.

4.4.3 Past Potato LCA Calculations

While there have been many environmental impact papers written about different food products, there are only a handful that address potatoes [103, 132], and even fewer that discuss French Fries specifically [133]. The most descriptive and complete study found was completed by Mouron et al. focusing on Swiss French Fries. They compared the impact of French fries to fresh potatoes in Switzerland, finding that 1 kg of French fries cause 3-5 times more environmental impact than the same weight of fresh potatoes. They noted that the frying process was the main "hot spot" in the supply chain for highest proportion of total environmental impact. Due to the comprehensiveness of this paper, we decided to use it as a baseline for comparison of our own LCA calculation [133].

4.4.4 Data

In order to complete our own LCA calculation, we pull data from the literature sources addressed in the previous section (excluding Mouron et al.) in combination with a few supplemental online sources. The majority of our data is drawn from Haverkort & Hillier's article in Potato Research which mainly supports the Agricultural Production and Wholesaler segments of the supply chain. We also draw information from Food Research International, the EPA, Corrugated.org and Curtin University of Technology. The sources of each component of the supply chain can be seen in the figures in the Methods section

4.4.5 Method

We complete a process based LCA calculation by using data from a number of sources. First, we outlined the entire Fry food supply chain. This image was adapted from the one created by Mouron et al. and information to populate it was gathered through informal interviews with different actors within the supply chain [133]. Note that the names of the centers are blacked out for confidentiality reasons. The inputs can be seen in the first column preceding the red arrows. The middle column outlines the processes

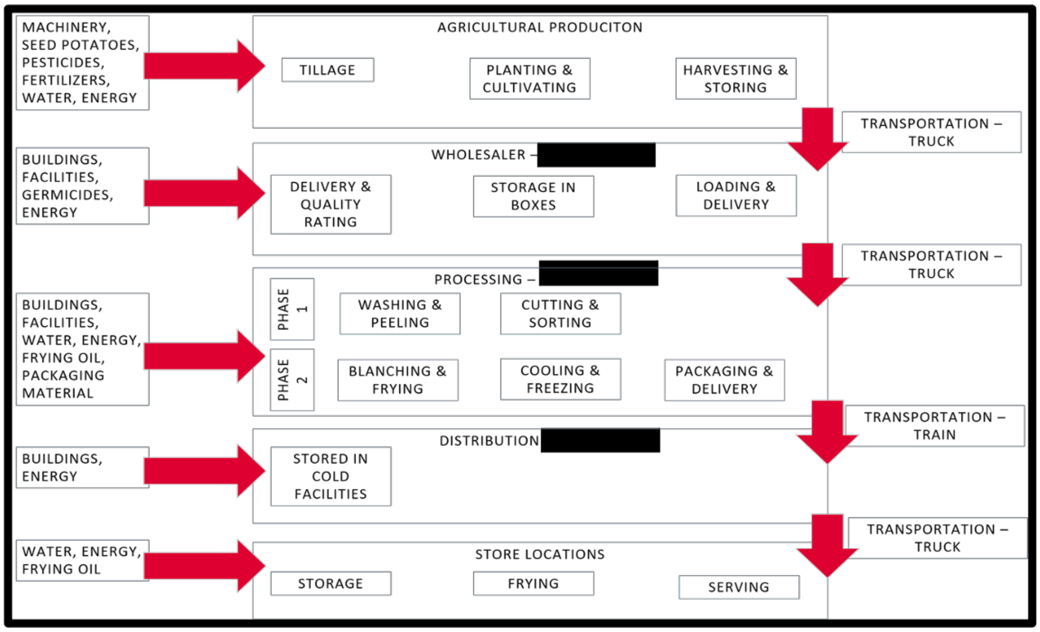

Figure 4.2: Estimated QSR Fry Supply Chain

involved and the right most column indicates transportation between different components of the supply chain. Using this chart, we break our calculations into 6 main components, Agricultural Production, the Wholesaler, Processing, Cold Distribution Storage, Store Locations and transportation. Each component is made up of one or more subcomponents for which we calculate the CO_2 emissions. In our case we convert input data into kg of CO_2 emissions/ 1lb of fries which is approximately the size of a large fry at at a QSR.

4.4.6 Impact Calculation

Agricultural Production

The first step in the process is Agricultural production. This includes everything from the planting of the potato seed to the harvesting and storage. The Potato Research article provides CO_2 emissions in kg/metric ton, so we convert this to lb/lb and then kg/lb for the final total component [132].

From this, we found that the subcomponent with the highest contribution was the Fertilizer & Biocides category due to their fumes. After our calculation we compared to our

Agricultural Production	Components	Source	Kg/ton	Lb/lb
Fertilizer & Biocides	Fertilizer, Biocides, Sprout Inhibition, Nitrification Inhibition, Fertilizer Technology, Slurry	Potato Research	248.4	.25
Water	Irrigation	Potato Research	1.1	0.001
Energy	Seeding, Operations, Storage	Potato Research	21.1	0.02
Induced Field Emissions	N2O Production from soil	Potato Research	25.1	0.025
			Total	0.296 or 0.13kg/lb

Figure 4.3: Breakdown of Agriculture Production Carbon Emissions

reference document (Mouron et al.) and foodemissions.com and found that our answer was in the same ballpark.

Source	Final CO_2 emissions
foodemissions.com	0.15 kg/lb
Mouron et al.	0.20 kg/lb
Our Calculation	0.13 kg/lb

Figure 4.4: Comparison of our results to other CO2 calculations

Wholesaler

The next step in the process was the wholesaler. Since the wholesaler simply stores the goods, there was little emissions produced in this step. There were two main sub components germicides to prevent the potatoes from rotting and energy needed to run the buildings. This data was also pulled from the Potato Research Article, so we converted from kg/metric ton to lb/lb and the total is converted to kg/lb.

Wholesaler	Components	Source	Kg/ton	Lb/lb
Germicides	Germicide	Potato Research	5.1	.005
Energy	Buildings	Potato Research	10.1	0.01
			Total	0.015 or 0.0068 kg/lb

Figure 4.5: Breakdown of Wholesaler Carbon Emissions

Processing

The next step was processing. We broke this into 3 subcomponents: Frying oil, Energy and Packaging. We cut out washing, peeling and cutting because we could not find reliable data for these processes. However, we expect them to be low, as more water is used for planting and even that was a negligible amount. In order to calculate the contribution of the Frying Oil, we took data from the EPA about the actual frying process (.0009 kg/lb) and the emissions of the oil itself from a paper done by Curtin University of Technology (.800 kg/lb). The frying process produces so few emissions because it happens within minutes. We estimated the oil used to fry one potato based on a review of several online recipes. We found that the larger the number of potatoes fried, the less amount of oil per potato needed so we estimated that a processing setting would use half the amount of oil per potato as compared to in restaurant due to the large batch volume occurring in processing plants. The building energy usage is the same as in the previous step. And lastly, we calculate processing by estimating the size/weight of a box (proportion of a larger box) needed for 1lb of potatoes and calculated the emissions using corrugated.org's carbon footprint calculator.

Processing	Components	Source	Varied	Kg/lb
Frying Oil	Deep Fat Fryer, Oil	EPA + Curtin University of Technology	40 kg/ton	.8009
Energy	Buildings	Potato Research	10.1 kg/ton	0.001
Packaging	Fraction of Box for shipping	Corrugated.org	-	0.006
			Total	0.808

Figure 4.6: Breakdown of Processing Carbon Emissions

Cold Distribution Storage

In cold distribution storage, we calculated the amount of emissions produced from cold storage of the fries. We took data from an article in Food Research International which told us the KW h/year used for 1 frozen chamber of 910 m^2. We then estimated the volume of one lb of fries and assumed that they would stay in cold storage for one week on average based on the information we received in interviews. We then estimated the amount of emissions used by that number of Kw/h using the Greenhouse Gas Equivalencies Calculator provided on the EPA's website.

Cold Distribution Storage	Components	Source	kg/lb
Energy	Building Refrigeration	Food Research International	.001
		Total	0.001 kg/lb

Figure 4.7: Breakdown of cold storage Carbon Emissions

Store Locations

For store location we use three main subcomponents of Frying Oil, Energy and Packaging. We calculate frying oil in the same manner that we did in processing except we assume that twice the oil per lb of potato is needed since they are being fried in much smaller batches. We assume the energy usage is the same as before. We realize that a restaurant likely uses a different amount of energy than a plant. However, since we were not able to find this information publicly, and the amount of energy was small we used the same data as used in previous steps. Lastly, we calculated the emissions of the fry holder. We first calculated the weight of the fry holder and then used corrugated.org's carbon footprint calculator.

Store Locations	Components	Source	Varied	Kg/lb
Frying Oil	Deep Fat Fryer, Oil	EPA + Curtin University of Technology	40 kg/ton	1.6009
Energy	Buildings	Potato Research	10.1 kg/ton	0.001
Packaging	Fry holder	Corrugated.org	-	0.005
			Total	1.607 kg/lb

Figure 4.8: Breakdown of individual QSR Store Location Carbon Emissions

Transportation

The final calculation was estimating the emissions produced in transportation throughout the supply chain. This included farm-to-wholesaler, processor-to-cold distribution and cold-distribution to stores. There was no calculation of wholesaler-processing because both the wholesaler and processor for the QSR were owned by the same company and the buildings were adjacent, requiring no transportation. The data used was taken from the EPA's 2014 Emission Factors for Greenhouse Gas Inventories. Distances were calculated assuming that the potatoes were sourced from Idaho and the cold distribution warehouse was located within 25 miles of the QSR store location. The QSR saves a lot of emissions by transporting their fries long haul by train. Trains produce far fewer emissions than trucks do.

Transportation	Components	Source	Kg/lb
Farm to Wholesaler	100 – miles	EPA	.015
Wholesaler to Processing	N/A	EPA	0
Processor to Cold Distribution	Train – 2000 miles	EPA	0.026
Cold Distribution to Stores	25 miles	EPA	.004
		Total	0.045 kg/lb

Figure 4.9: Breakdown of individual QSR Store Location Carbon Emissions

4.4.7 Results

When we add together the results from each of the 6 components, we find that each pound of fries produces 2.60 kg of CO2 as seen below:

Agriculture	Wholesaler	Processing	Cold Storage	Store	Transportation	Total
0.13	0.0068	.808	.001	1.607	0.045	2.60 kg/lb

Figure 4.10: Total emissions for QSR Fries

We acknowledge that this is a rough estimate of what the total Carbon Emissions would be for the QSR French Fry supply chain. We chose to focus on carbon emissions, other wastes that could have been examined in this LCA including rotten potatoes at the farm, food scraps at the restaurant, wastewater, and goods damaged in transportation. However, our results present a reasonable number for total emissions born from relatively reliable data sources.

Discussion

Based on our comparative research it seems like our final number for French fry carbon emissions does fall within the right ballpark when compared to Mouron et Al. and Pendo-Verlag [133].

Source	Final CO_2 emissions
Pendo-Verlag	2.59 kg/lb
Mouron et al.	0.45 kg/lb
Our Calculation	2.60 kg/lb

Figure 4.11: French fry emissions calculation comparison

However, it is interesting that Mouron's value is so small, especially since they were able to capture wastewater in their calculation. We were surprised that the French fry oil contributed the most to emissions. Our expectation was that the highest proportion of emissions would be generated by transportation and cold storage. With this information, it would be interesting to do further studies focusing on the cooking oil and comparing different types of cooking oil. Since it is by far the largest contributor, a change in cooking oil could drastically change the carbon emissions of the fries.

When comparing the emission of the fries to other QSR menu items we also find that the QSR's fries are on-par with its competitors. Figure 4.12 compares the final CO_2 emissions between a sampling of Cool Food Menu items found on Panera's current menu and the QSR's fries. Even though the oil used in frying contributed to a higher CO2 emissions final number, we still find it to be comparable to vegetarian options found at Panera.

4.4.8 Conclusion

In conclusion, we were able to answer our problem statement by calculating a process-based LCA for the selected QSR's fries. The number of emissions calculated was on par with comparative literature for French fries and fell within reasonable bounds for similar

Source	Final CO_2 emissions
Panera Vegetable Soup	0.97 kg/meal
Panera Mediterranean Bowl	1.74 kg/meal
Panera Broccoli Cheddar Soup	3.64 kg/meal
Panera Fuji Apple Salad with Chicken	4.48 kg/meal
[redacted] Fries	2.60 kg/meal

Figure 4.12: Comparison of carbon emissions of Different QSR menu items

menu items found at other QSR's. However, the biggest takeaway from this study was discovering that the largest contributor to emissions for the waffle fries was oil. Further research should delve into this further and figure out why oil produces such a high amount of carbon emissions. It may also be interesting to compare cooking methods and study whether baking fries results in a change in emissions. In a broader context, this study shows that it is possible to calculate a rough LCA on a short timeline (on the order of one month). It can also be used to identify areas for emissions reductions and improvement. This study format can be duplicated to fit other products to conduct rough estimate LCA calculations using public and limited interview data.

4.5 Case Study: Incorporating Decay and Customer Segmentation into Logistics Decisions in the Fresh Cut Flower Industry

4.5.1 Vase Life Decay/Perishability Model for Fresh Cut Roses

The ability to predict vase life in transit is useful for several reasons. Knowledge of vase life allows us to select transportation routes, which are cost effective and fall within conditions that result in a sellable flower. Knowledge of vase life can also affect pricing of flowers within stores and from wholesalers. Since there is no current flower decay/perishability function in relation to temperature, we created our own, using existing data found in horticulture literature [119, 116]. We created a table to identify vase life acceleration or deceleration at certain temperatures for fresh cut roses. The table is based data from Celikel's work [119] and then it is tested on data from Leonard's work [116] for validity. From this table, we are able to see that the vase life deterioration is suggested to be generally linear from 0° to 12.5°. For temperatures above 15° there is less data, but it is seen that the decay grows from linear to exponential. Once the temperature exceeds 20 degrees the rate of the decay can be upwards of 5 Vase Life Days/Day. This follows similarly to perishability models used in food [109, 110, 111, 112].

Rates below are based on *Temperature and Postharvest Performance of Rose (Rosa hybrida L.'First Red') and Gypsophila (Gypsophila paniculata L. 'Bristol Fairy') Flowers* by F.G. Çelikel M.S. Reid for the Rose [119].

Table 4.1: Rose Vase Life decay rate as a function of Temperature

Room Temperature Celsius	**Daily Decay Rate** Vase Live Days/Day	**Hourly Decay Rate** Vase Life Days/Hour
0°	0.95	0.0396
2.5°	1.08	0.045
5°	1.22	0.0508
7.5°	1.4	0.0583
10°	1.55	0.0646
12.5°	1.7	0.0708
15°	1.95	0.0813

Rates were tested with data from *Postharvest Performance of Selected Colombian Cut Flowers after Three Transport Systems to the United States* by Ria T. Leonard, Amy M. Alexander, and Terril A. Nell [116] for one day transist, three day transit and seven day transit. We simply apply our rates for the time spent at each temperature and we get the result seen in Figure 4.13. As shown in the graph, there is less than one day difference in each mode of transport between the prediction and the actual value showing the promise of our simple decay model.

This vase life predictor is can be used strategically when applied to customer segmentation in logistics.

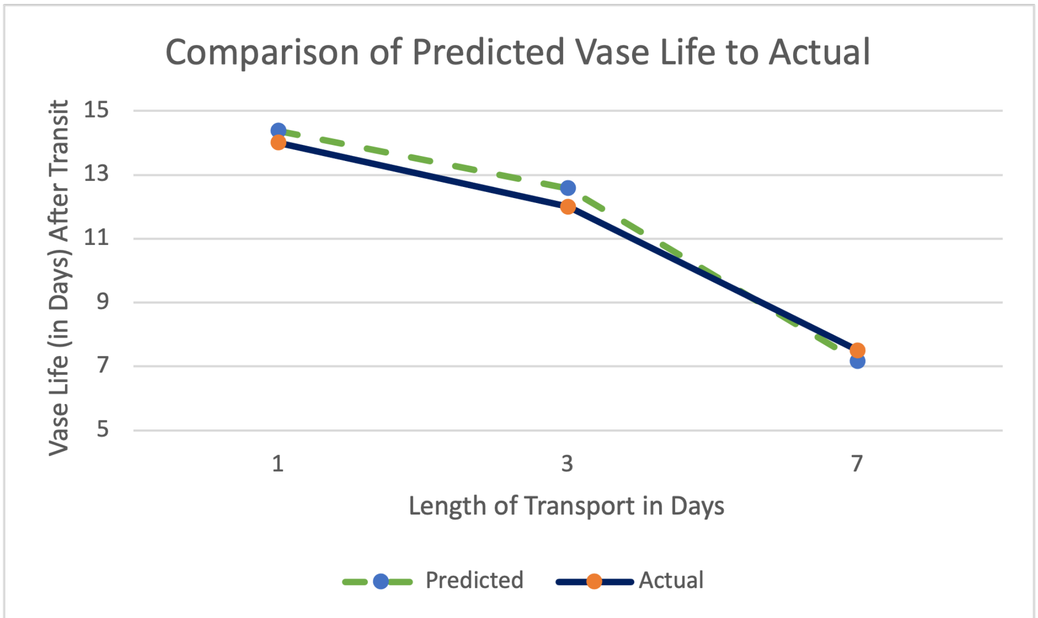

Figure 4.13: Comparison of Rose Vase Life Calculations between the results from our Decay model and the actual results from Leonard [116]

4.5.2 Flower Customer Segments and Their Supply Chain Impact

We use customer segmentation to address the different customers within the Fresh cut flower market place. Upon analysis, we realized that we need to eliminate the assumption that fresh food/products have to be shipped fast. As seen in the sections below, some customers do not need flowers to last for a long time. We can use this information to adjust logistics planning to save money.

Classical categorizations of flower customers are typically made up of the following groups: individual consumers, businesses and government agencies. Our in-depth examination of customers has revealed that a different classification can be achieved through characterizing why and how customers buy flowers. This has led us to build a functional customer categorization made up of spot customers, events customers, and subscription customers. This classification has profound impact on the understanding of flower demand and supply chains, for example challenging the generally accepted premise that fresh flower delivery must be fast.

Spot Customers

First, consider a customer who purchases flowers spontaneously, upon occasions such as a birthday, a date or Mothers' Day. This customer represents what we call a spot buyer. Such a customer will likely step into a flower store on the day of the occasion and purchase the flowers. A spot customer may alternatively order online for same-day or next-day delivery. The majority of spot customers likely do not buy flowers regularly. For spot customers, flowers are usually a gift or a treat for an individual or group of people (such as an office). Therefore, they generally want their purchased flowers to last a long time before decaying. Hence, both retail stores and online retailers have to be keen in insuring that they provide their spot customers with fresh flowers with a long vase life.

In order to fulfill spot customer demand, it is important that individual stores ensure that they have adequate stock of the desired flowers. To determine these desired flowers they must take into consideration their customer base and the impact of seasons and holidays. For example, around Valentine's Day they would want to make sure that they have a surplus of roses. Spot customers are likely to purchase during holidays. Thus, it is important for stores such as florist shops to have the ample stock of flowers signature to any upcoming holidays. There is also high uncertainty associated with spot customer demand and flower stores typically have low storage capacity. These factors lead to a need for securing fast replenishment sources in the case that flower stores near stockout on high demand days.

Spot customers ordering flowers from online retailers generally require fast delivery, either for the same day or next day. In order to minimize delivery lead-time and cost, online retailers should have access to nearby flower stock. For example, they could exploit stock in a nearby fulfillment center or at a neighboring florist shop. As online retailers are bound to have numerous spot customers, it is important for them to secure sufficient stock of flowers demanded by spot customers. Ample stock is necessary to guarantee that they maintain high service levels, notably in terms of flower availability. This also creates a secondary source of spot customer induced demand for flower stores serving as proximity fulfillers for online retailers.

Event Customers

Now consider what we call an event customer, one who is buying flowers for events such as weddings and ceremonies. Generally, such a customer orders routinely through an event/wedding planning business or through their functions within a large organization. In the case of a wedding or other special event, the events customer often wants special types of flowers, and significant amounts of each to create bouquets and arrangements. Such a customer is rarely impulsive and would plan the special events and their flower needs far in advance. They would buy the required flowers through regular sources such as national, local or online wholesalers and distributors.

In terms of the flowers themselves, events customers usually only need them to last a few days at the most, often the single day of the event. Furthermore, the customer is bound to prefer a fully bloomed flower to a still not yet fully opened flower as it is more majestic. The combination of advanced flower ordering and limited vase life requirements induces quite different supply chain requirements than in the case of spot customers. There is no inherent need for fast delivery from source to the location prescribed by the event customer, and there is no strong pressure to minimize the time from flower cutting in the field or the greenhouse and the time it reaches the customer specified location, as long vase life is not a key requirement. This said, it is paramount for the supply chain to take high care of the flowers through its storage, handling and transport in order for them to remain top quality.

Subscription Customers

Finally, consider customers who are subscription based, who like to have fresh flowers automatically delivered every week or every 2 weeks for example. We simply call these subscription customers. Some of these want the same type of flowers, or combination of flowers year long. They are the simplest to serve, as long as there is a yearlong harvesting supply of these flowers, as they are highly stable and predictable. Some other subscription customers will more likely prefer changes across the year, adapting to seasons and availability of flowers. These are somewhat less predictable yet may offer more flexibility, with the most flexible being those who permit the supplier decide on the set of flowers among a predetermined portfolio, allowing the supplier to advantage of seasonality and low-prices inducing overproduction relative to market needs.

As with events customers, subscription customers provide a luxury of supply chain time. Since these are consistent customers, the flowers may also be ordered far in advance by the supplier at low bundled prices. If the supplier knows that Customer X wants flowers every Friday, it can plan the shipment ahead of time, and will not need a rush order. Also, if they are receiving flowers every week, then the life span of the provided flowers before decay needs not be more than a week once it hits their doorstep.

4.5.3 Application of Customer Segments to Logistics Strategies

In the previous section, we discussed different customer segments and their needs. We can apply these needs to differentiated logistics plans as seen below. In each of these cases we are looking at the supply chain of fresh cut roses which have an expected shelf life of around 21 days from the cut at the farm to it wilting at the end customer. In each of these cases we identify the expected vase life, and then from there determine the allowance for days the roses spend in transit.

Spot Customers

Spot customers are what most consider traditional customers who order online for next day delivery or stop in a store to pick up some flowers. Of the three customer types they likely have the longest expectation for Vase life. In Figure 4.14, we see an overview of a spot customer that purchases roses in a flower shop.

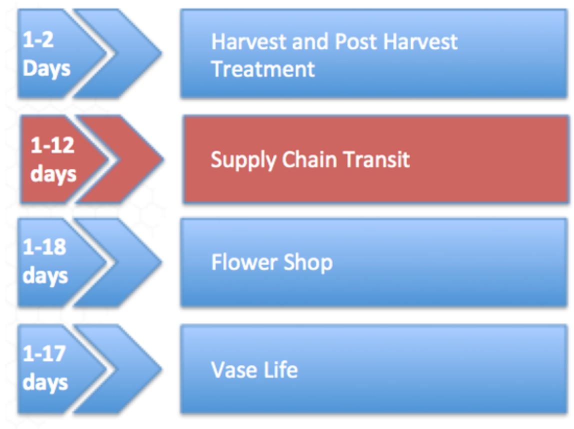

Figure 4.14: Overview of breakdown of logistics for a spot customer

Now if we focus on the component of supply chain transit, we see two examples of transit that could occur within the flexibility of the 1-12 days spent in supply chain transit in Figure 4.15.

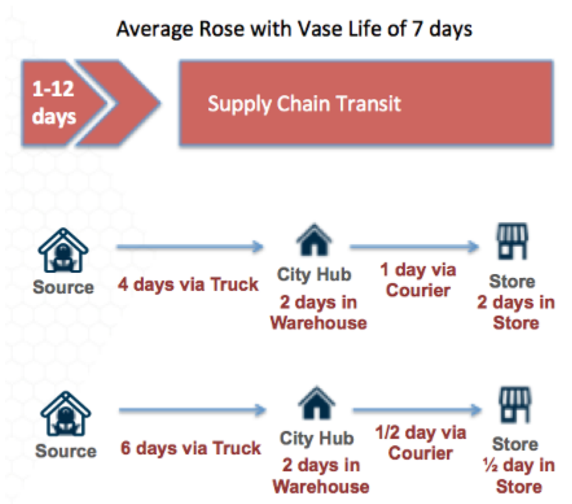

Figure 4.15: Spot Customer flower shop purchase potential supply chain transit

Event Customers

Event customers often make their purchases well in advance and only need a vase life for the span of the event. Of the three customer types, they likely have the shortest expectation for Vase life. In Figure 4.16 we see an overview of an event customer.

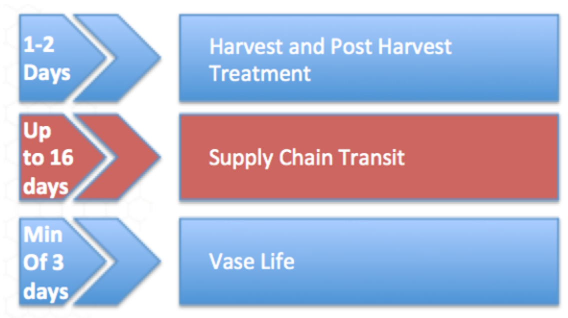

Figure 4.16: Overview of breakdown of logistics for a event customer

Now if we focus on the component of supply chain transit, we see two examples of transit that could occur within the flexibility of the 1-16 days spent in supply chain transit in Figure 4.17.

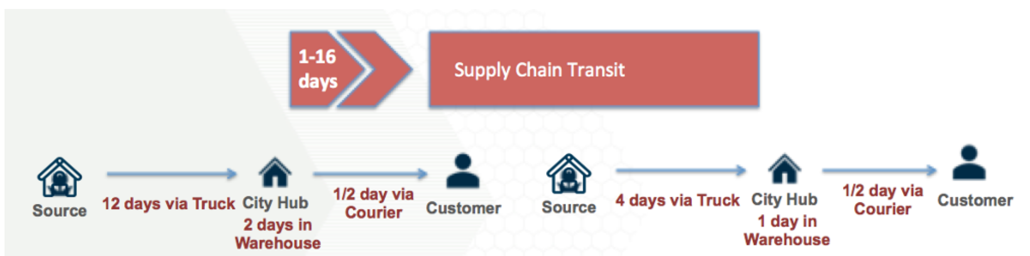

Figure 4.17: Event flower shop purchase potential supply chain transit

Subscription Customers

Subscription customers have flowers delivered on a recurrign basis. For these customers, it is most important that the vase life lasts until the next delivery. In Figure 4.18 we see an overview of a subscription customer that has a weekly subscription.

Now if we focus on the component of supply chain transit, we see an example of transit that could occur within the flexibility of the 1-13 days spent in supply chain transit for a weekly subscription customer in Figure 4.19.

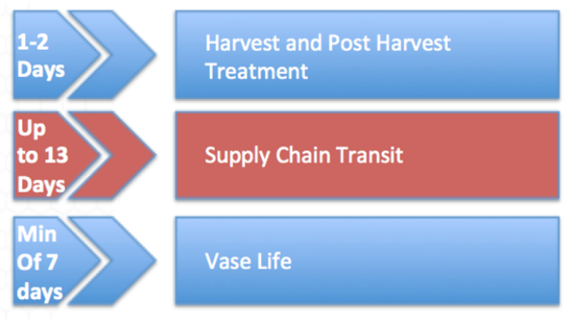

Figure 4.18: Overview of breakdown of logistics for a subscription customer

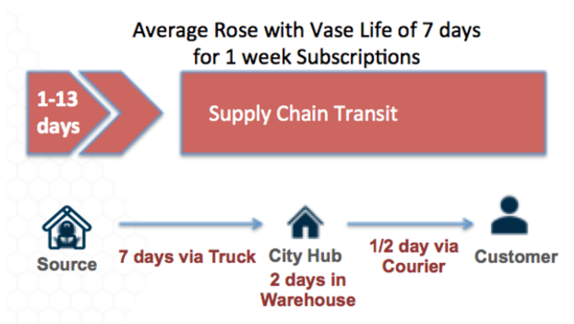

Figure 4.19: Weekly Subscription Customer potential supply chain transit

4.5.4 Conclusion

In this case study, we are able to create a decay formula that can be used in conjunction with customer segmentation to rethink cut flower logistics. By opening our mindset to realizing the fresh deliveries do not always need to be fast, there are more transportation opportunities. Instead of using fast truck or air transit, it may be cheaper and more energy efficient to look at other modes of transportation like by sea, rail or long haul truck shipping based on the customer segment. This can potentially improve sustainability of transit.

4.6 Conclusion

In this chapter we have proposed a three-prong system to examine the state of a company's supply chain and identify improvements that can be made to increase sustainability through: the creation or adaptation of a perishability or decay model, customer segmentation analysis for logistics, and Life Cycle Assessment (LCA) Calculations. We were able to test each of these prongs through well defined case studies. We apply the LCA calculation to a case study concerning a QSR's fries. We then use customer segmentation and decay modeling to shape logistics strategies for the fresh cut flower industry. Through both of these case studies we demonstrate how this framework can be applied across different fresh industries.

This strategy can be applied to companies who quickly want to assess their supply chains and look for changes to improve sustainability. It provides a framework that can generate questions and help analysts understand their supply chains at a big picture level. The Atlanta QSR that was examined in the french fry case study, presented our analysis in a board meeting at the corporate level to help support a new sustainability initiative within the company. Their case was successful. The case study concerning fresh cut flowers was used by an international logistics provider to help restructure the way they thought about flower transit. These two examples demonstrate the usefulness of our methodology to companies in industry. We provide a framework that can be used as a first step in building an effort to address sustainability.

In future work we would like to see applications of some of the methodologies discussed in this work directly into routing algorithms. For example, adding customer segmentation and decay to the vehicle routing problem to better assign vehicles reducing waste. We would also like to see routing focused on sustainability, where routing is a multi-objective model for cost and emissions with incorporation of LCA and decay modeling. A first application area could be the fresh cut flower industry, as there has been little improvement in routing efforts in the last 10 years.

CHAPTER 5
CONCLUSION AND FUTURE RESEARCH

5.1 Summary of Contributions and Results

In this dissertation we have presented a series of frameworks to manage fresh supply chains and improve their infrastructure. By utilizing methodology from Operations Research, GIS and Strategic Management, we build hybrid models that are able to accurately capture the intricacies within Fresh Supply Chains. We have applied each of our methodologies to case studies within local food, quick service restaurant and the fresh cut flower industries. Our methodologies have been implemented by companies ranging from startups to fortune 500 companies, illustrating their usefulness and importance.

In our chapter on market deployment, we build a framework that companies can use to plan their market expansion. We start from the bottom up by using semi-structured interviews to capture the input of leaders across the supply chain. This is important because in most papers that use executive factors, the authors create the factors themselves, leaving themselves open to missed factors. We then create a unique complementary solution approach which utilizes both optimization and heuristic methods which provide alternative roadmaps to be considered by the decision maker. In both of our models we are able to capture dynamic model across a time horizon which is not commonly done in market deployment models. Our model was applied by a farm-to-table Atlanta based platform and one heuristic roadmaps was implemented.

In our chapter on mobile hubs, we build a framework for selecting effective dynamic hub location. In this hub location problem we address a small local system, with service (time) requirements, and real transportation costs. This addresses a gap in literature for models that consider systems with ”more realistic transportation costs and service measures.” We also explore a smaller network for which traditional hub location models do not work as well. Our model was applied to a farm-to-table Atlanta based platform and a mobile hub was implemented and lead to cost savings and service improvements.

In our chapter on Sustainable Supply Chain Design, we address the industry need for a model to assess the current state of fresh supply chains analytically and identify areas for improvement in sustainability goals. Fresh supply chains have the unique added characteristic of perishability that many other supply chains do not have. We create a framework, that incorporates a decay model, customer segmentation and LCAs, that can be done within a month and provide a base for more sustainability efforts to take place within the company. We explored a case study on fresh cut flowers where we built a decay model and used it in combination with customer segmentation to address improvements that could be made in logistics strategies. We also conducted a case study analyzing a Quick Service Restaurant which looked at using LCAs to identify areas that could be improved for better sustainability. Our model has been implemented by both a Fortune 500 QSR and an international logistics provider.

In summary, this dissertation has addressed the two main types of fresh supply chains. One that does not need to consider perishability, local supply chains, and one that does - national or international supply chains. In Chapters 1 and 2 we address the needs of local fresh supply chains and create frameworks to improve their infrastructure. In Chapter 3, we create a framework to be used by established larger fresh supply chains to quickly assess areas to improve for better sustainability.

5.2 Future Research

5.2.1 Market Deployment

- Incorporation of product differentiation seasonality into the model, considering the origins of products (meat, produce, dairy).

- Extension to cases where there is demand for fresh food grown in farms not necessarily in the same market, and downstream growth in a market's demand depends on multi-category food supply offering from farms.
- Examine resiliency in supply chain networks that can be generated through Market Deployment Frameworks by focusing on supply chain collaboration, supplier selection and supply chain network design.

5.2.2 Mobile Hubs

- Show the statistical significance of stop and distance reductions through t-testing on a larger set of days with a cost analysis of the hubs used.
- Investigation of the impact of time sensitivity, such as accounting for preferred and detrimental delivery times at client locations, as well as synchronicity impacts of arrival and departure times at the hub on overall performance.
- Application of work to other local supply chains such as local disaster relief or distribution of left over food at the restaurant level.

5.2.3 Sustainable Supply Chain Design

- Applications of some of the methodologies discussed in this work like LCA and decay modeling, directly into routing algorithms like the vehicle routing problem, specifically studying waste.
- Development of Multi-objective models considering cost and emissions with incorporation of LCA and decay modeling, especially within the fresh cut flower industry, as there has been little improvement in routing efforts in the last 10 years.
- Analysis of the performance of this model in other industries within Fresh Supply Chains.

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