A ROBUST OPTIMIZATION APPROACH TO MANAGE UNCERTAINTY IN LOCAL AGRICULTURAL PRODUCTION IN MID-WESTERN UNITED STATES

A Thesis presented to

The Faculty of the Graduate School

At the University of Missouri-Columbia

In Partial Fulfillment

Of the Requirements for the Degree

Master of Science, Industrial Engineering- Operations Research

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By

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JULY 2019

The undersigned appointed by the Dean of the Graduate School, have examined the thesis entitled:

A ROBUST OPTIMIZATION APPROACH TO MANAGE UNCERTAINTY IN LOCAL AGRICULTURAL PRODUCTION IN MID-WESTERN UNITED STATES

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a candidate for the degree of Master of Science and hereby confirm that, in their opinion,

is worthy of acceptance.

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Dr. Sharan Srinivas

Dr. Mary Hendrickson

ACKNOWLEGDEMENTS

I am thankful to my adviser, Dr. Ronald McGarvey, for his guidance, patience and understanding throughout the duration of the research. His mentorship has played a pivotal role in shaping my overall experience at the University of Missouri. It has been a pleasure to work under him and I sincerely thank him for making my Master's journey a memorable one. I would also like to thank Dr. Sharan Srinivas and Dr. Mary Hendrickson for their suggestions throughout the duration of the thesis and offering encouraging feedback during my oral defense.

I would also like to thank Melissa and Rae from the Missouri Coalition for the Environment (MCE) for giving me the opportunity to work with them. It was a pleasure collaborating with them over the course of the year and I hope we get to work again in the future.

I would like to thank the Industrial Engineering department collectively for providing me with the platform to excel in my academic as well as social life. The support provided by my Professors and peers has been instrumental in my development.

Finally, I would like to thank my parents, Narendra and Neelam, and my younger brother Nitish, for their love and support and providing me with the resources that have allowed me to reach my full potential. It has been a journey of emotions and I would not have completed it without them.

Table of Contents

LIST OF TABLES

Table Page

LIST OF FIGURES

Figure Page

ABSTRACT

Rapid industrialization of agricultural production in developed economies, advancements in information and logistics technologies, emergence of modern food retailers, customer concerns and increased food safety regulations has called for the adoption of supply chain management in the agriculture sector. The agriculture supply chain consists of a series of events in a "farm-to-fork" sequence that includes farming, processing, testing, packaging, warehousing, transportation and distribution. In this thesis, we developed a robust optimization approach to assist the Missouri Coalition for the Environment (MCE) in helping farmers from Missouri and Illinois route products from their farms to a central hub in St. Louis. The aim of this study was to minimize the ton-miles traveled by farmers and MCE vehicles in delivering agricultural products from farms to regional hubs to the central hub. First, a deterministic model was developed that considered the average production at all farms. After looking at historical data about variability of plant and animal products in the Greater Plains region, we developed a robust optimization model accounting for up to 50% variability in these annual production levels at farms. GAMS/CPLEX was used to solve the model under different configurations and identify potential locations for regional hubs.

Chapter 1

Introduction

A supply chain network consists of a series of stages that are physically distinct at which not only inventory of finished goods but also raw materials, subassemblies, etc. is stored and distributed upstream or downstream depending on the nature of the supply chain. The various decisions involved in building a supply chain can be broadly categorized into 3 categories- *strategic, tactical and operational(Ravindran & Warsing, 2012).* Strategic decisions are primarily concerned with the design of the supply chain network. These decisions are made over a relatively long period and have a greater impact on the company's resources. Examples of strategic decisions include selecting sites for facilities, setting up IT infrastructure, etc. Tactical decisions are planning decisions and are made over shorter time periods compared to strategic decisions and are made in an environment characterized by less uncertainty. Examples of tactical decisions are production planning decisions, purchasing decisions, etc. Operational decisions are short-term decisions made daily or weekly and typically have lesser impact over the company's resources. Examples include setting delivery schedules for suppliers, setting due dates for customer orders, etc. In this study, we focus on the strategic decision of locating and assigning regional hubs to farms in an agricultural network.

In the U.S., agriculture, food, and related industries contributed $992 billion to the gross domestic product (GDP) in 2015 (27% increase from a decade ago), a 5.5-percent share (Rosanna Mentzer Morrison, 2019, April 16). In 2012, U.S. agricultural land area amounted to nearly half of the total land area (Rosanna Mentzer Morrison, 2019, April 16).

In 2017 alone, 21.6 million jobs were directly related to the agricultural and food sectors which accounted for 11 percent of total U.S. employment. The U.S. population is projected to increase to 438 million in 2050 (Passel & Cohn, 2008), up from 328 million in 2019 and supply chains will play a key role in delivering food from farms to cities where much of the population resides.

A typical agricultural supply chain consists of farmers loading their products on trucks and delivering them to their closest regional hubs. The products are then transferred to the central hub where they are stored and later redistributed. In recent years, U.S. agricultural movements represented 30 percent of all ton-miles moved on highways, railroads, and waterways ("Agricultural Transportation Research and Information Center,") which is why it is extremely important to make the strategic decision of locating the appropriate number of regional hubs and assigning farms to them in order to minimize the distance traveled by farmers in the network.

Facility location models in the agricultural supply chain can be classified into two categories. The first category attempts to trade-off cost incurred in building a facility to the cost of transporting product from the farms to the regional hubs in our case. Literature has shown that as the number of potential drop-off locations is increased, the outbound distance (farmers to the regional hubs) traveled decreases (Love, Morris, & Wesolowsky, 1988).

The second category of problems tackles this issue from an environmental perspective. In the past 10 years, there has been an increased focus on problems caused by climate change. Several methods such as life cycle assessment (LCA) and carbon footprinting (CF) have been used to analyze the total impact of agricultural products on greenhouse gas emissions (GHG) from cradle to grave. According to (E. Svanes & A. K. S. Aronsson, 2013),

transportation and storage together account for 67% of the CF in the banana supply chain. Recognizing the impact that transportation has on the environment, this study attempts to reduce the gallons of fuel consumed and therefore the GHG emissions, by minimizing the ton-miles traveled in delivering agricultural products from farms to the central hub over a period of 12 months. It is important to note that this approach serves a dual purpose in that, cost incurred in transportation can also be derived based on the price of fuel in $/gallon.

The central concern in any facility location problem is to determine site/s for one or more new facilities with respect to a set of fixed points, typically referred to as demand points with which the new facility will interact (Love et al., 1988). The location of facilities can be determined by two methods: discrete or site selection models and continuous or site generation models. In discrete models, the location of sites is known *a priori*, represented by discrete variables (Love et al., 1988). In continuous location models, all points in the convex hull of the current sites are under consideration and the model decides the precise location for the new sites within this convex hull. For this study, we will assume that the potential new facility sites are known.

The agricultural supply chain involves plenty of strategic, tactical and operational decisions and researchers have developed mathematical models addressing these issues. Studies have included decisions such as purchasing, storage, pricing and demand, transportation, allocation, etc. Perishability of products makes managing inventory even more difficult as vendors must consider the cost of deterioration along with the carrying cost (Abad, 2003). Plenty of researchers have developed models accounting for perishability of products over a finite horizon (Akcay, Natarajan, & Xu, 2010; H. K. Chen, Hsueh, & Chang, 2009; Gallego & Hu, 2014; Wang, Wang, Ruan, & Zhan, 2016). The uncertainty in production

at farms combined with the uncertainty in demand at the retailers makes the problem even harder to solve. Researchers have utilized various tools at their disposal to address these uncertainties, such as stochastic programming, simulation models, and chance-constrained optimization to minimize the expected costs incurred in producing, storing and transporting product from farms to customers (Soto-Silva, Nadal-Roig, Gonzalez-Araya, & Pla-Aragones, 2016).

This research was motivated by a project with Missouri Coalition for the Environment (MCE) which is a non-profit state-level conservation organization located in St. Louis, Missouri. The organization's goal for this project is to route supplies from farms located within its network in Missouri and Illinois to its central hub located in St. Louis, Missouri, at minimum total distance. The quality of perishable food whether plant or animal decreases rapidly once they are produced and will keep decaying while being delivered (H. K. Chen et al., 2009). The revenue of the retailer and thus the farmer depends on the freshness of the products when they are delivered. Also, according to (Erik Svanes & Anna K. S. Aronsson, 2013), transportation accounts for the majority of costs in a supply chain for perishable products. Currently, farmers do not have fixed drop-off points to deliver their products and they end up traveling long distances to sell their products through different means like farmer's markets, community supported agriculture (CSA's), etc. resulting in not only additional transportation cost and lost revenue because of spoilage which is a result of highly unpredictable demand at these places but also increased GHG emissions and CF. In this study, a network of regional hubs is established, such that farmers transport their products a relatively short distance to a nearby regional hub, allowing

products to be consolidated at the regional hubs, creating increased density (and thus higher efficiency) over the longer regional hub-to-central hub transport legs..

In our study, we have selected potential candidate locations where regional hubs can be placed and how farmers can be assigned to them based on the number of hubs that MOE plans to construct. There are currently 171 farms under consideration that need to deliver their products. Products across different farms varied from vegetables, crops, value-added products, poultry, dairy, grains, etc. According to (Varnam, Sutherland, & Sutherland, 1995) the growth of spoilage organisms like pathogens and bacteria which grow exponentially over time, limit the shelf-life of meat, which is why it should always be refrigerated. For simplification, the products were divided into plant and animal type anticipating the additional need for refrigeration equipment in vehicles transporting animal products. A mixed integer linear program (MILP) was developed to determine how the two types of products would be delivered from farms to the central hub via the regional hubs. The objective function minimizes the total ton-miles traveled from the individual farms to the regional hubs and from the regional hubs to the central hub. As the farmers deliver their product over a period of 12 months on a weekly basis, the model was run for 52 time periods. Two versions of the model were considered- *deterministic and robust.* The deterministic model identifies the assignment of farms to regional hubs and the number of vehicles of each type (Plant or Animal) that travel from the regional hubs to the central hub to deliver the product. Because of uncertainty in production at farms, we assumed that production of Plant and Animal products at each farm has an upper and lower bound beyond its nominal value. The problem was coded using the General Algebraic Modeling Software (GAMS) and the solution was found using the CPLEX solver for both the

deterministic (i.e., nominal-value) and robust optimization (i.e., accounting for variations around the nominal values) versions of the problem. Based on historical data for the 2017-2018 year, the optimization models were able to tell us which sites should be selected for the regional hubs, how farmers would be assigned to the hubs and how many vehicles of Plant and Animal type would travel from the regional hubs to the central hub every week.

The remaining thesis is organized as follows. Chapter 2 provides an in-depth literature review of various optimization techniques that have been utilized to solve supply chain problems in the agricultural sector. Chapter 3 presents the two approaches that we considered for solving the problem under study along with their mathematical models. The solutions obtained from the models are discussed in Chapter 4, and in Chapter 5 conclusion is provided along with scope for future research.

Chapter 2

Literature Review

Research on agricultural supply chains (ASC) dates to the early 1950's when (Thornthwaite, 1953) determined the proper time to harvest peas for freezing on a 7000 acre farm developed a dynamic linear programming model to optimize resources needed in apple orchards by determining the optimum mix of different varieties of apples. They also developed a schedule to sow peas on farms in such a way as to minimize strain on labor resources. However, it is only in the last decade that the agricultural industry has recognized and started to embrace SCM and OR tools for its competitiveness (Lucas & Chhajed, 2004). The rapid industrialization of agricultural production in developed economies, advancements in information and logistics technologies, emergence of modern food retailers, customer concerns and increased food safety regulations are just few of the real-world challenges that have led to the adoption of SCM in the agriculture sector (Tsolakis, Keramydas, Toka, Aidonis, & Iakovou, 2014).

The ASC consists of a series of events in a "farm-to-fork" sequence that includes farming, processing, testing, packaging, warehousing, transportation and distribution (Iakovou, Vlachos, Achillas, & Anastasiadis, 2012) and supports primarily three kinds of flows, namely (i) product flow, (ii) financial flow, and (iii) information flow.

A review of ASC literature shows that most studies trade off the cost of building a facility to the cost incurred in transportation (Bohle, Maturana, & Vera, 2010; Bowling, Ponce-Ortega, & El-Halwagi, 2011; Kocoloski, Griffin, & Matthews, 2011; Saranwong &

Likasiri, 2017). The benefit of adopting such an analysis is that it helps decision-makers explore a wide variety of alternatives. The analysis is an excellent tool to determine whether the perceived benefits of a project outweigh expected costs in the long run. However, very fewer studies analyzed the environmental impact due to farming (Tegtmeier & Duffy, 2004), or perishability of products (Hickey & Ozbay, 2014) or transportation (González-Araya, Soto-Silva, & Espejo, 2015). Most studies that we came across either tried to maximize profit, revenue, yield, etc. or minimize cost, inventory levels, etc. (Erik Svanes & Anna K. S. Aronsson, 2013) shows that transportation accounts for the largest contributors to GHG emissions in an agricultural supply chain which is why for the purpose of this research, we will minimize the total ton-miles traveled across inbound (intermediate hubs to central hub) and outbound (farms to intermediate hubs) transportation.

2.1. Decision Level.

From a decision level perspective, (Soto-Silva et al., 2016) give a very good understanding of different decisions involved at the strategic, tactical and operational levels of an ASC.

Strategic level decisions, primarily concerned with high-level decisions that are relevant to whole organizations and overall business strategy, involve location, supplier selection, investment decisions, etc. and a rich body of literature has addressed problems on these decisions. (Saranwong & Likasiri, 2017) used a combination of MIP and heuristics and developed a bi-level model to transport produce from sugarcane farms to plants via intermediate hubs. (Blanco, Masini, Petracci, & Bandoni, 2005) developed a supply chain planning model to determine production capacity at a facility and maximize profits by considering raw material, storage and labor costs. (Catala, Durand, Blanco, & Bandoni,

2013) developed a strategic planning model to determine optimal investment policies for farms to maximize net present value.

Tactical decisions are shorter in scope and have a lower impact than their strategic counterparts and require less of the company's resources. For tactical supply-chain planning, the decision options and factors affecting them (eg production capacity, distribution capacity, demand forecast, variable costs) are clearly defined (MIT Sloan Management Review, 2003, October 15). (Bohle et al., 2010) developed a mixed integer robust optimization model to maximize profit under labor uncertainty. (González-Araya et al., 2015) developed an optimization model to minimize labor costs, equipment uses, and loss of fruit quality to meet demand. Their model led to a 16 percent decrease in both labor costs and loss of income when applied to three apple orchards in Chile. (W. C. Chen, Li, & Jin, 2016) developed inventory models to determine the optimal replenishment policy of an integrated ASC under stochastic demand. Compared to traditional methods, they observed a 16.27 percent decrease in cost if the SC adopt the new replenishment policy.

Operational decisions are characterized by the least uncertainty and are shorter in scope than tactical decisions. Operational decisions are made numerous times each day in a company. These are decisions that affect how products are manufactured, moved and sold to customers locally. In a manufacturing environment, an operational decision could involve maintaining inventory levels to avoid stockouts. In logistics, local management must make decisions to deliver products to customers where 3PL's cannot deliver by negotiating with regional logistics companies. (Bai, Burke, & Kendall, 2008) developed inventory control and shelf space allocation models to maximize profits in a store. The models are solved and compared for multiple products using four greedy heuristics.

(Ampatzidis, Vougioukas, Whiting, & Zhang, 2014) utilized a modified machine repair model (MRM) to model fruit harvest and bin loading and determine the appropriate number of workers and machines to improve the overall harvesting process. (Nadal-Roig & Pla, 2014) developed a linear programming model to help pig managers of multisite systems make short-term decisions on pig transfers between farms during multiple periods to maximize the total gross margin.

Table 2- 1 shows the classification of these papers based on the decision levels they tackle.

Author	**Decision Level**		
	Strategic	**Tactical**	**Operational**
Blanco et al. (2005)	X	X	
Bai et al. (2008)			X
Van Der Vorst et al. (2014)	X	X	
Bohle et al. (2010)		X	X
Sharma et al. (2014)	X		
Banaeian et al. (2012)		X	
Ampatzidis et al. (2013)			X
Amorim et al. (2012)		X	X
Català et al. (2013)	X		
Gonzàlez-Araya et al. (2015)		X	X
Nadal-Roig and Plà (2015)			X
Sawik (2015)	X	X	
Wenchong Chen et al. (2016)		X	
Saranwong & Likasiri (2016)	X		
da Silva and Marins (2014)	X	X	
Zhang and Guo (2018)		X	

Table 2- 1: Literature Review based on Decision Levels in Supply Chain.

2.2. Mathematical modeling techniques.

Applications of quantitative models to the ASC date back decades. Modeling approaches in agriculture have been used in problems related to production, transportation, distribution, facility location, and risk management. MIP has been the mostly widely used approach to solve problems partly because of its ability to model various scenarios as well as availability of a variety of solvers to solve such problems to optimality. However, tremendous advancements in the field of computing and increasing complexity decisions

involved in ASC over the years, researchers have adopted a variety of tools to tackle problems. The following section provides a brief overview of some of these techniques:

2.2.1. Multi Objective Programming

Multi objective programming involves optimizing a collection of objective functions simultaneously. As opposed to single objective optimization, a solution to multi-objective optimization involves determining a set of points that all fit a predetermined definition for an optimal solution (Marler & Arora, 2004). The predetermined concept in defining the optimal point is of *Pareto optimality* (Pareto, 1906). (Klein, Holzkamper, Calanca, Seppelt, & Fuhrer, 2013) utilized multi-objective optimization to identify optimum land management for a crop under conflicting productivity and environmental goals.

2.2.2. Simulation

Simulation is used as a substitute to optimization models when the problem under consideration is too complicated and often difficult to express by mathematical equations. Due to exponential increase in computing power during recent decades, the field of computer simulation has been gaining a lot of attention and researchers have utilized it in a variety of fields including finance, military, manufacturing, etc. (Sulistyawati, Noble, & Roderick, 2005) employed simulation to study the impacts of greater involvement of cash cropping in swidden agriculture. Their model simulated land use decisions on the type, number and location of swidden cultivation and tracked the consequences of those decisions at the landscape level as well as the economic welfare of households. They applied their simulated model to the cultivation of rice as well as explored different land strategies under scenarios of fluctuating price of rubber crop.

2.2.3. Heuristics

As the problem size increases so does the search space, and the time required to arrive at an optimal solution increases exponentially. Even with today's computing prowess, it takes considerable time (weeks or even months in some cases) to arrive at the optimal answer. This led to the birth of heuristics which are procedures used to reduce the number of searches in problem-solving (Tonge, 1961) or means to obtain meaningful solutions within limited computing time (Lin, 1975). Over the years, researchers have put forth various heuristics, some inspired by nature (ant colony optimization, genetic algorithms, etc.), to obtain acceptable (not optimal) solutions to difficult problems quickly. (Davijani, Banihabib, Anvar, & Hashemi, 2016) utilized genetic algorithm and particle swarm optimization to optimally allocate water resources between agriculture and industry sectors.

Often there are multiple uncertainties that can occur within a supply chain (weather conditions, animal or crop diseases, price variability, etc.). Hence it is imperative to account for variability while modeling ASC problems. Over the years, researchers have developed numerous techniques to account for uncertainty while solving problems in ASC. The following section provides a brief summary of some of these methods:

2.2.4. Stochastic Optimization

Stochastic optimization (SO) includes a wide array of techniques for minimizing or maximizing an objective function in the presence of randomness. Randomness can be associated with the objective function coefficients, or constraint coefficients, or both. Often, stochastic optimization involves the assumption that the underlying probability

distribution of the unknown outcome is known. However, that is rarely true. One way to tackle this is to estimate the distribution from the relevant data, and then to use this estimated distribution in stochastic optimization. Since its inception in 1955, it has found applications in essentially all fields. Unlike deterministic optimization there is no single solution in SO. Instead, we usually try to optimize the expected value.

2.2.4.1. Multi-stage stochastic optimization

Multi-stage SO problems involve making an optimal sequence of decisions over an extended period to minimize or maximize an expected cost function. Examples include determining inventory policies for a product over ten years in the face of uncertain demand, scheduling water releases from dams over a two-year period, making moves in a game of chess, etc. Multi-stage SO problems are hard to solve, and solution methodologies are problem specific. This is because, decisions made at every stage affect all future decisions. (W. C. Chen et al., 2016) developed a multi-period stochastic inventory model to determine order replenishment policies to minimize total supply chain cost over the planning horizon. (Sawik, 2016) developed a multi-period stochastic MIP model under risk with weighted bi-objective criteria in a multi-echelon supply chain.

2.2.4.2. Chance constrained optimization

(Charnes & Cooper, 1959) first developed chance constrained programming (CCP) in 1959 to solve optimization problems under uncertainty. CCP has found applications in energy management, risk management as well as finance because of its robustness. In CCP, certain constraints are violated by the model with given probability values (Charnes & Cooper, 1959). It is generally difficult to solve CCP problems because checking the feasibility of

an obtained solution is almost impossible and since the feasible region is typically non-convex, optimizing the objective function is quite challenging (Ahmed, 2014). (Xu & Qin, 2010) developed an inexact double-side fuzzy CCP model for agricultural water quality management under uncertainties. They allowed violation of constraints at specified confidence intervals. (Zhang & Guo, 2018) utilized fractional linear programming and fuzzy chance-constrained programming and applied it to an agricultural water management system to develop irrigation schedules for crops.

2.2.5 Fuzzy optimization

Fuzzy mathematical programming (FMP) was first developed by Bellman and Zadeh (Bellman & Zadeh, 1970). In FMP, a real-world problem is first modeled using fuzzy parameters. FMP problems are solved in three phases. First, the fuzzy model is converted to a mathematical model by managing the uncertainties based on various interpretations of the problem. Then, the model is solved to optimality using one of the many known optimization techniques. It is important to note that this solution is not the optimal solution to the original fuzzy problem, which is why in the third phase, the optimality check is performed (Inuiguchi & Ramik, 2000). (Sharma, 2016) utilized fuzzy goal programming for optimal allocation of land to crops under multiple conflicting objectives. (da Silva & Marins, 2014) developed a fuzzy goal programming model to solve a multi-objective aggregate production-planning under uncertainty for a sugar company over multiple time periods.

Table 2- 2 shows the acronyms for various techniques adopted by researchers in solving problems and their corresponding meaning. Table 2- 3 classifies the literature based on these techniques.

Notation	Modeling Approach
MILP	Mixed Integer Linear Programming
FO	Fuzzy Optimization
MOP	Multi-Objective Programming
SIM	Simulation
SO	Stochastic Optimization
HS	Heuristics and Metaheuristics

Table 2- 2: Model nomenclature.

Author	Optimization methods used					
	MILP	FO	MOP	SIM	SO	HS
Blanco et al. (2005)	X					
Bai et al. (2008)						X
Van Der Vorst et al. (2014)				X		
Bohle et al. (2010)	X					
Sharma et al.		X	X			
Banaeian et al. (2012)	X					
Ampatzidis et al. (2013)				X		
Amorim et al. (2012)			X			
Català et al. (2013)	X					
Gonzàlez-Araya et al. (2015)	X					
Nadal-Roig and Plà (2015)	X					
Sawik (2015)	X				X	
Wenchong Chen et al. (2016)				X	X	
Saranwong & Likasiri (2016)	X					X
da Silva and Marins (2014)		X	X			
Zhang and Guo (2018)		X			X	

Table 2- 3: Modeling techniques used.

2.3. Scope

An ASC can have various decision-making levels across multiple stages. In this section, we segregate papers based on the types of decisions they tackle. We followed the procedure adopted by (Soto-Silva et al., 2016) and segregated papers based on five types of decisions: Planting (decisions on mix), Production (decisions on production planning), Distribution (decisions on allocation and transportation), Inventory (decisions on stock levels, shortages, etc.) and Harvesting (decisions across multiple seasons).

(Van Der Vorst, Tromp, & Zee, 2009) proposed an integrated approach towards logistics, sustainability and food quality analysis linked to distribution and inventory using discrete-event simulation. They presented a case study outlining the flow of product from supplier to consumer through multiple channels. (Banaeian, Omid, & Ahmadi, 2012) applied Data

Envelopment Analysis to improve the energy use efficiency in a strawberry greenhouse. They concluded that production levels could be maintained by reducing the total input energy by 16%.

Author	**Decisions Based On**				
	Planting	Production	Distribution	Inventory	Harvesting
Blanco et al. (2005)		X			
Bai et al. (2008)			X	X	
Van Der Vorst et al. (2014)			X	X	
Bohle et al. (2010)					X
Sharma et al.	X	X			
Banaeian et al. (2012)		X			
Ampatzidis et al. (2013)					X
Amorim et al. (2012)		X	X		
Català et al. (2013)	X				
Gonzàlez-Araya et al. (2015)					X
Nadal-Roig and Plà (2015)			X	X	
Sawik (2015)		X	X		
Wenchong Chen et al. (2016)				X	
Saranwong & Likasiri (2016)			X		
da Silva and Marins (2014)		X	X	X	
Zhang and Guo (2018)	X				

Table 2- 4: Classification of literature based on scope

As can be seen from the literature, majority of the existing optimization models built for solving problems in ASC deal with uncertainty using techniques like fuzzy optimization, simulation and stochastic optimization. In this research, we put forward an efficient robust optimization model for solving problems in ASC. We solve the problem by incorporating both strategic (location) and tactical (scheduling) decisions, which is not typically seen in optimization models as noted by (Rappold & Van Roo, 2009). Due to the efficiency of the formulation and the relatively small problem size, both decisions can be made simultaneously, and the model gives a solution in a relatively short amount of time.

Chapter 3

Methodology

3.1. Overview of problem and Data Analysis

MCE would like to develop a consolidated network to transport products from farms across Illinois and Missouri to their central hub in St. Louis. Typical flow of products from farms to the central hub is shown in figure 3- 1. First, the products are loaded onto their truck by farmers and transported to one of the 12 available intermediate hubs. It was assumed for the purpose of this research that farmers deliver all the product they make every week (whether Plant or Animal) to their assigned regional hub. Once products are delivered to the intermediate hub, MCE segregates them into plant and animal type and prepares them for delivery to the central hub in the corresponding vehicles. Depending upon the vehicle availability and capacity, and the amount of incoming product, MCE can utilize single or multiple trips to deliver product to the central hub.

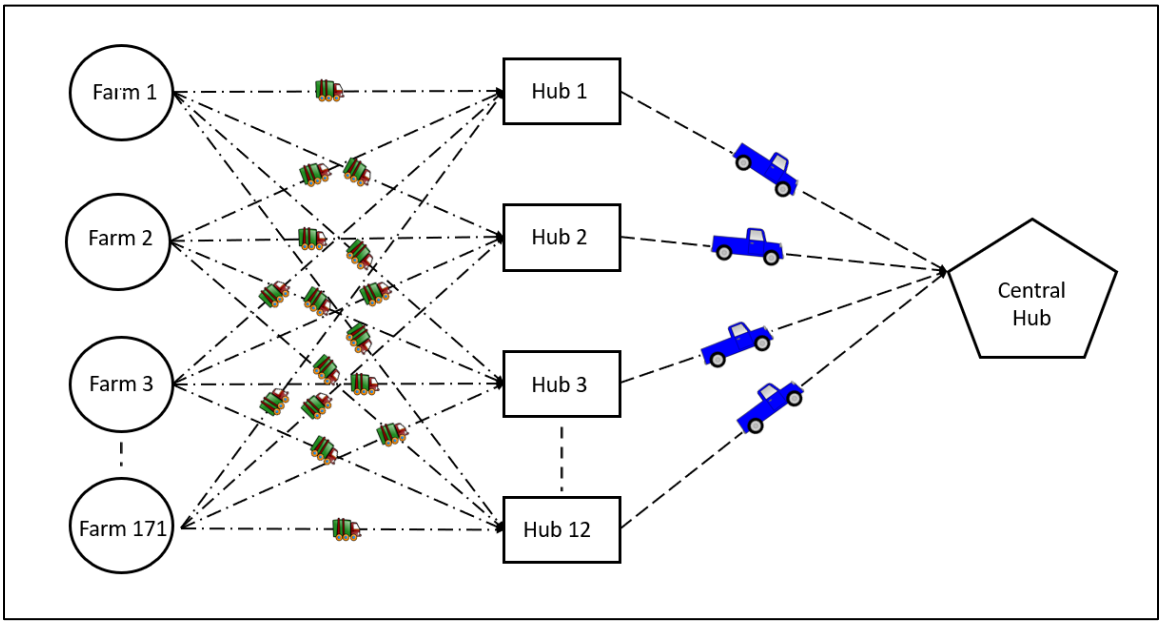

Figure 3- 1: Pictorial representation of product flow.

Mixed integer linear programs (MILP), because of their ability to model virtually any user-defined scenario and potential to identify optimal solutions, have found applications in numerous fields. Therefore, given MCE's requirements and the problem structure, it was decided that it would be best solved by a MILP.

Data on farms was provided by MCE in a Google spreadsheet. It included information on 225 farms such as its name, the city and state it is in, and the different types of products it sells. A small number of farms had duplicate entries or missing addresses and were excluded from the analysis. Moving forward, a Google search was performed on the remaining farms. For a very small number of farms, Google did not return any results because they either went out of business or did not exist on the mentioned address. These farms were also excluded from further consideration and the final data had 171 farms. The latitudinal and longitudinal coordinates of each farm were extracted from Google maps and exported to a spreadsheet. The spreadsheet data was exported to a mapping software called Google Earth, to visualize the locations of farms with respect to St. Louis. Figure 3- 2 shows a visual representation of all farms.

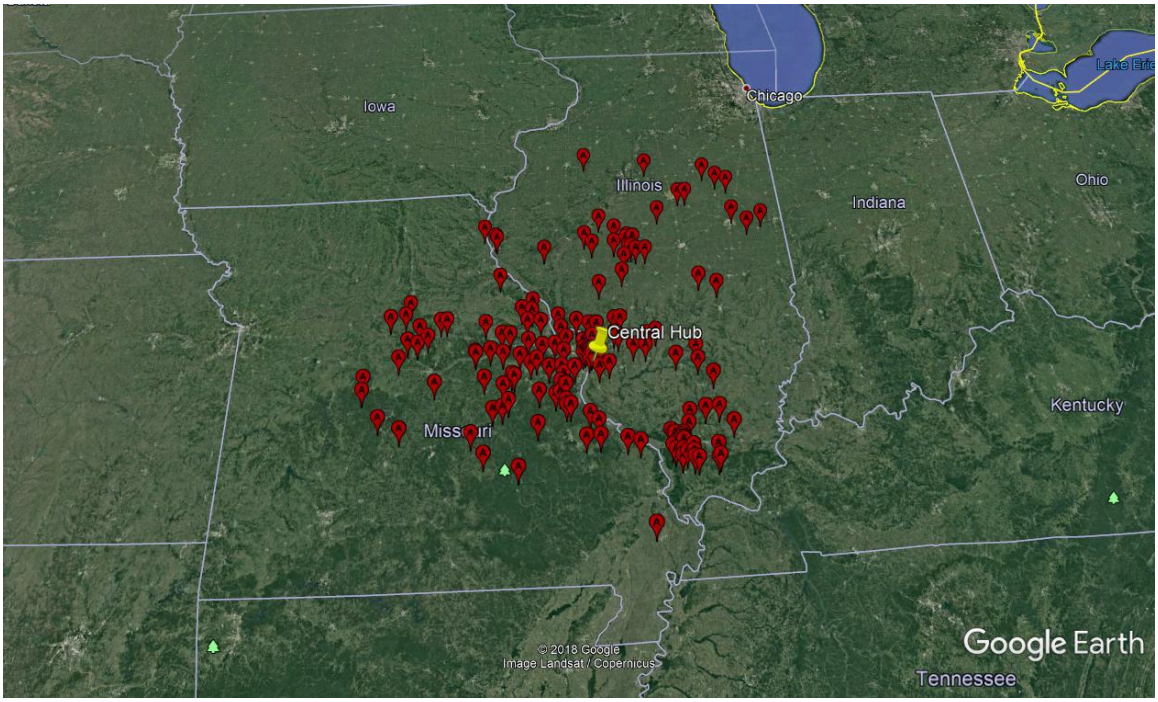

Figure 3- 2: Distribution of farms around St. Louis.

A close examination of the map shows that many farms are in and around St. Louis. Allowing farmers living closer to the central hub to drop off their produce directly at the central hub would have a three-fold advantage. It would result in substantial savings in time and resources for farmers. Also, farmers delivering their products directly to the central hub would result in a significant reduction in the inflow of products to the intermediate hubs which would result in substantial savings in labor and processing costs. Moreover, vehicles owned and operated by MCE would need to make fewer trips to the central hub. Figure 3- 3 shows the updated supply chain network allowing delivery of products from farms to the central hub.

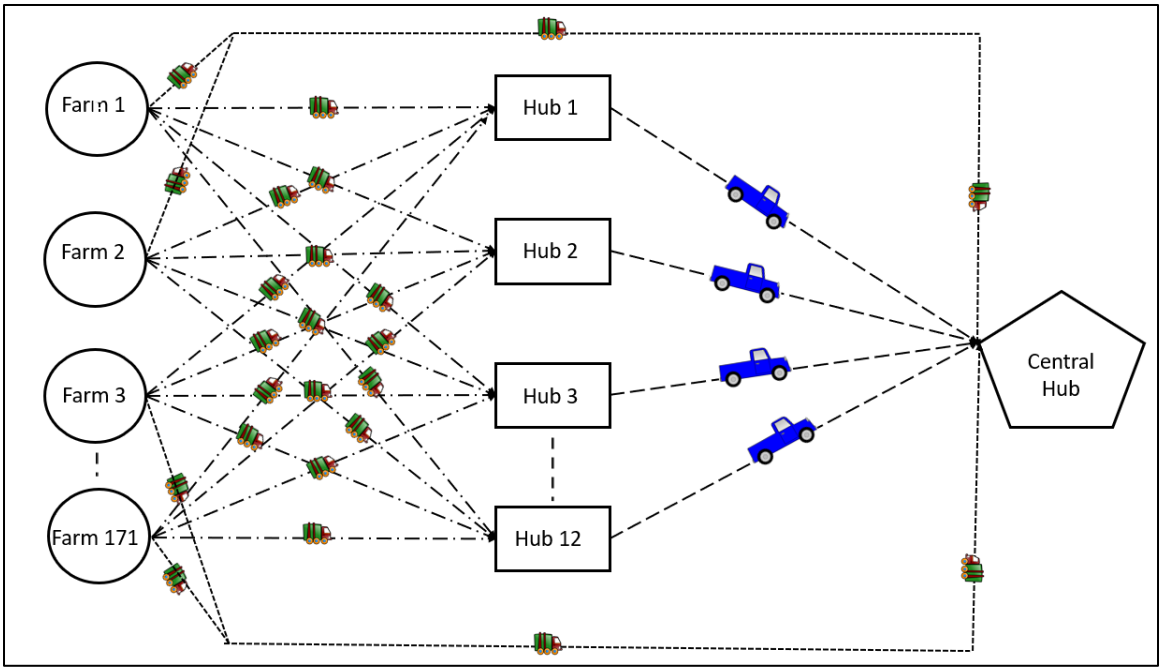

Figure 3- 3: Modified network flow from farms to central hub

Segregating products into similar groups was a challenging task. There were more than 200 different types of products being produced and delivered across all farms and treating each product type individually would result in an extremely complicated model. After consulting with MCE, the products were divided into two types-*Plant based and Animal based.* This is because it was envisioned that MCE would utilize two types of vehicles to transport products from intermediate hubs to the central hub. Vehicles transporting animal-based products would need to be refrigerated as bacterial growth is rapid in these products. Plant-based vehicles would not need refrigeration and hence capacity of the plant vehicles would be larger than animal vehicles.

Data on annual production was known only for a handful of farms. Also, since vehicles would be making weekly trips to the central hub, this data had to be divided across 52 time periods. After consulting with MCE, it was decided that the annual production for the remaining farms (plant or animal) would be derived from the mean of the corresponding

farms (plant or animal) having known production values. The percent production of farms for each month was derived from the production numbers for farms whose monthly production was known. Table 3- 1 shows the monthly production numbers for all farms. Within each month, the production for a given farm was divided equally across all weeks of the month.

Jan	Feb	Mar	Apr	May	June	July	Aug	Sept	Oct	Nov	Dec
2.6	2.9	3.9	5.6	9	12.4	13	14.5	13.9	11.9	6.7	3.6

Table 3- 1: Monthly percent production for all farms (All values are in percentage).

Since we were building a discrete location model, candidate locations for the hubs were selected *apriori*. After initial discussions with the stakeholders, twelve candidate locations were identified for the intermediate hubs. The hubs were located such that they coincided with one of the 171 farms on the network. The location of candidate intermediate hubs with respect to St. Louis is shown in figure 3- 4.

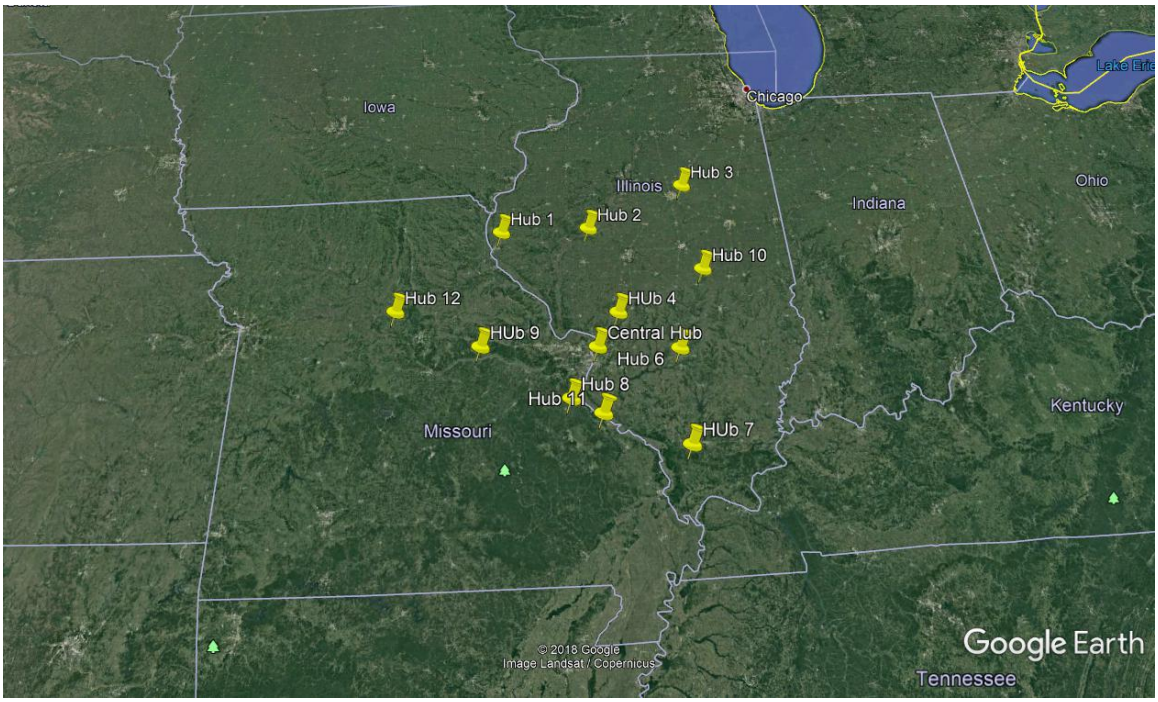

Figure 3- 4: Distribution of candidate intermediate hubs around St. Louis.

The modified haversine formula as shown below was used to calculate the distance between each hub and farm.

$$1.25 * 3959 * \text{acos}\big[\cos\big(radians\big(90 - latitude(m)\big)\big) * \cos\big(radians\big(90 - latitude(n)\big)\big) + \sin\big(radians\big(90 - latitude(m)\big)\big) * \sin\big(radians\big(90 - latitude(n)\big)\big) * \cos\big(radians\big(longitude(m) - longitude(n)\big)\big)\big]\big]\big]\big]\big]\big]$$

where,

m = 1, … ,171

n = 1, … ,12

The haversine formula gives the great-circle distance between two points on Earth given their longitude and latitude. However, distance traveled by vehicles on a road network can be highly variable from region to region and dependent on factors such as road network density, travel obstacles, hilliness, etc. (Ballou, Rahardja, & Sakai, 2002). In order to approximate actual travel distance, a correction factor called the circuity factor must be included. For the purpose of this research, a circuity factor of 1.25 was utilized based on the study by (Ballou et al., 2002).

The location of the central hub in St. Louis was known *apriori*. Distance between intermediate hubs and the central hub was calculated using the haversine formula using the same correction factor and are shown in table 3- 2.

Hub 1	Hub 2	Hub 3	Hub 4	Hub 5	Hub 6	Hub 7	Hub 8	Hub 9	Hub 10	Hub 11	Hub 12
139.6	116.7	180.5	36.7	2.7	67.7	112.2	50.9	96.5	117.8	59.1	172.7

Table 3- 2: Distance of intermediate hubs from central hub (in miles).

3.2. Model formulation and assumptions

The problem under study is determining the number of hubs to open from 12 potential candidates and allocating them to farms to minimize the overall ton-miles traveled in one

year. The problem will be solved by developing a MILP. In order to develop a tractable model, certain simplifying assumptions are necessary:

- Every farmer delivers their weekly product in one round-trip irrespective of the amount of product they are carrying. This assumption was made as no information about the vehicle specifications of the farmers was known.
- Production at farms is known and fixed (for the deterministic model).
- All product grown or produced at farms and delivered at the central hub is consumable (no loss of food due to perishability).
- Farmers can drop off their produce any time during the week and similarly MCE vehicles can transport product to the central hub any day of the week.
- MCE vehicles are filled to complete capacity when transporting product to the central hub.

3.2.1. Core deterministic model

Consider the facility location-allocation problem of opening regional hubs within a network and assigning them to farms to minimize the total ton miles traveled across farmers and MCE vehicles. The model consists of a set of 12 potential sites for regional hubs located across Illinois and Missouri. Farm-hub assignments are made by the model based on the decision maker's (in this case MCE) preference on the number of regional hubs to open. Products produced at farms are divided into two types-*Plant and Animal.* Two types of vehicles are used to deliver these products from the corresponding regional hubs to the central hub in St. Louis, Missouri. A MILP model was developed to represent the binary

decision of opening and closing a regional hub and provide the optimal farm-hub assignments for various scenarios

Minimize

$$\sum_{i}\sum_{j}\sum_{k}\sum_{w} d_{ik}p_{kjw}z_{ik} + \sum_{i}\sum_{j}\sum_{w} e_i c_j n_{ijw}$$

Subject to:

$$\sum_{k}\sum_{j} p_{kjw}z_{ik} \leq u_i h_i \qquad \forall\, i,j,k,w \qquad (1)$$

$$\sum_{i} z_{ik} = 1 \qquad \forall\, k \qquad (2)$$

$$\sum_{i} u_i = \emptyset \qquad (3)$$

$$z_{ik} \leq q_{ik} \qquad \forall\, i,k \qquad (4)$$

$$d_{ik}z_{ik} \leq d_{ik}u_{\acute{i}} + M(1-u_{\acute{i}}) \qquad \forall\, k,i,\acute{i} \qquad (5)$$

$$\sum_{k} p_{kjw}z_{ik} \leq n_{ijw}c_j \qquad \forall\, i,j,w \qquad (6)$$

$$u_i = 0 \; or \; 1 \qquad \forall\, i \qquad (7)$$

$$z_{i,k} = 0 \; or \; 1 \qquad \forall\, i,k \qquad (8)$$

$$n_{i,j,w} \geq 0; Integer \qquad \forall\, i,j,w \qquad (9)$$

3.2.1.1. SETS

The sets are defined as follows:

I	Regional hubs
J	Product types
K	Farms
W	Weeks of the year

3.2.1.2. DECISION VARIABLES

Decision Variables in the model are as follows:

$$u_i \begin{cases} 1 & if\ regional\ hub\ i\ is\ open \\ 0 & otherwise \end{cases}$$

$z_{i,k} \begin{cases} 1 & if\ farm\ k\ is\ assigned\ to\ regional\ hub\ i \\ 0 & otherwise \end{cases}$

$n_{i,j,w}$ $Number\ of\ trips\ for\ vehicle\ carrying\ product\ j\ from\ regional\ hub\ i\ to\ central\ hub\ in\ week\ w$

3.2.1.3 PARAMETERS

The input parameters of the model are as follows:

h_i	Capacity of regional hub i
$p_{j,k,w}$	Pounds of product j produced by farm k in week w
c_j	Capacity of vehicle type j
$d_{i,k}$	Distance between regional hub I and farm K
e_i	Distance between regional hub I and central hub
M	Sufficiently large positive number
Ø	Number of regional hubs to be opened
$q_{i,k}$	Binary parameter equals 1 if farm k is located within 100 miles of regional hub i

3.2.1.4 Description of the Objective Function and Constraints:

The objective function minimizes the total ton-miles across all farmers and MCE vehicles over 52 weeks. The first term calculates the ton-miles traveled in the downstream supply chain that is from a farmer to a regional hub for a product type in a given week. This is summed over all product delivered by all farmers to all regional hubs over all weeks. Similarly, the second term calculates the ton-miles traveled in the upstream supply chain that is product type delivered from a regional hub to the central hub in a given week. This is summed over all product delivered by vehicles from all regional hubs to the central hub over all weeks. Summing the two equations gives us the total ton-miles traveled across the entire supply chain network across all weeks.

Equation (1) ensures that hub I can be utilized only if it is open. Equation (2) ensures that a farmer delivers all their product (whether plant or animal or both) to a single regional hub

only. Equation (3) decides the number of regional hubs to open which is predefined by the decision maker. Equation (4) ensures that no farmer travels more than 100 miles to deliver their products to the regional hub. Equation (5) ensures that every farmer is assigned to their closest open regional hub. Equation (6) calculates the necessary number of vehicles trips of each product type based on the amount of product arriving at each regional hub for the corresponding assignments of farms to regional hubs. Equation (7) and (8) ensure the binary nature of the corresponding variables. Equation (9) ensures that the number of vehicle trips for each product type is an integer number.

3.2.2. Modified deterministic model

After a closer examination of the solution obtained from the core deterministic model it was concluded that few farms around the St. Louis region were situated closer to the central hub than their closest assigned regional hub. It was decided to explore the impact of allowing these farmers to bypass the regional hubs and directly deliver their produce to the central hub. This would lead to a three-fold advantage:

- Farmers would travel shorter distances resulting in significant cost reduction in transportation over the course of 52 weeks.
- MCE would potentially need to make fewer trips (and perhaps even invest in fewer vehicles) because of the corresponding decrease in product flow into the regional warehouses.
- The size of the regional hubs to be leased/constructed can be reduced due to the drop in incoming product flow resulting in significant cost savings for MCE.

In order to allow farmers to make deliveries directly to the central hub, the core deterministic model needed some modifications, as follows.

- The $d_{i,k}$ matrix in the original model would now be modified to have an additional row that shows the distance between farms and the central hub.
- The e_i matrix in the original model would now be modified to have an additional dummy parameter that resembles the central hub. Since the e_i matrix corresponds to the distance between the regional hubs and the central hub, the value of this parameter will be set to 0.

These modifications will result in farmers situated closer to the central hub potentially traveling directly to the central hub. The remaining model remains the same as the original deterministic model.

3.2.3 Robust Optimization Model

Climate variability and trends affect global crop yields. The Midwestern states which include Missouri and Illinois, represent one of the most intense areas of agriculture in the world and consistently affect the global economy. In 2007, Midwestern states alone sold crop and livestock products of over $76 billion (USDA, 2017). Unfortunately, these areas are also characterized by evident climate variability which naturally impacts food production. Weather and climate are prominent drivers or influencers of agricultural systems and it has been shown that recent trends in change of climate variables may be responsible for substantially affecting crop yield trends despite advances in technology and other fronts. (Kukal & Irmak, 2018) evaluated the climate impacts on yields by analyzing crop yield and climate datasets from 1968-2013 in the Great Plains regions. They observed fluctuations of up to 10 million tons for some crop production. Such variability could have tremendous local, regional and national economic as well as social implications. Climate

change is also a threat to livestock production because of the quality of feed crop and forage, water, etc. The livestock sector contributes 14.5% of global GHG emissions (Gerber et al., 2013) and will thus increase land degradation, air and water pollution, and cause decline in biodiversity (Reynolds, Crompton, & Mills, 2010). The demand for livestock products is expected to increase by 100% by 2050 (Garnett, 2009). Therefore, the challenge is to maintain a balance between productivity, household food security, and environmental preservation (Wright et al., 2012). (Rojas-Downing, Nejadhashemi, Harrigan, & Woznicki, 2017) provide an excellent review of studies analyzing the impacts of climate change on livestock production and food security, and the livestock sector's contribution to climate change. They conclude that among the reviewed studies, diversification of livestock animals (within species), using different crop varieties, and shifting to mixed crop-livestock systems seem to be the most promising adaptation measures.

Based on the above statistics, it was imperative to account for variability (in both plant and animal production) in our mathematical model. Let us first analyze the impact of variability on our model. Since the capacity of regional hubs is derived based on the total product entering the hub, a sudden increase in incoming product may render the hub insufficient and lead to either excessive spoilage of product or increase in cost (and thus GHG emissions) due to increased transportation. Secondly, since the number of vehicle trips made every week is a function of the amount of product arriving at the corresponding regional hub, fluctuating product inflow will lead to increased trips to and from the central hubs to the regional hubs and lead to increased strain on the available resources. In order

to accommodate this uncertainty, we modified our optimization model using the robust optimization approach.

Robust optimization (RO), as developed by Ben-Tal and Nemirovski, is another approach for optimizing under uncertainty. Instead of considering probabilistic information to protect the solution against uncertainty, RO models construct a solution that is feasible for any realization of the uncertainty in a given set. In this section, we present an RO formulation to account for uncertainty in the plant and animal production at each farm. This RO model minimizes the total ton-miles traveled over a multi-period time horizon according to the user's pre-specified level of robustness. The model identifies the optimal number of vehicles trips of each product type that will be needed every week as well as help determine the capacity of each regional hub under varying levels of robustness.

We assume in this RO formulation that uncertainty exists in the objective function and in constraints two and eight in the original formulation. The remaining constraints remain unchanged. Given below is the new RO formulation as well as the new data parameters and variables associated with the RO formulation.

Minimize

$$\sum_{i}\sum_{j}\sum_{k}\sum_{w} d_{ik}p_{kjw}z_{ik} + \sum_{i}\sum_{j}\sum_{w} e_i c_j n_{ijw} + f_0 g_0 + \sum_{k\epsilon\Omega}\sum_{j\epsilon\Omega}\sum_{w\epsilon\Omega} f_{0_{kjw}}$$

$$\sum_{k}\sum_{j} p_{kjw}z_{ik} + l_{1_{iw}}g_{1_{iw}} + \sum_{k\epsilon\Omega}\sum_{j\epsilon\Omega} f_{1_{ikjw}} \leq u_i h_i \qquad \forall\, i, w \qquad (R1)$$

$$\sum_{i} z_{ik} = 1 \qquad \forall\, k \qquad (2)$$

$$\sum_{i} u_i = \emptyset \qquad (3)$$

$$d_{ik}z_{ik} \leq d_{ik}u_{\acute{\imath}} + M(1 - u_{\acute{\imath}}) \qquad \forall\, k, i, \acute{\imath} \qquad (4)$$

$$\sum_{k} p_{kjw} z_{ik} + l_{2_{ijw}} g_{2_{ijw}} + \sum_{k \epsilon \Omega} f_{2_{ikjw}} \leq n_{ijw} c_j \qquad \forall\, i, j, w \qquad (R2)$$

$$l_0 + f_{0_{kjw}} \geq v_{kjw} r_{1_{ik}} \qquad \forall\, i, j, k, w \qquad (R3)$$

$$l_{1_{iw}} + f_{1_{ikjw}} \geq v_{kjw} r_{1_{ik}} \qquad \forall\, i, \forall\, j, k, w \,\epsilon\, \Omega \quad (R4)$$

$$l_{2_{ijw}} + f_2 \geq v_{kjw} r_{1_{ik}} \qquad \forall\, i, \forall\, j, k, w \,\epsilon\, \Omega \quad (R5)$$

$$-r_{1_{ik}} \leq z_{ik} \qquad \forall\, i, k \qquad (R6)$$

$$z_{ik} \leq -r_{1_{ik}} \qquad \forall\, i, k \qquad (R7)$$

$$u_i = 0 \; or \; 1 \qquad \forall\, i \qquad (11)$$

$$z_{i,k} = 0 \; or \; 1 \qquad \forall\, i, k \qquad (12)$$

$$n_{i,j,w} \geq 0; Integer \qquad \forall\, i, j, w \qquad (13)$$

3.2.3.1. SETS

The sets are defined as follows:

I	Regional hubs
J	Product types
K	Farms
W	Weeks of the year

3.2.3.2. DECISION VARIABLES

Decision Variables in the model are as follows:

$$u_i \begin{cases} 1 & if\ regional\ hub\ i\ is\ open \\ 0 & otherwise \end{cases}$$

$$z_{i,k} \begin{cases} 1 & if\ farm\ k\ is\ assigned\ to\ regional\ hub\ i \\ 0 & otherwise \end{cases}$$

$f_{0_{k,j,w}}$ $Robustness\ variable\ for\ the\ objective\ function$

l_0 $Robustness\ variable\ for\ objective\ function$

$f_{1_{i,k,j,w}}$ $Robustness\ variable\ for\ constraint\ R1$

$l_{1_{i,w}}$ $Robustness\ variable\ for\ constraint\ R1$

$f_{2_{i,k,j,w}}$ $Robustness\ variable\ for\ constraint\ R2$

$l_{2_{i,j,w}}$ $Robustness\ variable\ for\ constraint\ R2$

$r_{1_{i,k}}$ $Robustness\ variable\ common\ to\ objective\ function, and\ constraints\ R1\ and\ R2$

$n_{i,j,w}$ $Number\ of\ trips\ for\ product\ j\ made\ from\ regional\ hub\ i\ to\ central\ hub\ in\ week\ w$

3.2.3.3 PARAMETERS

The input parameters of the model are as follows:

h_i	Capacity of regional hub i
$p_{k,j,w}$	Pounds of product j produced by farm k in week w
c_j	Capacity of vehicle type j
$d_{i,k}$	Distance between regional hub I and farm K
e_i	Distance between regional hub I and central hub
M	Sufficiently large positive number
Ø	Number of regional hubs to be opened
$v_{k,j,w}$	Maximum allowable deviation of the production of plant and animal product from its nominal value
g_0	Robustness level for the objective function
g_1	Robustness level for constraint (R1)
g_2	Robustness level for constraint (R2)

3.2.3.4 Description of the objective function and constraints:

The RO model is quite similar to the deterministic model with some modifications. The last two terms in the objective function, which account for robustness, are based on the RO formulation of Bertsimas and Sim (2003) to account for variability in the production of plant and animal products at farms. The uncertain production parameter is denoted by $p_{j,k,w}$. It is assumed that this parameter is bounded and varies symmetrically inside the interval $[p_{k,j,w} - v_{j,k,w}, p_{k,j,w} + v_{k,j,w}]$ where $p_{k,j,w}$ is the nominal value of the production of plant or animal product at a particular farm in a particular week, while $v_{k,j,w}$ is the maximum-allowable deviation (half-width) of the potential values.

Let $\Omega = \{k, j, w | v_{k,j,w} > 0\}$; that is Ω is the subset of the production parameters that can potentially deviate from their nominal values. g_0 is the input parameter which must take integer values, to allow the user to control the level of robustness in the objective function. When the user sets $g_0 = 0$, it means that no parameters are allowed to deviate from their nominal value; what remains is the non-robust model. When $g_0 = \Omega$, all parameters in the subset Ω are allowed to deviate from their nominal values and the optimal solution obtained is based on the worst-case scenario. For an intermediate value, say $g_0 = 5$ between these two endpoints, the terms

$$l_0 g_0 + \sum_{k \epsilon \Omega} \sum_{j \epsilon \Omega} \sum_{w \epsilon \Omega} f_{0_{k,j,w}}$$

calculate the additional ton-miles above the nominal value associated with the 5 worst-case-impact values of decision variable $z_{i,k}$. To control for the desired level of robustness g_0 in the objective function, it is necessary to add constraints (R3), (R6) and (R7) which are presented in the RO formulation.

Similarly, constraint (R1) ensures that the amount of product coming into any regional hub does not exceed the capacity of the regional hub, subject to a user-specified level of robustness. The final two terms on the left-hand-side are based on the RO formulation by Bertsimas and Sim (2003). As in the objective function, the constraint coefficients that were assumed to be uncertain are the production of plant and animal products at a particular farm during a particular week.

g_1 is the input parameter which must take integer values, to allow the user to control the level of robustness in constraint (1). When the user sets $g_1 = 0$, it means that no parameters

are allowed to deviate from their nominal value; what remains is the non-robust model. When $g_1 = \Omega$, all parameters in the subset Ω are allowed to deviate from their nominal values and the optimal solution obtained is based on the worst-case scenario. For an intermediate value of g_1 between these two endpoints, the terms

$$l_{1_{i,w}} g_{1_{i,w}} + \sum_{k \epsilon \Omega} \sum_{j \epsilon \Omega} f_{1_{i,k,j,w}}$$

calculate the additional ton-miles above the nominal value associated with the g_1 worst-case-impact values of decision variable $z_{i,k}$. To control for the desired level of robustness g_1 in constraint (R1), it is necessary to add constraints (R4), (R6) and (R7) which are presented in the RO model.

A similar explanation follows for constraint (R2), except g_1 is replaced by g_2 . When the user sets $g_2 = 0$, it means that no parameters are allowed to deviate from their nominal value; what remains is the non-robust model. When $g_2 = \Omega$, all parameters in the subset Ω are allowed to deviate from their nominal values and the optimal solution obtained is based on the worst-case scenario. For an intermediate value of g_2 between these two endpoints, the terms

$$l_{2_{i,w}} g_{2_{i,w}} + \sum_{k \epsilon \Omega} \sum_{j \epsilon \Omega} f_{2_{i,k,j,w}}$$

calculate the additional ton-miles above the nominal value associated with the g_2 worst-case-impact values of decision variables $z_{i,k}$ and $n_{i,j,w}$. To control for the desired level of robustness g_2 in constraint (R2), it is necessary to add constraints (R5), (R6) and (R7) which are presented in the RO model.

The CPLEX solver in GAMS was used to solve the deterministic and robust models to identify capacities of the regional hubs and the number of vehicles of each type that would travel to and from the regional hubs to the central hub every week under different levels of user-defined robustness.

Chapter 4

Results

This section discusses the application of the mathematical models to a real-life problem faced by MCE. Data provided by MCE was used to test and validate the models.

The models identify the regional hubs to be opened out of the 12 candidate locations depending on the number of locations defined by the decision maker to minimize the total ton-miles traveled. The model also allocates farm-hub assignments based on the number of regional hubs to be opened and the maximum number of vehicles trips of each type that would be made from each regional hub to the central hub every week. Two versions of the model were developed-*deterministic and robust.* The deterministic model was run under two configurations; one where farmers would strictly deliver their products to the regional hubs only and another where farmers could bypass the regional hubs and deliver products directly to the central hub if it was in their best interest. Because of uncertainty in the production at the farms, a robust equivalent of the model was also developed, and the two models are compared.

4.1 Deterministic model without bypass

As discussed in the Methodology, the deterministic optimization model was coded into the GAMS environment and solved using IBM's CPLEX solver to minimize the maximum ton-miles traveled over the entire supply chain network over 12 months.

Assumptions:

- For the model to decide on the number of vehicle trips of each type that would be required each week from the regional hubs to the central hub, we needed to provide the capacity of each vehicle type. After consulting with MCE about their vehicle specifications, it was decided that vehicle carrying plant products would have a capacity of 4000 lbs. and the vehicle carrying animal products would have a capacity of 2500 lbs. due to anticipated refrigeration needs.
- MCE vehicles were assumed to be filled to full capacity when transporting products from regional hubs to the central hub.
- It was assumed that the central hub would have sufficient capacity to handle the incoming flow of Plant and Animal product from either the regional hubs (in case of no bypass) or regional hubs and farms (in case farmers are allowed to bypass).

In order to see how our assumptions fared, we looked at the maximum amount of product that was being transported by any farmer in any week to a particular regional hub. After looking at the values in our p_{ijk} matrix we discovered that one farmer grows 3057 lbs. of plant product at their farm, another farmer generates 870 lbs. of animal product at their farm while farmers that sell both plant and animal products generate a maximum of 417 lbs. of plant and animal product every week. Since the capacity of MCE's plant and animal vehicles is greater than these values, it is reasonable to assume that farmers would have sufficient capacity to transport products grown every week from farms to the regional hubs or central hub in a single trip. It is important to note that we assume that a farmer who produces both plant and animal products would be able to transport these products to the hub in a single trip, and not require use of one vehicle for plant products and a separate vehicle for animal products.

We explored the option of opening multiple regional hubs in order to understand how farm-hub assignments vary for different configurations. Figure 4- 1 below shows the farm-hub assignments when 4 regional hubs are opened.

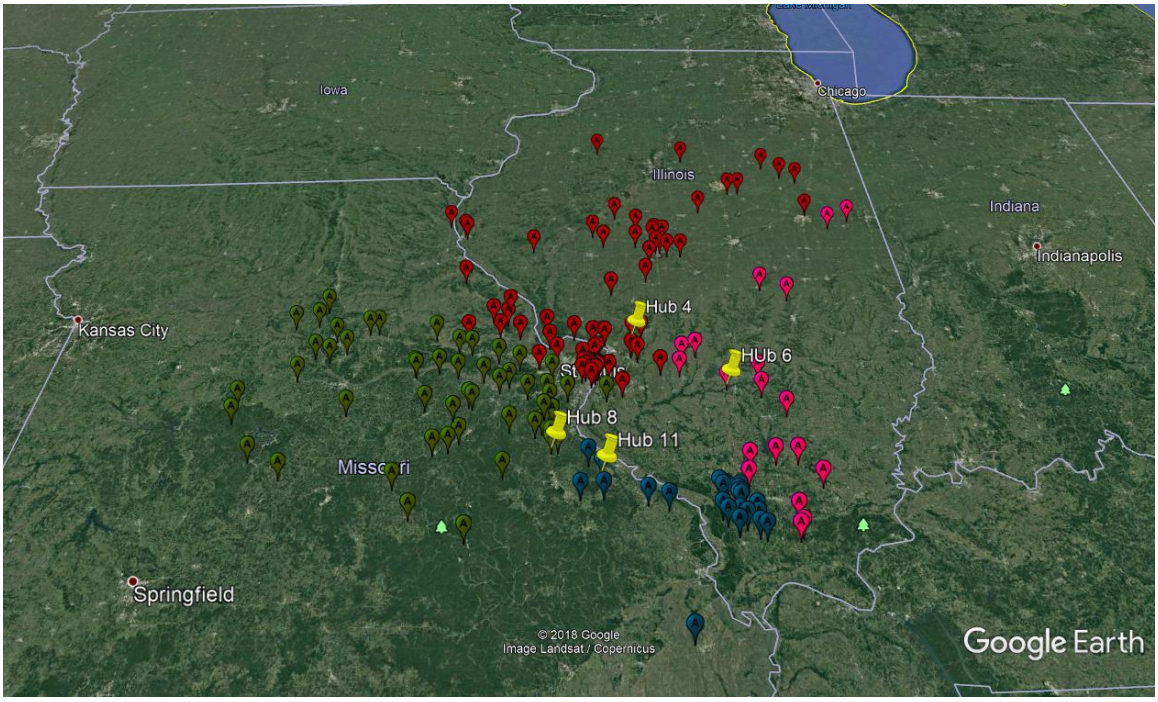

Figure 4- 1: Farm-hub assignments for four regional hubs.

Table 4- 1 below shows the maximum number of weekly vehicle trips for each product type that would be made from the corresponding regional hubs to the central hub for the 4-hub configuration. Table 4- 2 shows the total distance traveled in miles on a round trip by all farmers (assuming that each farmer performs a single trip) along with the distance traveled by MCE vehicles in a year.

	Hub 4	Hub 6	Hub 8	Hub 11
Plant	7	2	3	2
Animal	2	2	4	2

Table 4- 1: Maximum weekly trips between regional hubs and central hub for each vehicle type

Farmers	MCE Vehicles
2,403,189	80,212

Table 4- 2: Yearly truck miles driven for five hubs (round trip)

Figure 4- 2 shows the farm-hub assignments when 5 regional hubs are opened.

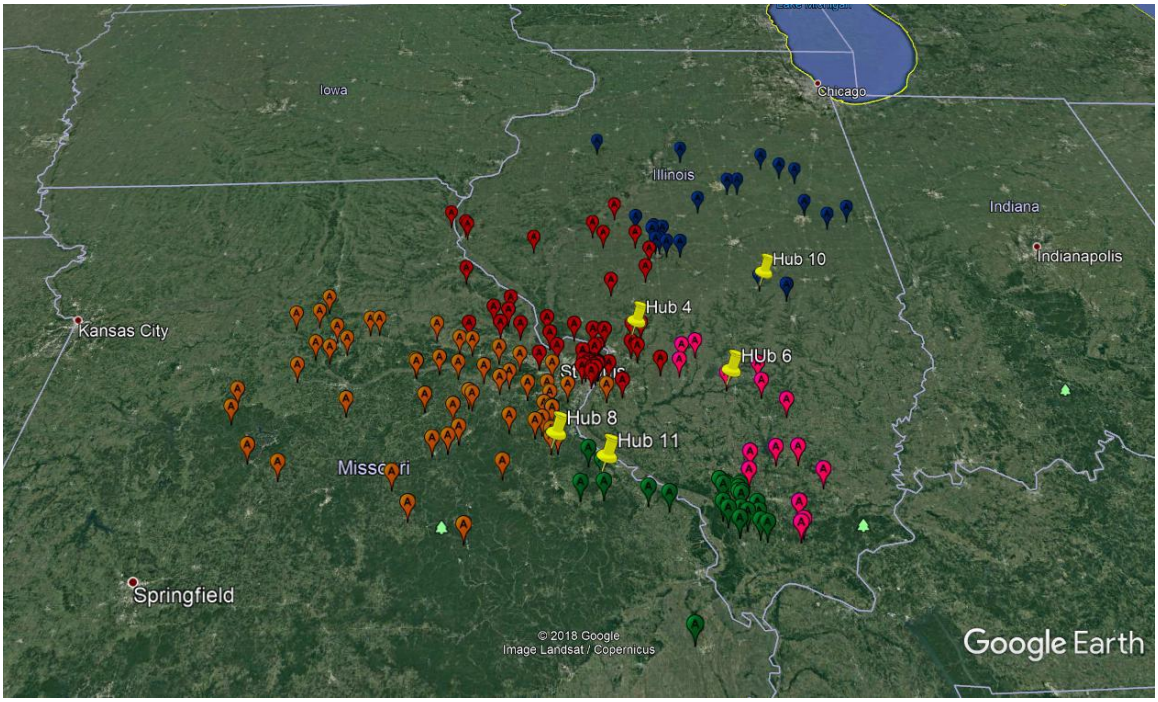

Figure 4- 2: Farm-hub assignments for five regional hubs.

Table 4- 3 below shows the maximum number of weekly vehicle trips for each product type that would be made from the corresponding regional hubs to the central hub for the 5-hub configuration. Table 4- 4 shows the total distance traveled in miles on a round trip by all farmers (assuming that each farmer performs a single trip) along with the distance traveled by MCE vehicles in a year.

	Hub 4	Hub 6	Hub 8	Hub 10	Hub 11
Plant	6	1	3	2	2
Animal	2	1	4	1	2

Table 4- 3: Maximum weekly trips between regional hubs and central hub for each vehicle type

Farmers	MCE Vehicles
2,222,050	103,453

Table 4- 4: Yearly truck miles driven for five hubs (round trip)

Figure 4- 3 shows the farm-hub assignments when 6 regional hubs are opened.

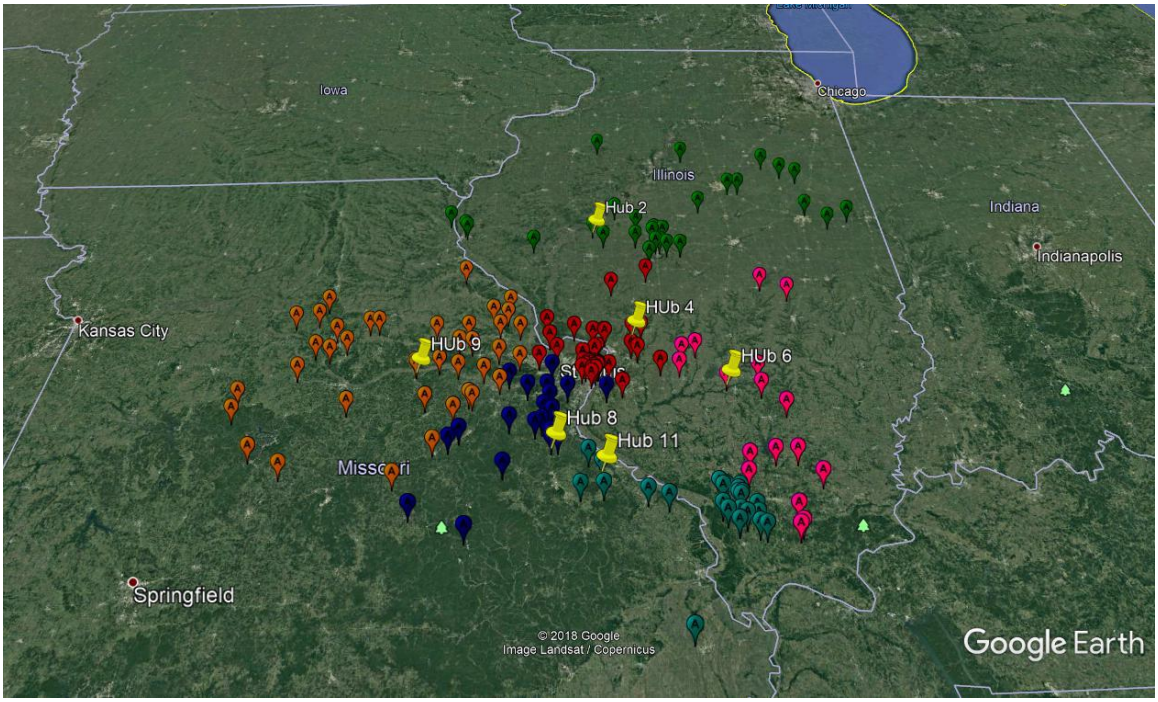

Figure 4- 3: Farm-hub assignments for six regional hubs.

Table 4- 5 below shows the maximum number of weekly vehicle trips for each product type that would be made from the corresponding regional hubs to the central hub for the 6-hub configuration. Table 4- 6 shows the total distance traveled in miles on a round trip by all farmers (assuming that each farmer performs a single trip) along with the distance traveled by MCE vehicles in a year.

	Hub 2	Hub 4	Hub 6	Hub 8	Hub 9	Hub 11
Plant	4	4	2	2	2	2
Animal	1	2	2	2	2	3

Table 4- 5: Maximum weekly trips between regional hubs and central hub for each vehicle type

Farmers	MCE Vehicles
1,732,491	131,328

Table 4- 6: Yearly truck miles driven for five hubs (round trip)

We observe that the distance traveled by MCE vehicles (central hub to regional hubs) increases while the distance traveled by farmers (regional hubs to farms) decreases as we increase the number of regional hubs to be opened.

Consider for a moment how the model opens regional hubs as we go from 4- to 5- to the 6-regional hub solution. For the 4-hub solution, the model opens the 4 nearest hubs to the central hub. As we move from 4 to 5 regional hubs, the model opens hub 10, which is not necessarily the next nearest regional hub. After looking at the farms in the northern Illinois region that get taken away from hub 4 and assigned to hub 10, we see that these farms have an annual production that is lower than the average production of all farms in the network. This is evident by the fact that the number of vehicle trips made by MCE vehicles from hub 10 is also lower than trips made from hubs which are much closer to the central hub (except for hub 6, since 4 farms that were initially assigned to hub 6 in the 4-hub solution are now assigned to hub 10 in the 5-hub solution). Since, our objective is to minimize the overall ton-miles, these farmers that were initially traveling to hub 4 now travel less when they are assigned to hub 10 in the 5-hub solution. Similarly, from 5 hubs to 6, the model now opens hub 9 to prevent farmers located in west Missouri from making the long trip to hub 8. This results in longer but much small number of trips for MCE vehicles from hub 9. The benefits are evident, in that, although MCE vehicles have to travel slightly longer distances over the course of the year, farmers now travel almost 500,000 miles less compared to the 5 hub solution with most of these miles saved owing to farmers traveling to the closer hub 9 instead of hub 8.

In order to gain more insights on how the model allocates farms to regional hubs, we ran the model for seven regional hubs and eight regional hubs opened. Figure 4- 4 shows how the total distance traveled by farmers and MCE vehicles varies across the different scenarios.

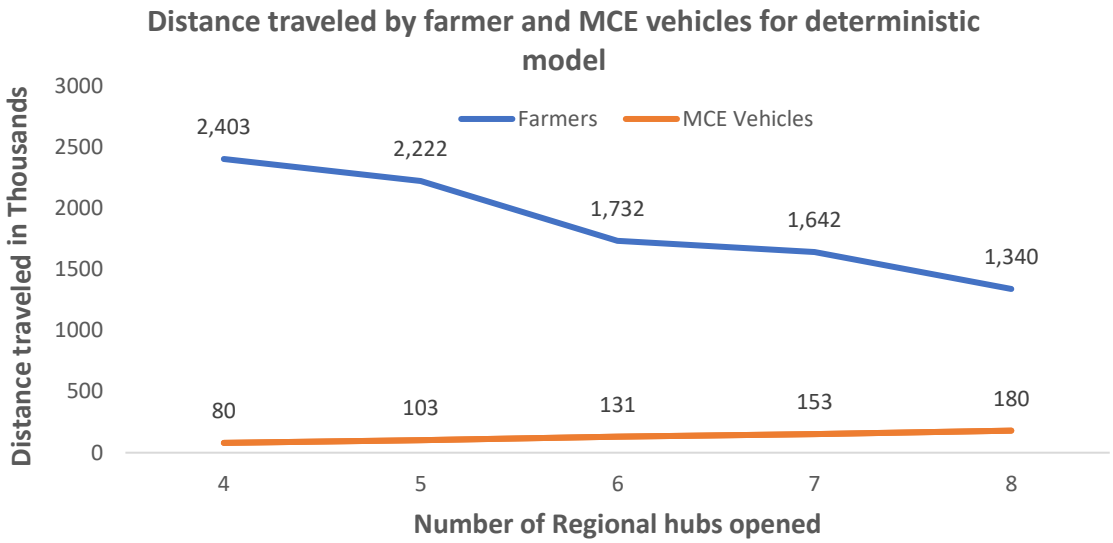

Figure 4- 4: Yearly distance traveled by farmers and MCE vehicles for deterministic model.

4.2 Deterministic model with bypass allowed

As discussed towards the end of Chapter 3, we observed that there were few farms in the network that were located closer to the central hub than their assigned regional hubs. The existing deterministic GAMS model was modified slightly, as mentioned in the previous chapter, allowing farms to potentially deliver directly to the central hub, and solved using CPLEX.

Figure 4- 5 shows the farm-hub assignments when 4 regional hubs are opened, and farmers can choose to bypass the regional hubs. As expected, some farmers skip the regional hubs and directly travel to the central hub.

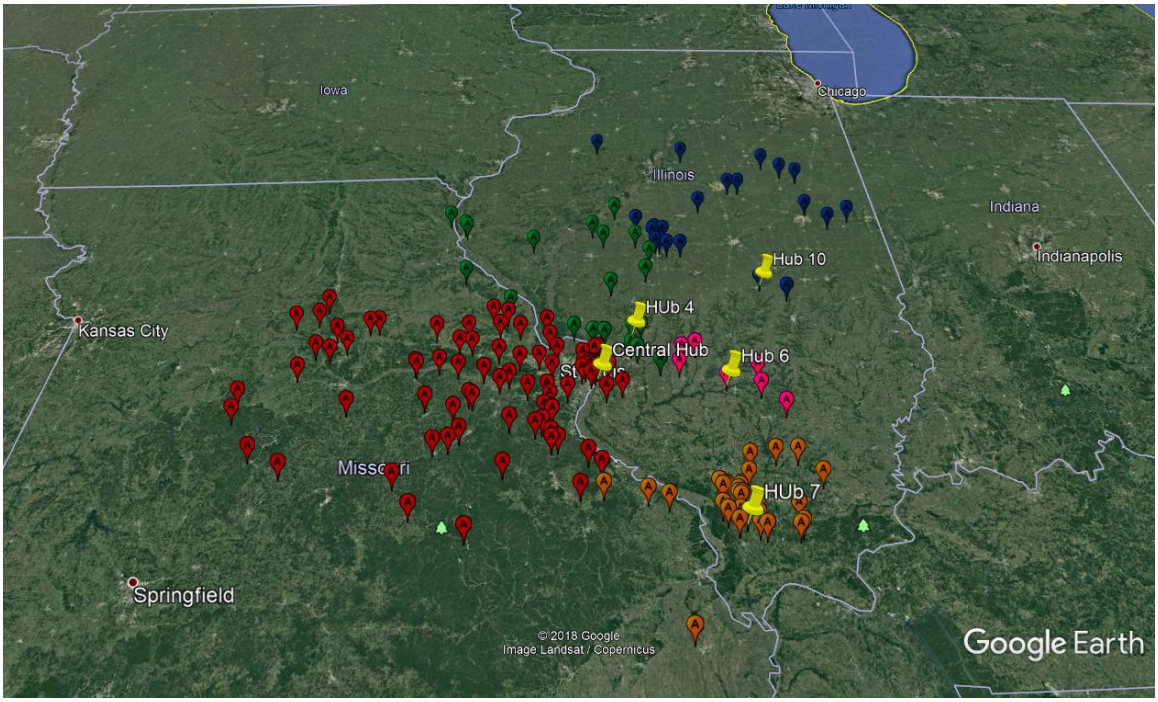

Figure 4- 5: Farm-hub assignments for four regional hubs and bypass allowed.

Table 4- 7 below shows the maximum number of weekly vehicle trips for each product type that would be made from the corresponding regional hubs to the central hub for the 4-hub configuration. Table 4- 8 shows the total distance traveled in miles on a round trip by all farmers (assuming that each farmer performs a single trip) along with the distance traveled by MCE vehicles in a year. As expected, we see a significant decrease in total distance traveled by farmers.

	Hub 4	Hub 6	Hub 7	Hub 10
Plant	3	1	3	2
Animal	1	1	1	1

Table 4- 7: Maximum weekly trips between regional hubs and central hub for each vehicle type

Farmers	MCE Vehicles
1,953,984	89,356

Table 4- 8: Yearly truck miles driven for four hubs (round trip)

Figure 4- 6 shows the assignments of farms to the corresponding regional hubs for the 5-hub solution with the central hub located in St. Louis. This time, the model allows farmers

closer to hub 2 to travel directly to that hub leading to further decrease in the overall miles traveled by farmers.

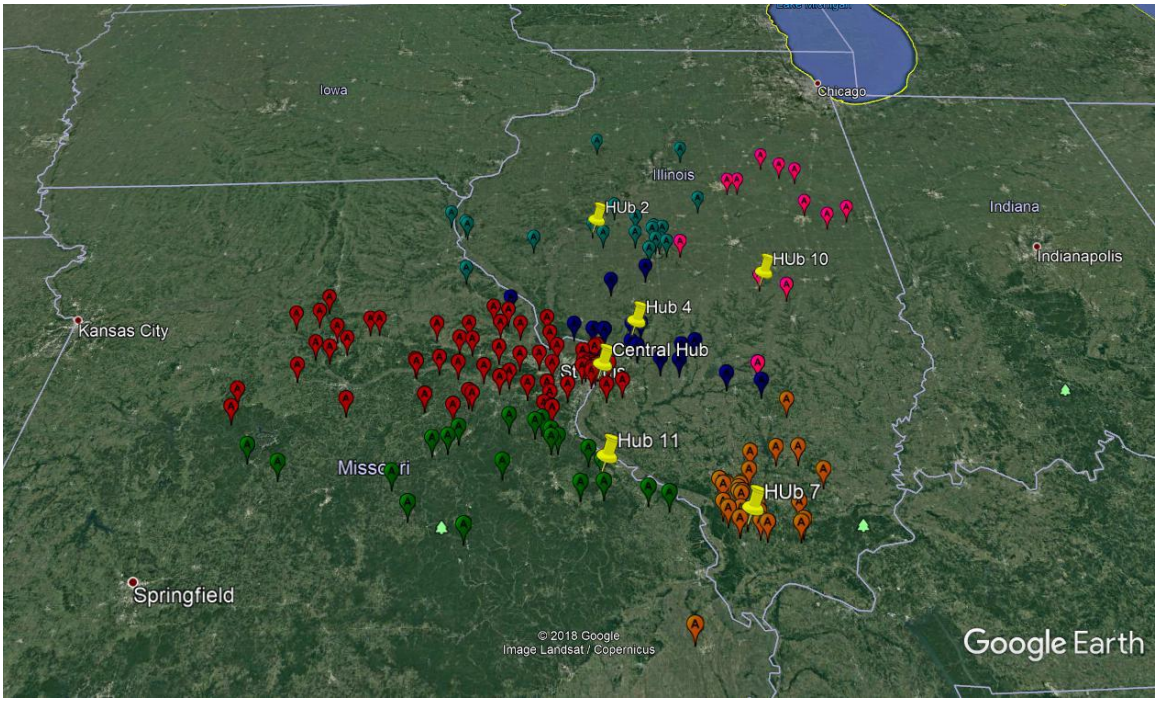

Figure 4- 6: Farm-hub assignments for five regional hubs and bypass allowed.

Table 4- 9 below shows the maximum number of weekly vehicle trips for each product type that would be made from the corresponding regional hubs to the central hub for the 5-hub configuration. Table 4- 10 shows the total distance traveled in miles on a round trip by all farmers (assuming that each farmer performs a single trip) along with the distance traveled by MCE vehicles in a year. A similar trend follows as for the 4-hub solution.

	Hub 2	Hub 4	Hub 7	Hub 10	Hub 11
Plant	3	2	3	2	1
Animal	1	2	1	1	2

Table 4- 9: Maximum weekly trips between regional hubs and central hub for each vehicle type

Farmers	MCE Vehicles
1,723,359	120,695

Table 4- 10: Yearly truck miles driven for five hubs (round trip)

Similarly, for the 6-hub solution, the model allowed farmers closer to hub 6 to travel directly to that hub. Figure 4- 7 shows the assignments of the farms to the corresponding regional hubs.

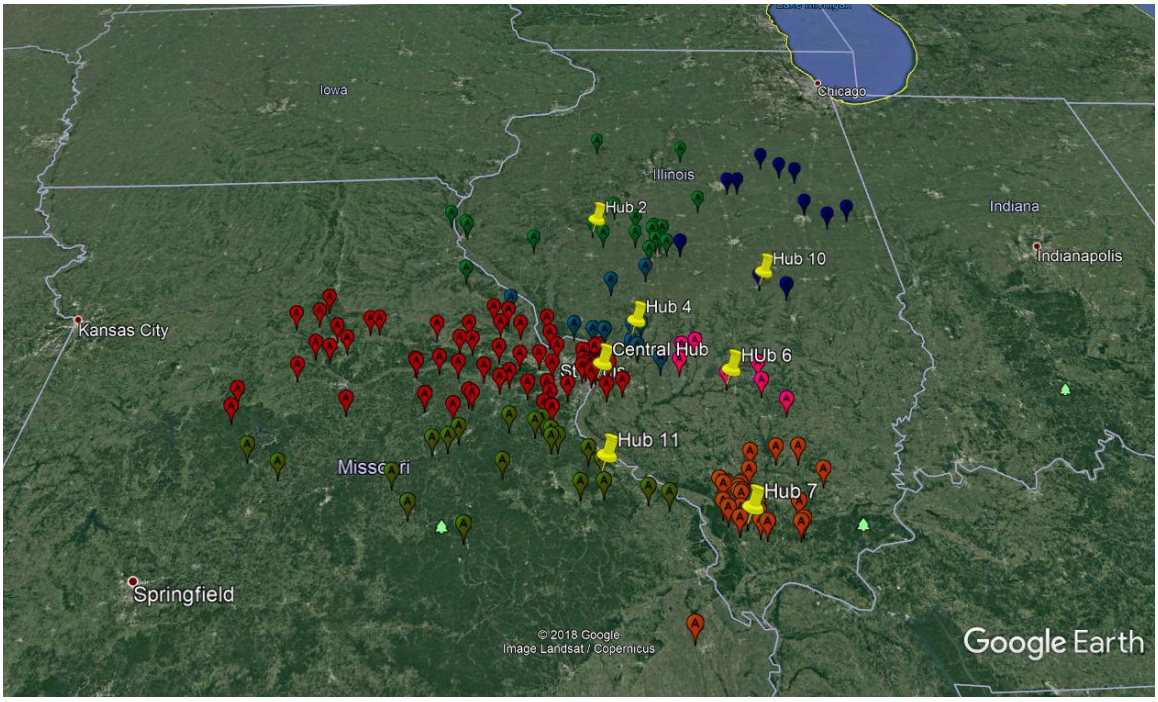

Figure 4- 7: Farm-hub assignments for six regional hubs and bypass allowed.

Table 4- 11 below shows the maximum number of weekly vehicle trips for each product type that would be made from the corresponding regional hubs to the central hub for the 5-hub configuration. Table 4- 12 shows the total distance traveled in miles on a round trip by all farmers (assuming that each farmer performs a single trip) along with the distance traveled by MCE vehicles in a year. Similar trend follows as for the 4-hub and 5-hub solutions.

	Hub 2	**Hub 4**	**Hub 6**	**Hub 7**	**Hub 10**	**Hub 11**
Plant	3	1	1	3	2	1
Animal	1	1	1	1	1	2

Table 4- 11: Maximum weekly trips between regional hubs and central hub for each vehicle type

Farmers	MCE Vehicles
1,676,505	131,157

Table 4- 12: Yearly truck miles driven for six hubs (round trip)

Comparing the four, five and six-hub solutions for the original and modified deterministic models it is evident that allowing farmers to bypass regional hubs is better for farmers.

Regional Hubs	% drop in miles for farmers	% drop in miles for MCE vehicles
4	18.69	-11.34
5	12.06	-16.66
6	3.23	-0.13

Table 4- 13: Percent drop in miles traveled by farmers and MCE vehicles across 4, 5 and 6 regional hubs for modified deterministic model

Once again, let's analyze how farm-hub assignments vary as we increase the number of regional hubs. As we move from the 4-hub solution to the 5-hub solution, the model opens hub 2 to prevent farmers in Northern Illinois from making the long trip to hub 4. Similarly, as we move from 5 to 6 regional hubs, the model now opens hub 6. If we look at the farms that are assigned to hub 6, particularly the two farms (one each) that were initially making longer trips to hub 7 and hub 10 respectively, we see that these farmers now travel much shorter distances every week to hub 6. These farms along with others that get reassigned from hub 4 to hub 6, travel about 48,000 miles less over 52 weeks as compared to the 5-hub solution and this is enough to offset the increased travel by MCE vehicles. Another interesting observation is that in most solutions where farmers are allowed to travel directly to the central hub, the model does not open any of the two regional hubs located in eastern and central Missouri. Rather it makes farmers situated further away to travel all the way to the central hub. Since there is a capacity limitation on MCE vehicles (and not on farmer vehicles as is assumed for the model), the number of additional trips that MCE vehicles would make to deliver products to the central hub would offset the savings in miles that would occur from allowing farmers to travel shorter distances by delivering their product

to their closest regional hub. A nice example of this can be seen in the original deterministic model with 6 hubs open where the model opens hub 9 whose distance from the central hub is about 100 miles. While an additional 4 trips (2 for Plant and 2 for Animal) by MCE vehicles may not seem like a lot, these weekly trips add plenty of miles over the course of the year.

We see from Table 4- 13 that although distance traveled by farmers decreases, distance traveled by MCE vehicles increases as we increase the number of regional hubs. This is because of two reasons:

1. The capacity of regional hubs for the model configuration allowing farmers to bypass is set far less than the model configuration where farmers are not allowed to bypass as shown in figure 4- 8. Recall from our discussion in Chapter 3 that one of the advantages of allowing farmers to bypass the regional hubs was that the size of the regional hubs to be leased or constructed could be reduced. If we look at the capacity graph in figure 4- 8 and compare the objective function values shown in figure 4- 11 , we can see that the ton-miles traveled by farmers when they travel directly to the central hub is slightly less than the ton-miles traveled when they are not allowed to bypass. This is essentially what we did! We continued to reduce the regional hub capacities till the ton-miles traveled when farmers are allowed to bypass the regional hubs is just less than the ton-miles traveled when farmers aren't allowed to bypass. This leads to increased vehicle trips from the regional hubs to the central hub.

2. For the model configuration allowing farmers to bypass the regional hub and travel directly to the central hub, the model opens hubs that are further away from the central hub leading to longer trips back and forth to the central hub.

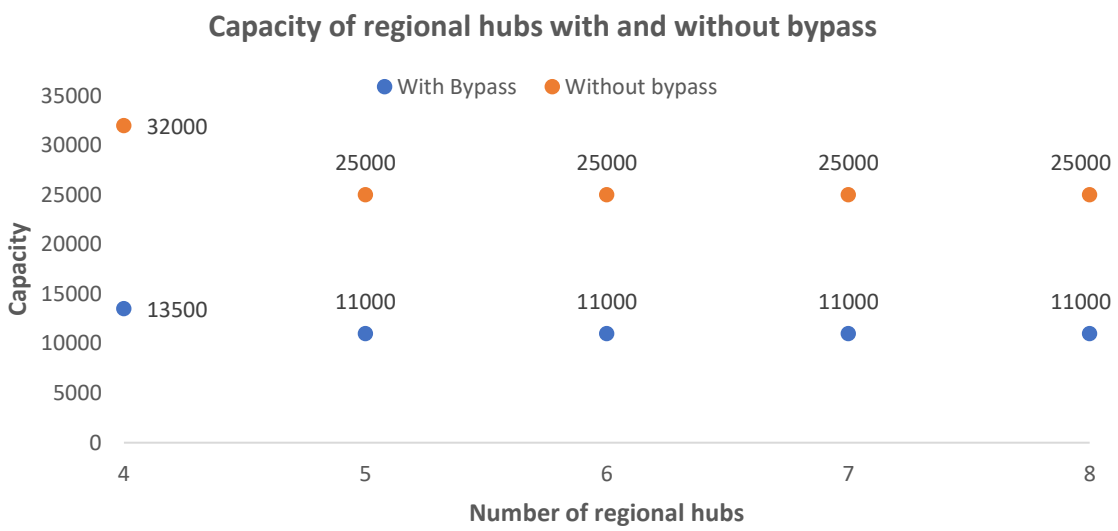

Figure 4- 8: Capacity of regional hubs with and without bypass for deterministic model

We ran the modified model by keeping the capacity of the regional hubs at par with that of the original model and observed that distance traveled by MCE vehicles decreases considerably since the model not only opens hubs closer to the central hub but also the frequency of vehicle trips decreases due to increased capacity of the hubs. MCE will need to decide on this trade-off based on the resources available to them. One important thing to note about figure 4- 8 is that the capacity values presented in the graph are not the minimum possible values that are needed to give us a feasible solution. The point we are trying to make is that it is possible to reduce the capacity of regional hubs if we allow farmers to bypass and travel directly to the central hub.

Another interesting observation is that as the number of hubs is increased, the capacity required at each hub remains the same beyond the 5-hub solution. At first, this solution

may seem incorrect since, by intuition, we should be able to decrease the capacity of each hub if we increase the number of hubs to be opened. Consider the modified deterministic models with 5, 6, 7 and 8 hubs opened. After investigating the solutions, we observed that a certain subset of farms in the network always get allocated to the same regional hub (the hubs may change from one solution to another, but this subset of farms get allocated to one hub only). This is evident since, the maximum capacity allocated across all hubs for 5, 6, 7 and 8 hubs is 8013 lbs. Said differently, these farms together carry 8013 lbs. of product to their nearest regional hub (again, the hubs may change going from 5, 6, 7 to 8 regional hubs) in one of the 52 weeks. Since we have a constraint in our model that allows farmers to travel to their closest regional hub only, and we assume that all regional hubs in the network have the same capacity, if the capacity of the hubs is reduced below 8013 lbs., the model becomes infeasible. Said differently, it is possible to reduce the capacity of the hubs that these farms are not assigned to below 8013 lbs. and still have the model return a feasible solution. Figure 4- 9 below shows how the capacity of hubs impacts the miles traveled by farmers, vehicles and objective function value for the 5-hub solution. Similar analysis can be done for the 6, 7 and 8-hub solutions.

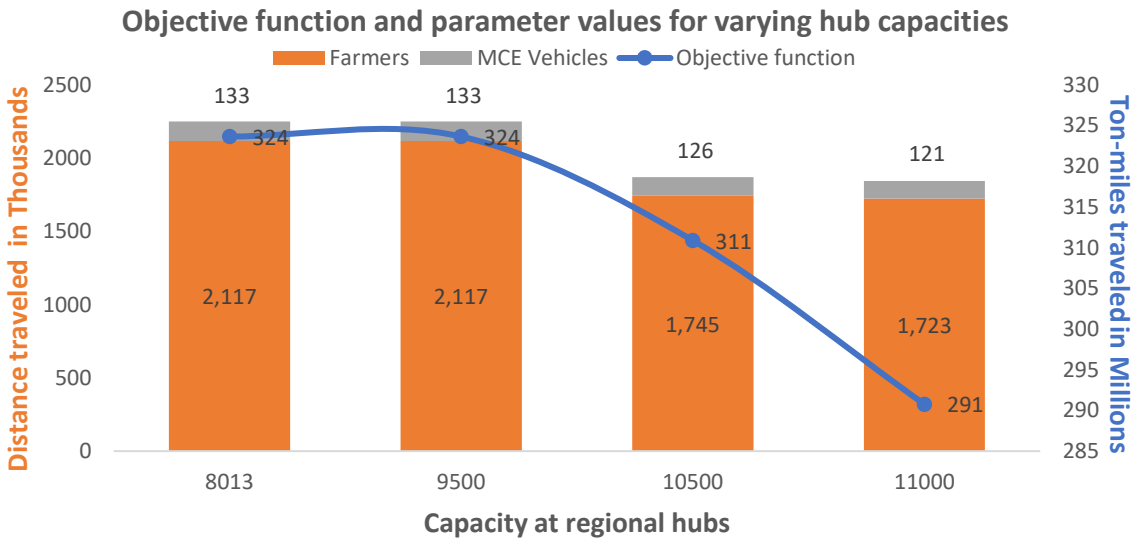

Figure 4- 9: Miles driven by farmers and vehicles on round trip, and objective function values for modified deterministic model

Once again as expected, the distance traveled by MCE vehicles (central hub to regional hubs) increases while the distance traveled by farmers (regional hubs to farms) decreases as we increase the number of regional hubs to be opened. Figure 4- 10 shows how the total distance traveled by farmers and MCE vehicles varies across different scenarios when farmers can bypass the regional hubs.

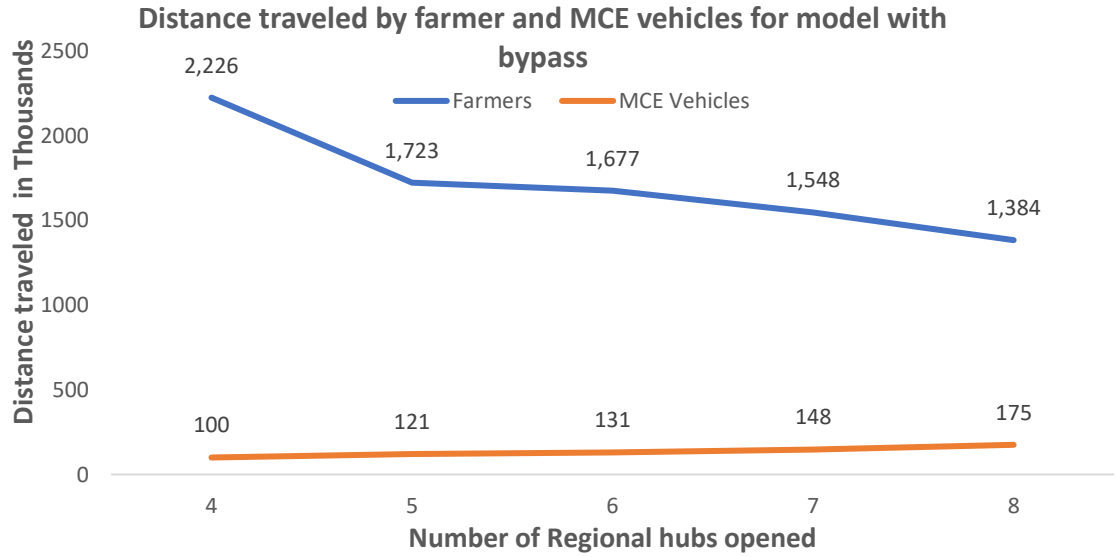

Figure 4- 10: Yearly distance traveled by farmer and MCE vehicles for deterministic model with bypass

Although the modified deterministic model causes an increase in the number of miles traveled by MCE vehicles it is important to note that our model utilizes an objective function equal to the sum of the ton-miles for MCE vehicles plus farmer vehicles. This is evident from figure 4- 11 below where we see that the reduction in miles traveled by farmers is enough to compensate for the increase in miles traveled by MCE vehicles thus reducing the overall objective function value for the modified model. Another important thing to note is that, the objective function values for the model with bypass presented in figure 4- 11 are a result of the capacity values of the regional hubs presented in figure 4- 8 and are not the minimum possible ton-miles achievable. It is possible to further reduce the ton-miles traveled by increasing the capacity of the regional hubs.

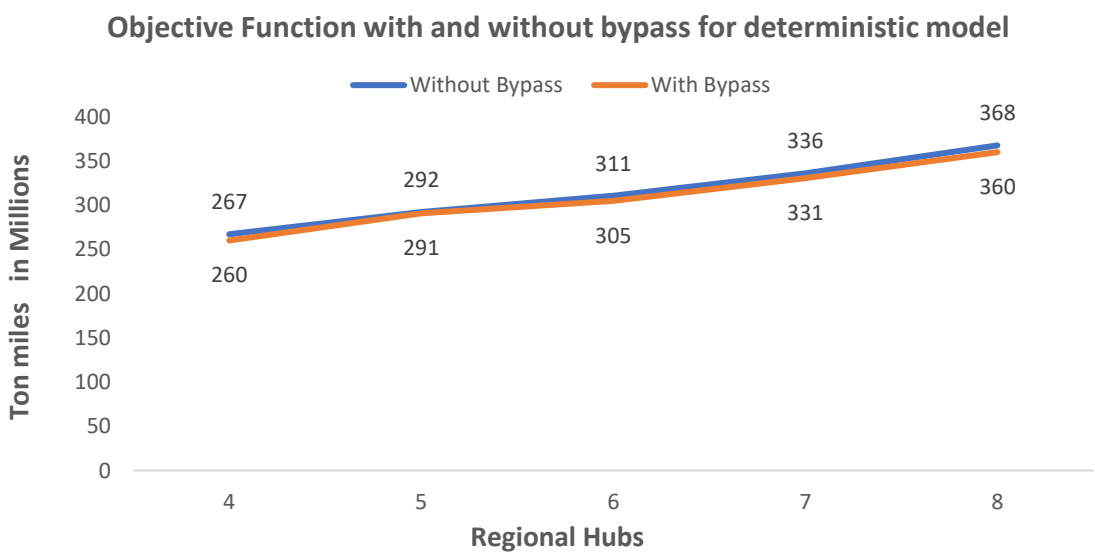

Figure 4- 11: Objective function values for deterministic model with and without bypass.

Table 4- 14 shows the minimum capacity values for which the model returns a feasible solution with and without bypass and the corresponding objective function values. The table also shows the minimum achievable objective function values for the 4, 5 and 6-hub solutions with and without bypass.

Number of hubs opened	Bypass allowed?	Minimizing	Hub capacity	Ton-miles
4 Hubs	No	Hub capacity	**20,500**	313,013,480
		Ton-miles	31,017	**267,210,895**
	Yes	Hub capacity	**12,732**	260,180,069
		Ton-miles	18,966	**237,150,0289**
5 Hubs	No	Hub capacity	**16,125**	304,607,842
		Ton-miles	27,541	**285,422,009**
	Yes	Hub capacity	**8,013**	323,654,916
		Ton-miles	16,974	**259,728,759**
6 Hubs	No	Hub capacity	**16,125**	310,783,677
		Ton-miles	27,541	**309,115,016**
	Yes	Hub capacity	**8,013**	375,037,175
		Ton-miles	16,974	**283,421,766**

Table 4- 14: Minimum feasible values for capacity of regional hubs and corresponding ton-miles traveled for deterministic model.

If we look at the solutions for the 4, 5 and 6-hub configurations where we are minimizing the overall ton-miles traveled and not allowing farmers to bypass hubs, we see that the objective function values increase as we increase the number of hubs. Figures 4- 12, 4- 13 and 4- 14 show how these assignments vary for the 4, 5 and 6-hub solutions.

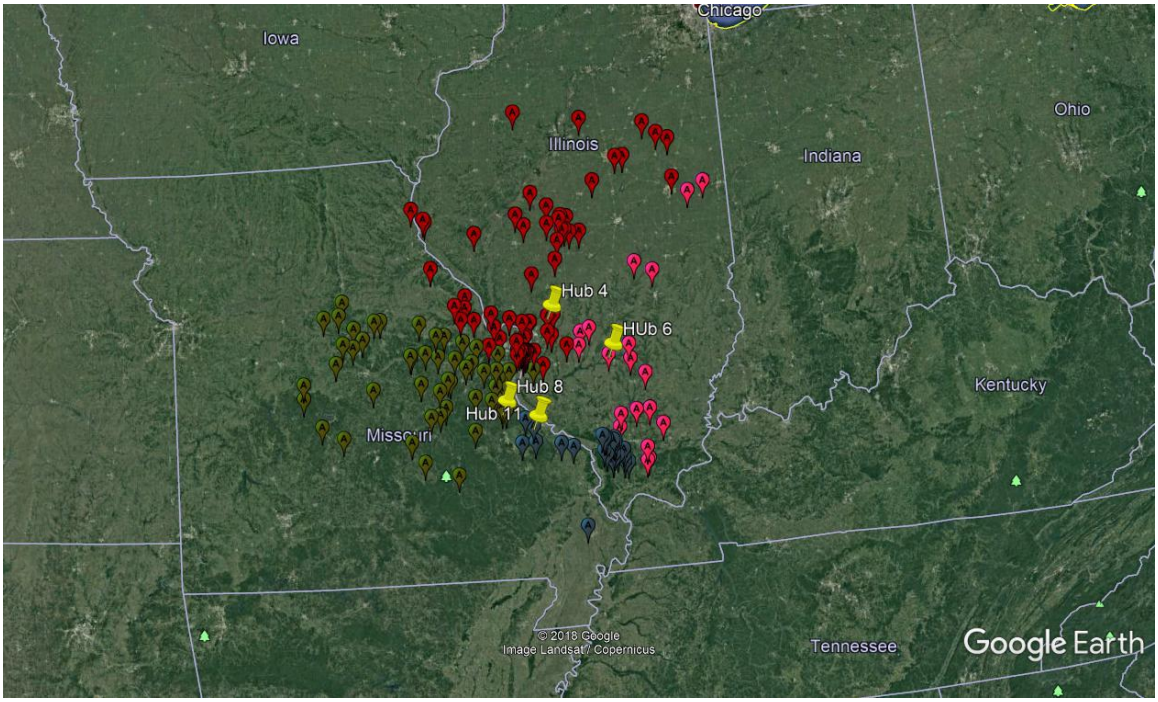

Figure 4- 12: Minimizing ton miles for deterministic model with 4 hubs open without bypass

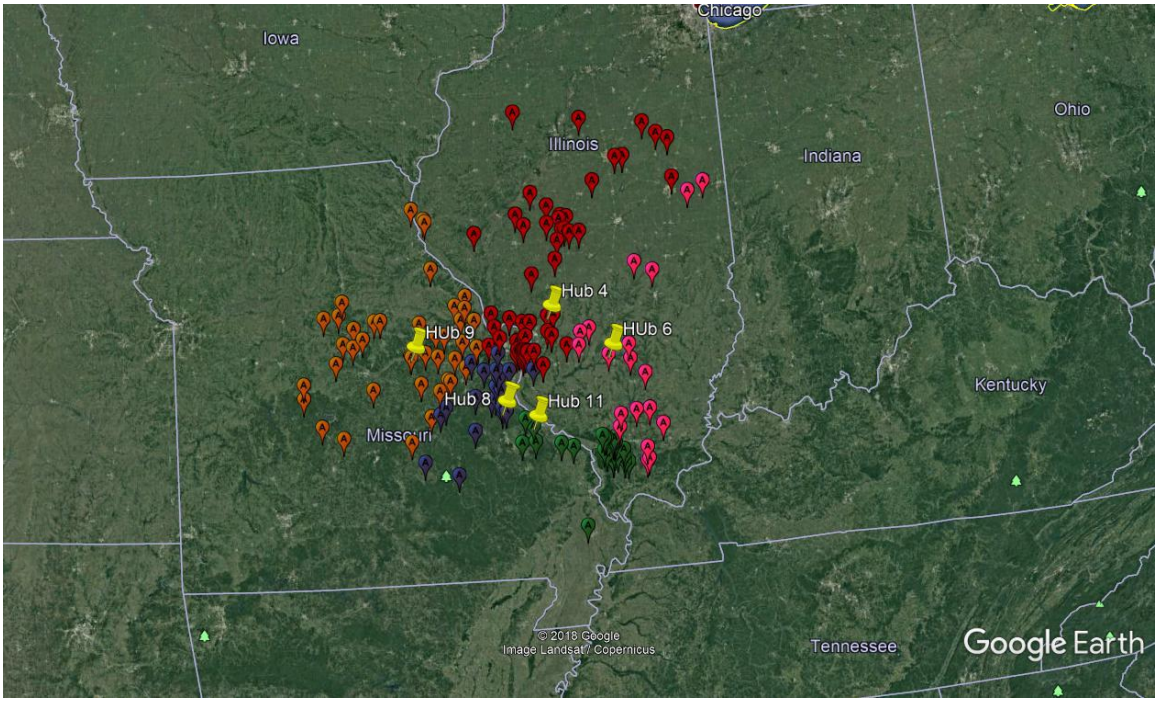

Figure 4- 13: Minimizing ton miles for deterministic model with 5 hubs open without bypass

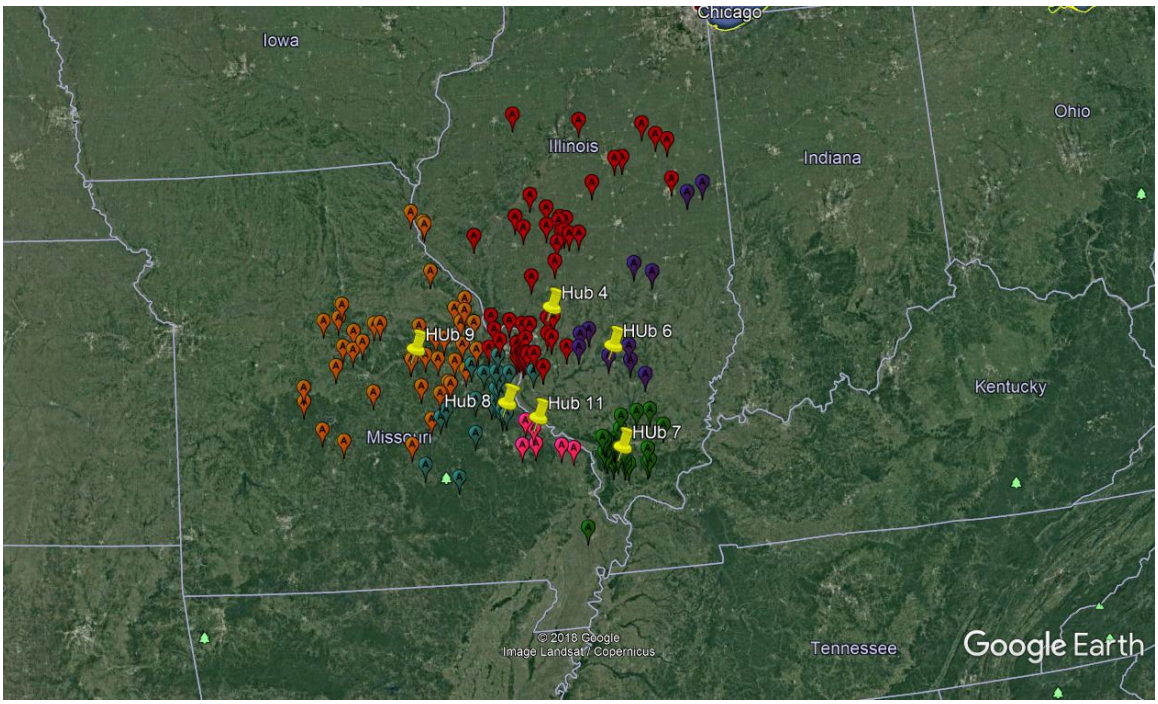

Figure 4- 14: Minimizing ton miles for deterministic model with 6 hubs open without bypass

We see that in the 5-hub solution, the model opens the same hubs as the 4-hub solution, along with hub 9. Similarly for the 6-hub solution, the model opens the same hubs as the

5-hub solution along with hub 7. Further farmer-travel decreases while MCE vehicles'-travel increases as we go from 4 to 5 to 6 hubs. However, total miles traveled by farmers and MCE vehicles decreases from 2.48 million in the 4-hub solution to 1.8 million in the 6-hub solution. Next, we compared the average number of outgoing trips for MCE vehicles from each hub as shown in the table below.

Configuration	Hub 4	Hub 6	Hub 7	Hub 8	Hub 9	Hub 11
4 hubs	2.79	1.32	-	2.29	-	1.28
5 hubs	2.58	1.32	-	1.20	1.87	1.28
6 hubs	2.58	1	1.33	1.20	1.87	1

Table 4- 15: Average number of vehicles trips for MCE vehicles for 4, 5 and 6-hub configuration (deterministic model without bypass)

If we compare figures 4- 12, 4-13 and 4- 14, and table 4- 15, it is evident that as we move from 4 to 5 hubs, some farms that were initially assigned to hubs 4 and 8 (which are closer to the central hub) are now assigned to hub 9 (which is much further away from the central hub). Since one of our model assumptions is that MCE vehicles are filled to their maximum capacity when delivering product from regional hubs to central hub, we can see how this adds additional ton-miles to the existing solution. Similarly as we move from 5 to 6 hubs, some farms assigned to hubs 6 and 11 (which are relatively closer to the central hub) are now assigned to hub 7 (which is much further away from the central hub). Once again we see that the reduction in distance traveled (and hence ton-miles) by these farmers and the reduction in ton-miles for MCE vehicles from hubs 6 and 11 is not enough to counter the increase in ton-miles that occur when these farmers are assigned to hub 7 which is further away from the central hub.

If we look at the solutions for the 4, 5 and 6-hub configurations where we are minimizing the overall ton-miles traveled and allowing farmers to bypass hubs, we see once again that the objective function values increase as we increase the number of hubs. Figures 4- 15, 4- 16 and 4- 17 show how these assignments vary for the 4, 5 and 6-hub solutions.

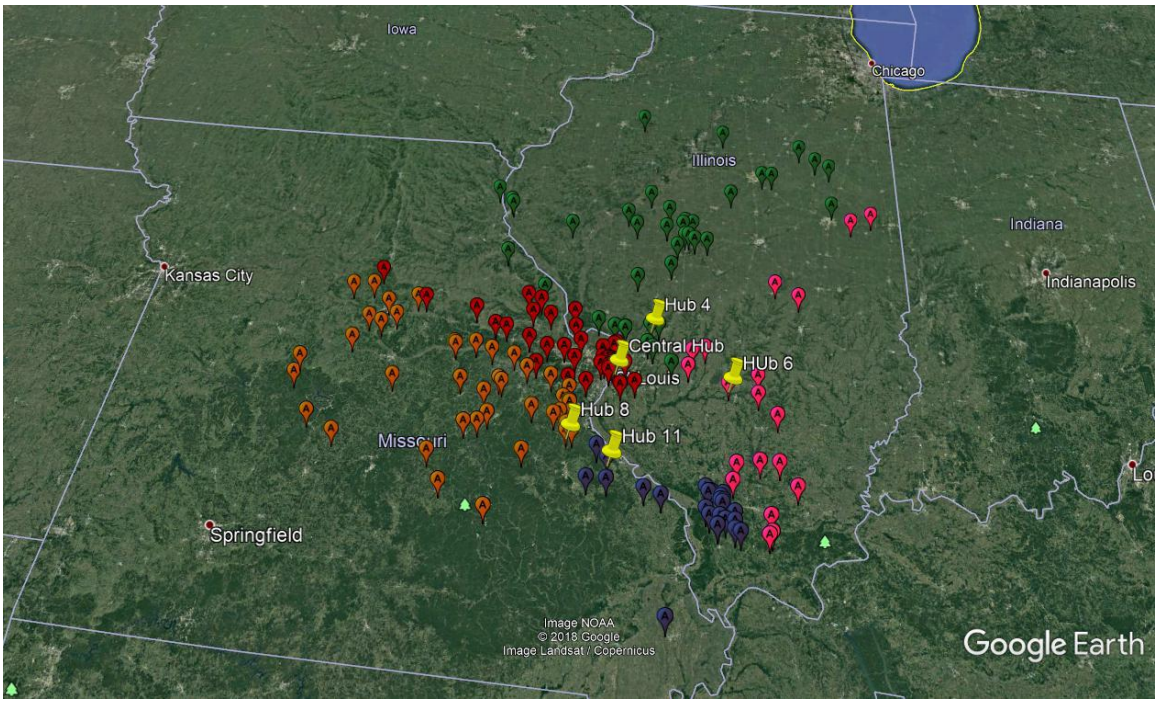

Figure 4- 15: Minimizing ton miles with 4 hubs open with bypass

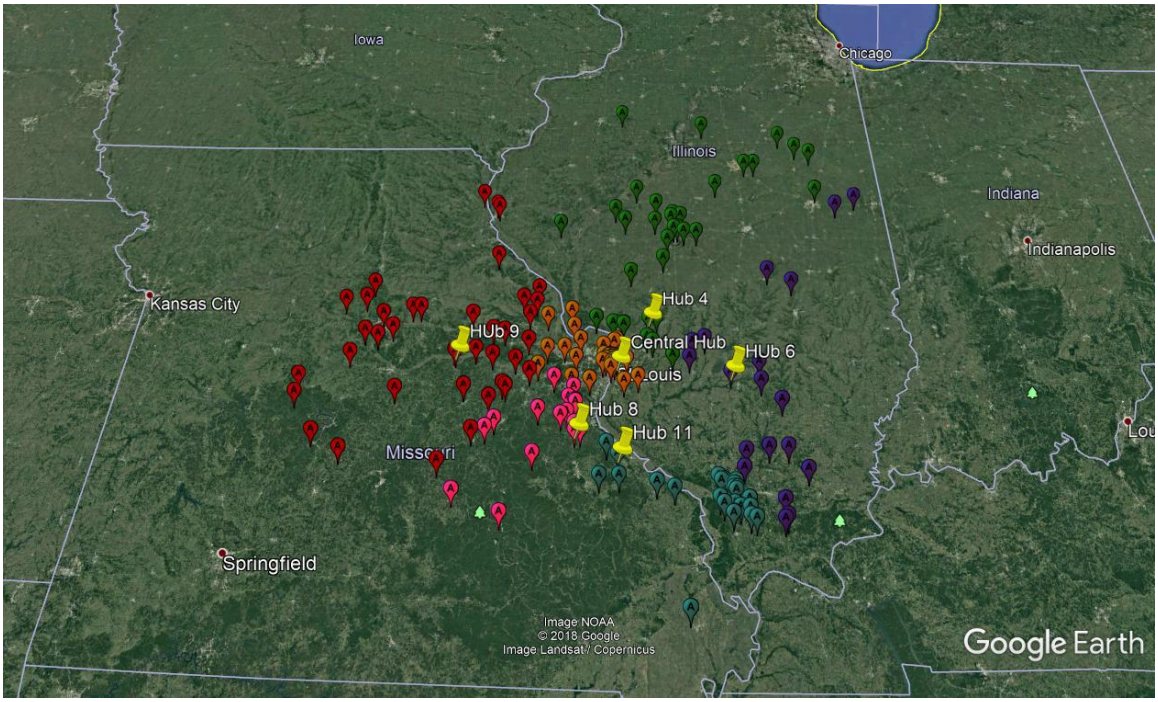

Figure 4- 16: Minimizing ton miles with 5 hubs open with bypass

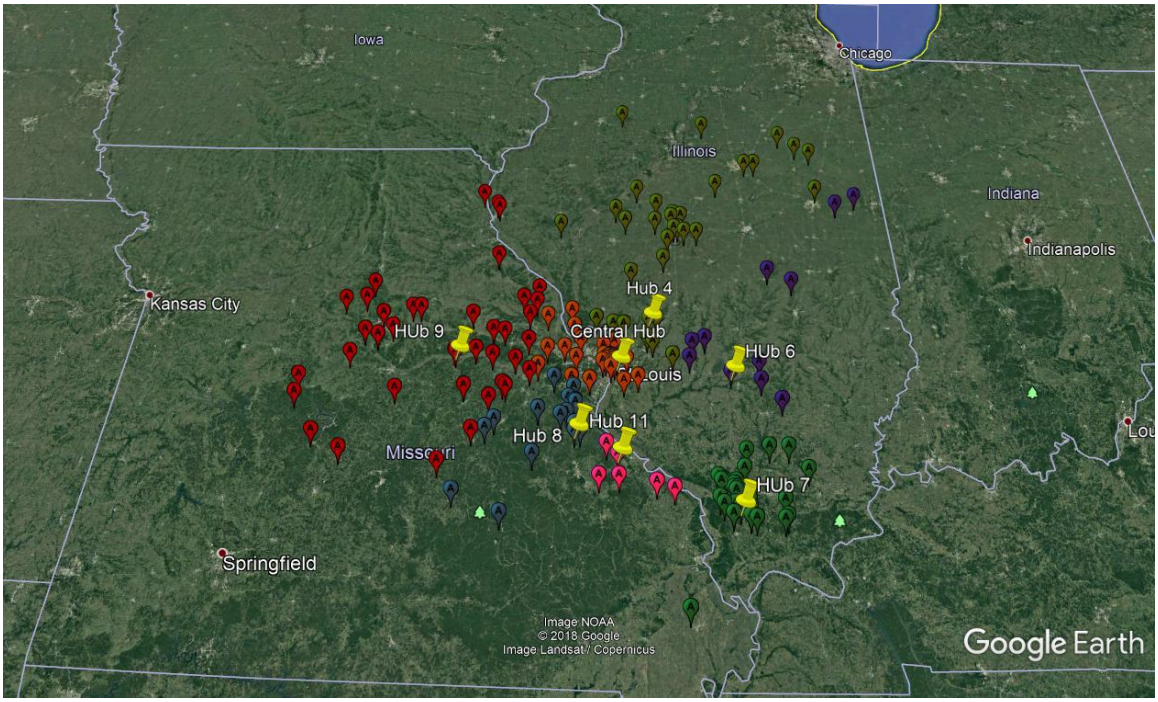

Figure 4- 17: Minimizing ton miles with 6 hubs open with bypass

We see that in the 5-hub solution, the model opens the same hubs as the 4-hub solution along with hub 9. Similarly for the 6-hub solution, the model opens the same hubs as the 5-hub solution along with hub 7. Further, we observed that farmer-travel decreases while

MCE vehicles'-travel increases as we go from 4 to 5 to 6 hubs. However, total miles traveled by farmers and MCE vehicles decreases from 1.95 million in the 4-hub solution to 1.64 million in the 6-hub solution. Next, we compared the average number of outgoing trips for MCE vehicles from each hub as shown in the table below.

Configuration	Hub 4	Hub 6	Hub 7	Hub 8	Hub 9	Hub 11
4 hubs	2	1.32	-	1.79	-	1.28
5 hubs	1.82	1.32	-	1.16	1.75	1.28
6 hubs	1.82	1	1.33	1.16	1.75	1

Table 4- 16: Average number of vehicles trips for MCE vehicles for 4, 5 and 6-hub configuration (deterministic model with bypass)

If we look at figures 4- 15, 4-16 and 4- 17, and table 4- 16, it is evident that as we move from 4 to 5 hubs, some farms that were initially assigned to hubs 4 and 8 (which are closer to the central hub) are now assigned to hub 9 (which is much further away from the central hub). Since one of our model assumptions is that MCE vehicles are filled to their maximum capacity when delivering product from regional hubs to central hub, we can see how this adds additional ton-miles to the existing solution. Similarly as we move from 5 to 6 hubs, some farms assigned to hubs 6 and 11 (which are relatively closer to the central hub) are now assigned to hub 7 (which is much further away from the central hub). Once again we see that the reduction in distance traveled (and hence ton-miles) by these farmers and the reduction in ton-miles for MCE vehicles from hubs 6 and 11 is not enough to counter the increase in ton-miles that occur when these farmers are assigned to hub 7 which is much further away from the central hub. We also see that the average number of trips by MCE vehicles from hubs 4 and 8 when farmers are allowed to bypass also drops significantly as we compare table 4- 15 and table 4- 16.

As discussed in the previous section, climate variability in the region makes it imperative to test our model for robustness. Like the deterministic model presented above, we analyzed the RO model under two configurations - with and without bypass. We assumed a 50 % variation in both Plant and Animal products corresponding to parameter p_{ijk} in our formulation for all farms across all weeks. The variation assumed with respect to Plant and Animal products is denoted by v_{ijk}. No variation was assumed for farms not generating either Plant or Animal products.

4.3 Robust model without bypass

We ran the RO model without bypass for four, five and six regional hubs as well. We allowed all robust parameters in our RO model to take their worst-case possible values and observed the solutions given by the model.

Figure 4- 18 shows the assignments of farms to the corresponding regional hubs for the 4-hub solution.

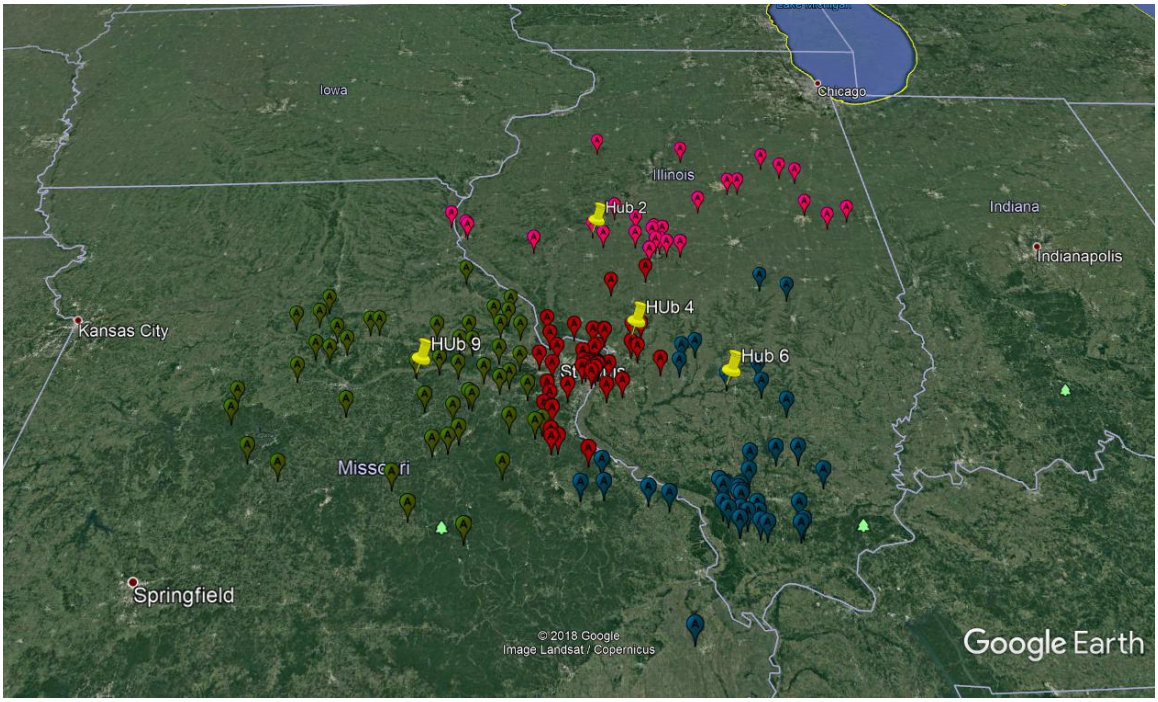

Figure 4- 18: Farm-hub assignments for RO model with four regional hubs open.

Table 4- 17 below shows the maximum number of vehicle trips for each product type that would be made from the corresponding regional hubs to the central hub for the 4-hub configuration. Table 4- 18 shows the total distance traveled in miles on a round trip by all farmers (assuming that each farmer performs a single trip) along with the distance traveled by MCE vehicles in a year.

After comparing the solution with its deterministic counterpart, we see that the distance covered by MCE vehicles has now increased more than two-folds. The number of Plant and Animal vehicle trips has also significantly increased since you now have more product inflow into the regional hubs as a result of the model accounting for variation of Plant and Animal product at each farm from their nominal values. The model also does not open all the same regional hubs that it did for the original deterministic model.

	Hub 2	Hub 4	Hub 6	Hub 9
Plant	5	6	5	4
Animal	2	4	3	5

Table 4- 17: Maximum weekly trips between regional hubs and central hub for each vehicle type

Farmers	MCE Vehicles
2,035,097	165,494

Table 4- 18: Yearly truck miles driven for four hubs (round trip)

Figure 4- 19 shows the assignments of the farms to the corresponding regional hubs for the 5-hub solution.

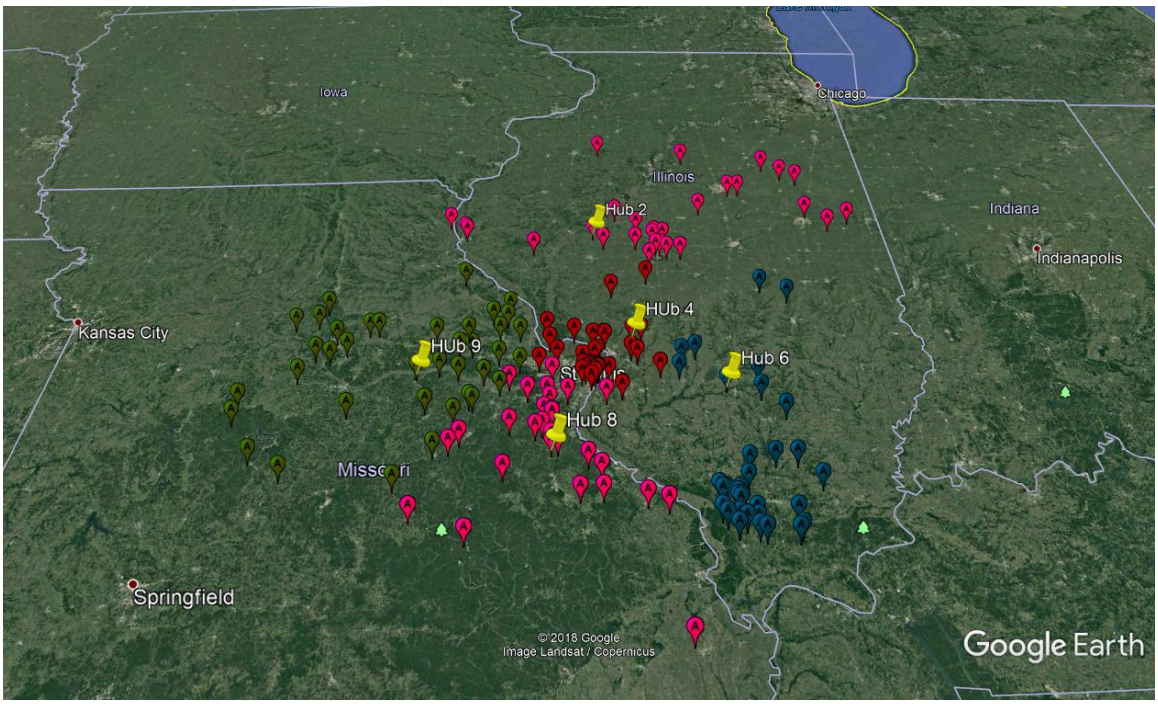

Figure 4- 19: Farm-hub assignments for RO model with five regional hubs open.

Table 4- 19 below shows the maximum number of vehicle trips for each product type that would be made from the corresponding regional hubs to the central hub for the 5-hub configuration. Table 4- 20 shows the total distance traveled in miles on a round trip by all farmers (assuming that each farmer performs a single trip) along with the distance traveled by MCE vehicles in a year. Similar observations are seen for its deterministic counterpart as in the case of the 4-hub solution.

	Hub 2	Hub 4	Hub 6	Hub 8	Hub 9
Plant	5	6	5	3	3
Animal	2	2	3	1	5

Table 4- 19: Maximum weekly trips between regional hubs and central hub for each vehicle type

Farmers	MCE Vehicles
1,800,821	169,639

Table 4- 20: Yearly truck miles driven for five hubs (round trip)

Figure 4- 20 shows the assignments of the farms to the corresponding regional hubs for the 6-hub solution.

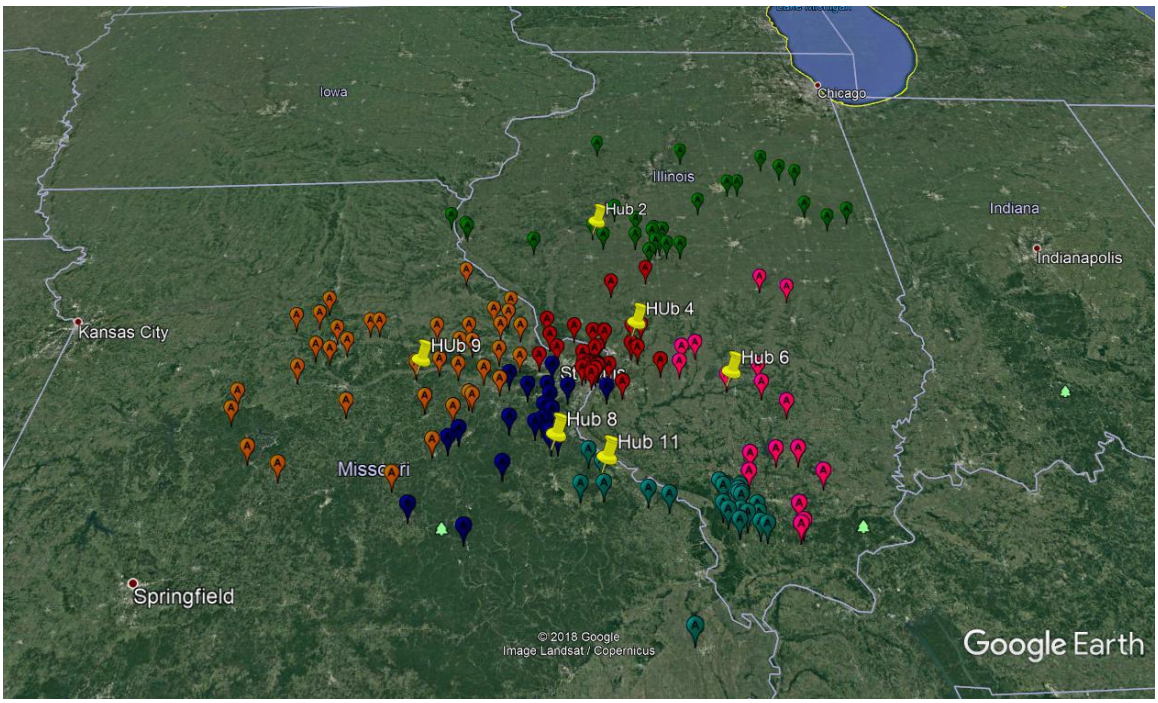

Figure 4- 20: Farm-hub assignments for RO model with six regional hubs open.

Table 4- 21 below shows the maximum number of vehicle trips for each product type that would be made from the corresponding regional hubs to the central hub for the 6-hub configuration. Table 4- 22 shows the total distance traveled in miles on a round trip by all farmers (assuming that each farmer performs a single trip) along with the maximum distance traveled by MCE vehicles in a year. Similar observations are seen for its deterministic counterpart as in the case of the 4-hub and 5-hub solutions.

	Hub 2	Hub 4	Hub 6	Hub 8	Hub 9	Hub 11
Plant	6	6	3	2	3	3
Animal	2	2	2	3	5	2

Table 4- 21: Maximum weekly trips between regional hubs and central hub for each vehicle type

Farmers	MCE Vehicles
1,732,491	175,847

Table 4- 22: Yearly truck miles driven for six hubs (round trip)

Let us compare the 4-hub and 5-hub solutions. For the 4-hub solution, the robust model opens hubs 2 and 9 which are further away from the central hub in place of hubs 8 and 1 11 respectively which were much closer to the central hub resulting in reduced travel for farmers that were initially making the long travel from central and east Missouri to hub 8 since they now travel to hub 9 instead. Similar rationale follows for farms that get allocated to hub 2. We discovered that the average production at these farms is higher than the average production at all farms in the network. Since our objective is to reduce the ton-miles transported in the network, the model is reducing the ton-miles traveled by the farmers by opening hubs relatively closer to them. As a result, overall distance traveled by farmers decreases for the RO model as compared to its deterministic counterpart. On the other hand, distance traveled by MCE vehicles increases because of longer and increased number of trips associated with travel to and from the central hub. Similar observations can be seen when comparing the 5-hub solutions of the two models. Now in addition to hub 9, from the 4-hub RO model, the model opens hub 8 to prevent farmers in the southern part of the network from making trips to hub 4, hub 9 and hub 6 thus leading to roughly 68,330 miles saved for farmers in travels. If we compare this to farm-hub assignments in the 5-hub deterministic solution, we see how introducing hub 2 leads to reduced miles traveled by farmers. Now farmers in Northern Illinois that were initially making long trips to hubs

4 and hub 10 can travel to hub 2. The reduction is pretty evident, in that, farmers now travel about 421,000 miles less than in the deterministic counterpart.

Once again as expected, distance traveled by MCE vehicles (central hub to regional hubs) increases while the distance traveled by farmers (regional hubs to farms) decreases as we increase the number of regional hubs to be opened.

4.4 Robust model with bypass

We ran the RO model with bypass for four, five and six regional hubs as well. Once again, we allowed all robust parameters in our RO model to take their worst-case possible values and observed the solutions given by the model.

Figure 4- 21 shows the assignments of farms to the corresponding regional hubs for the 4-hub solution.

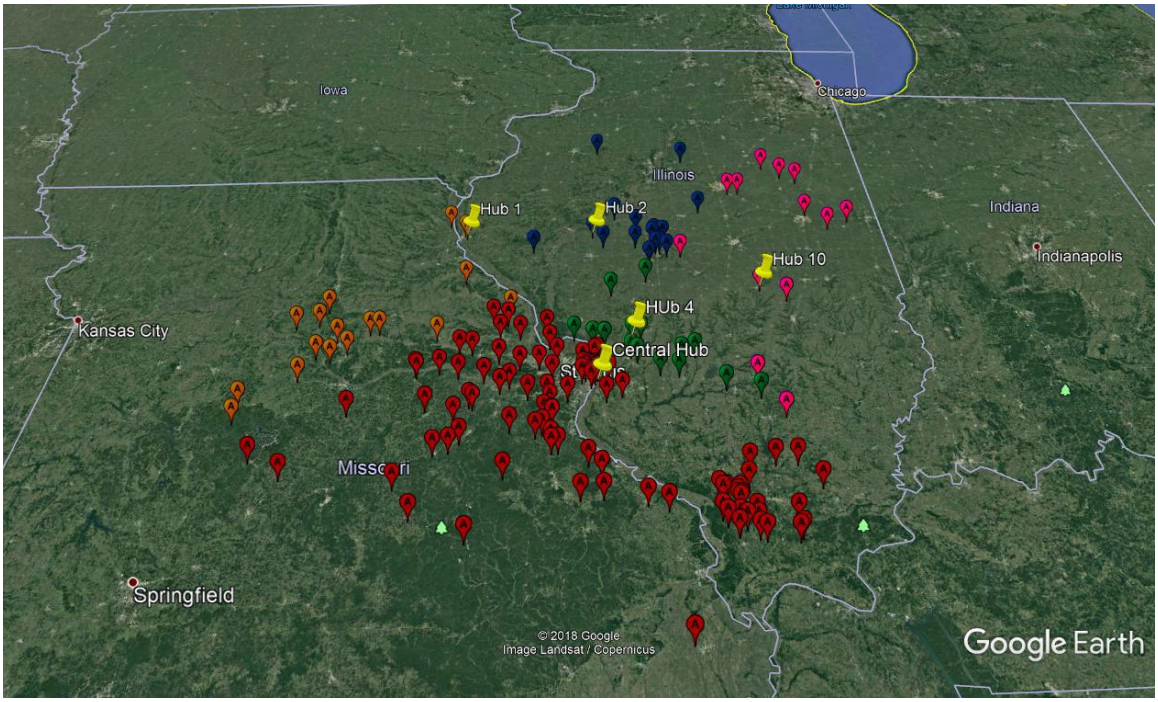

Figure 4- 21: Farm-hub assignments for modified RO model with four regional hubs open.

Table 4-23 below shows the maximum number of vehicle trips for each product type that would be made from the corresponding regional hubs to the central hub for the 4-hub configuration. Table 4- 24 shows the total distance traveled in miles on a round trip by all farmers (assuming that each farmer performs a single trip) along with the distance traveled by MCE vehicles in a year.

After comparing the solution with its deterministic counterpart, we see that the distance covered by MCE vehicles as well as farmers increases significantly. The number of Plant and Animal vehicle trips has also increased since you now have more product inflow into the regional hubs as a result of the model accounting for variation of Plant and Animal product at each farm from their nominal values. The model also does not open the same regional hubs that it did for the original deterministic model with bypass.

	Hub 1	**Hub 2**	**Hub 4**	**Hub 10**
Plant	2	3	2	3
Animal	2	1	2	1

Table 4- 23: Maximum weekly trips between regional hubs and central hub for each vehicle type

Farmers	MCE Vehicles
2,225,665	117,650

Table 4- 24: Yearly truck miles driven for four hubs (round trip)

Figure 4- 22 shows the assignments of farms to the corresponding regional hubs for the 5-hub solution.

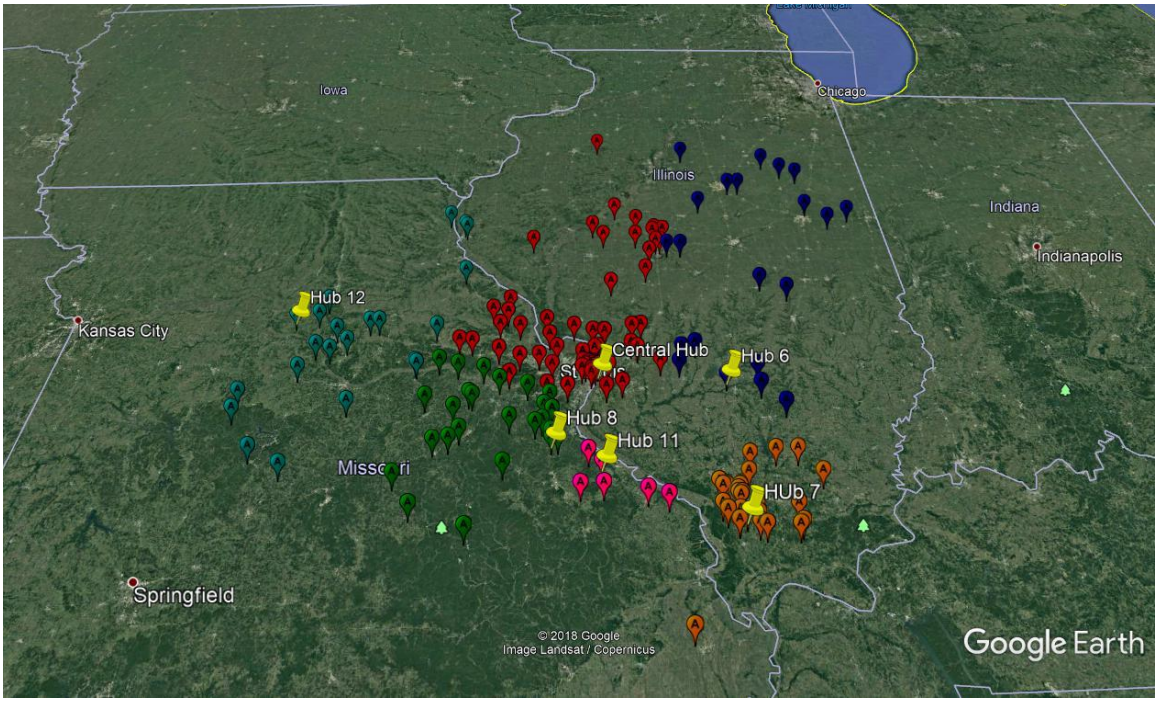

Figure 4- 22: Farm-hub assignments for modified RO model with five regional hubs open.

Table 4- 25 below shows the maximum number of vehicle trips for each product type that would be made from the corresponding regional hubs to the central hub for the 5-hub configuration. Table 4- 26 shows the total distance traveled in miles on a round trip by all farmers (assuming that each farmer performs a single trip) along with the distance traveled by MCE vehicles in a year. Similar observations are seen for its deterministic counterpart as in the case of the 4-hub solution.

	Hub 6	Hub 7	Hub 8	Hub 11	Hub 12
Plant	3	4	2	1	2
Animal	2	2	3	1	3

Table 4- 25: Maximum weekly trips between regional hubs and central hub for each vehicle type

Farmers	MCE Vehicles
1,745,143	150,488

Table 4- 26: Yearly truck miles driven for five hubs (round trip)

Figure 4- 23 shows the assignments of farms to the corresponding regional hubs for the 6-hub solution.

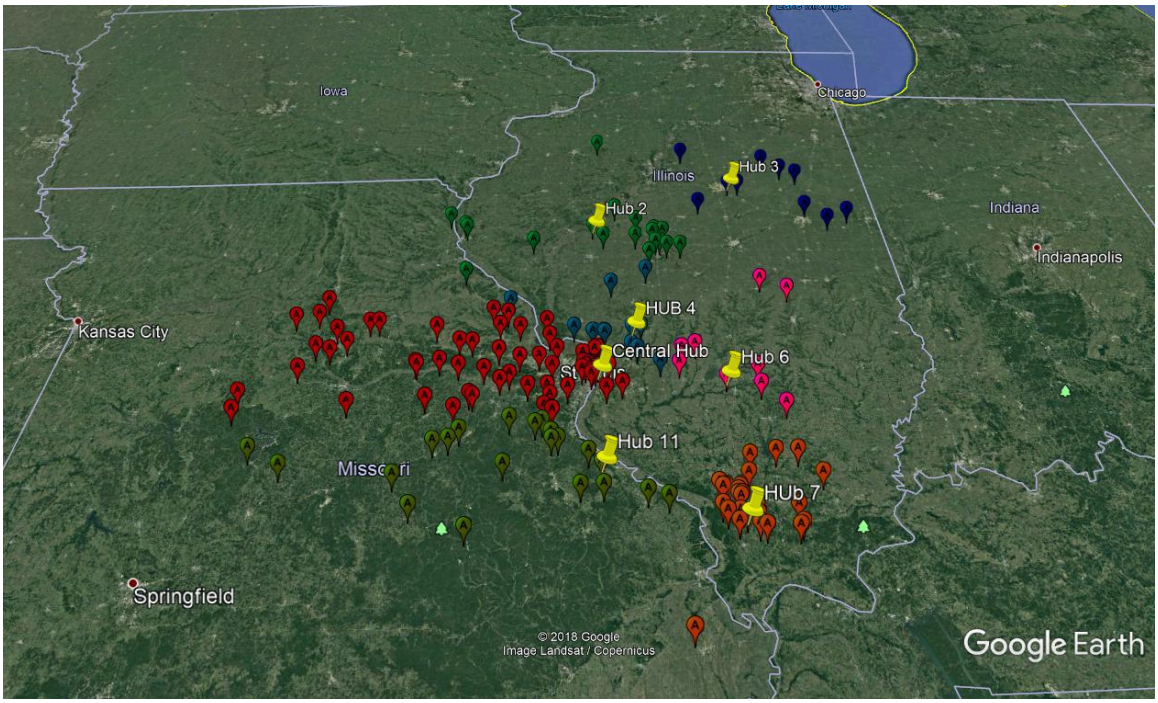

Figure 4- 23: Farm-hub assignments for modified RO model with six regional hubs open.

Table 4- 27 below shows the maximum number of vehicle trips for each product type that would be made from the corresponding regional hubs to the central hub for the 6-hub configuration. Table 4- 28 shows the total distance traveled in miles on a round trip by all farmers (assuming that each farmer performs a single trip) along with the distance traveled by MCE vehicles in a year. Similar observations are seen for its deterministic counterpart as in the case of the 4-hub and 5-hub solutions.

	Hub 2	Hub 3	Hub 4	Hub 6	Hub 7	Hub 11
Plant	4	1	2	2	4	2
Animal	1	1	2	2	2	3

Table 4- 27: Maximum weekly trips between regional hubs and central hub for each vehicle type

Farmers	MCE Vehicles
1,597,637	167,387

Table 4- 28: Yearly truck miles driven for six hubs (round trip)

Comparing the four, five and six-hub solutions for the original and modified RO models it is evident that allowing farmers to bypass regional hubs is better for farmers (except for the 4-hub case) and MCE vehicles.

Regional Hub	% decrease in miles for farmers	% decrease in miles for MCE vehicles
4	-9.36	28.91
5	3.09	11.28
6	7.78	4.811

Table 4- 29: Percentage drop in miles traveled by farmers and MCE vehicles when farmers can bypass regional hubs.

In order to understand why the modified RO model with bypass was making farmers travel longer distances than the original RO model for the 4-hub solution, we compared farm-hub assignments for farmers which were traveling longer distances under the modified configuration. We observed that there were 76 farmers in the network that were covering longer distances under the modified configuration. These farmers together traveled 3013 miles more every week. What is more interesting is that most of the farmers that were initially traveling to Hubs 6 and 9 under the original configuration were now made to travel all the way to the central hub by the modified model. These farmers accounted for more than 60% of the 3013 miles traveled. It is also evident from the respective maps. This explains the increased distance traveled by farmers over the course of the year. If we look at the number of trips that MCE vehicles make from hubs 6 and 9, they are certainly on the higher side. This implies that farmers assigned to these hubs have average production that is higher than the remaining farms in the network. By assigning these farms to the central hub, the model is reducing the number of trips (and hence the distance traveled) that MCE vehicles will make in the network. The model instead opens hubs 2 and 10, and assigns

farms to them that have lower average production. This is also evident when we look at the number of trips that MCE vehicles make from these hubs in the modified RO model.

Comparing farm-hub assignments for 5 regional hubs for the RO models we see that the modified RO model now opens hub 12 and assigns all the low production farms to them. This explains the reduced number of trips from hub 12 to the central hub by MCE vehicles. We see that all the high production farms that were assigned to hub 9 originally are now assigned to hub 8 which is much closer to the central hub resulting in reduced travel by MCE vehicles. Similarly some of the high production farms in northern Illinois that were initially assigned to hub 2 now travel directly to the central hub and some of the farms initially assigned to hub 6 in the original model get reassigned to hub 7 which reduces travel by these farmers in the modified network. The benefits are evident in that, farmers in the modified network travel around 56,000 miles less yearly as compared to the original RO model.

Comparing the modified RO model with 5 hubs open to 6 hubs open we see that now the model assigns all farms in the west of the network to travel directly to the central hub. When we look at the corresponding solution for the model without bypass we see that the model does not utilize hub 9 at all since the model is trying to reduce the travel made by MCE vehicles associated with all the high-production farms in this region. This can also be seen in our deterministic models with bypass where the model does not utilize hub 9 in either of the 3 configurations. Farmers in the modified RO model travel about 135,000 miles less than farmers in the original RO model. This is primarily due to hubs 7 and 3 which prevent farmers from making the long trips to hubs 11 and 2 as in the original model. The incremental increase in travel by MCE vehicles in the modified RO model as we move

from 5 to 6 regional hubs is because of opening hubs 2 and 3 located in the northern Illinois region.

Figure 4- 24 below shows the capacity requirements at each hub for different configurations of the RO model. Once again, we see significant reduction in the capacity requirements of the hubs when farmers can bypass the regional hubs with the most significant reduction seen in the 4-hub solution where the capacity reduces by 51.56 %. It is also interesting that for the model with bypass, going from 4 to 5 hubs allows us to reduce the capacity of each hub but going from 5 to 6 hubs the capacity of each hub once again increases. We would like to point out that our model is feasible for hub capacities of 13,000 for the 6-hub solution. However now, the ton-miles traveled are greater than what they were for the RO model without bypass. We incrementally increased the capacity of the regional hubs until the ton-miles travelled in the solutions with bypass allowed were just less than the ton-miles travelled in the solution where bypass is not allowed. We followed a similar procedure for the 7 and 8-hub solutions.

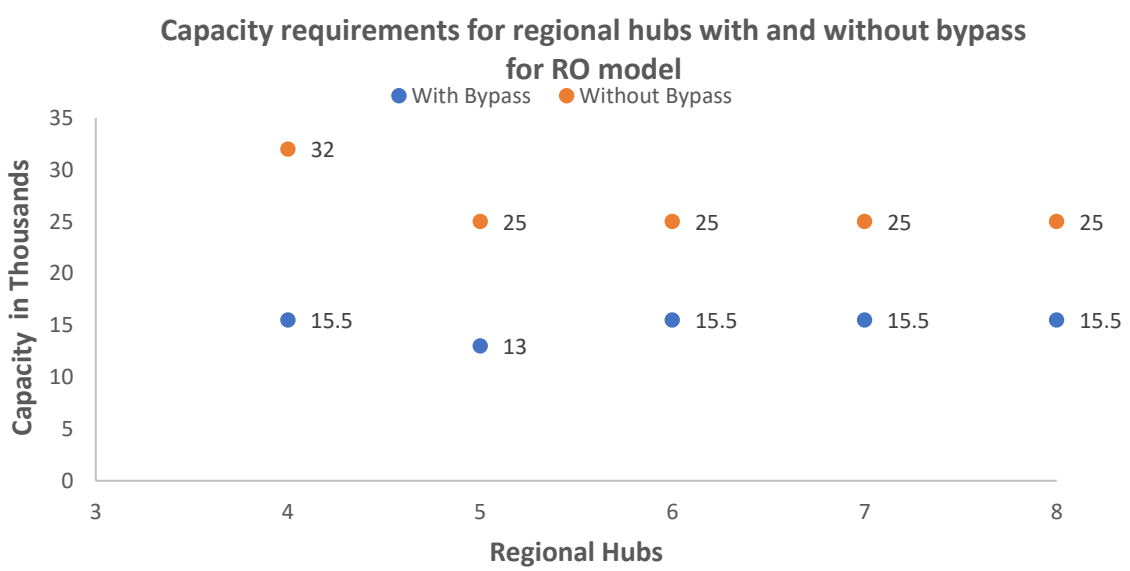

Figure 4- 24: Farm-hub assignments for RO model with five regional hubs open.

It is important to note here that just like in the case of the deterministic models, the capacity values presented in figure 4- 24 are not the minimum possible values that are needed to give us a feasible solution. The point we are trying to make again is that it is possible to reduce the capacity of hubs if we allow farmers to bypass and travel directly to the central hub.

Figure 4- 25 shows the objective function values for the two RO models with different number of regional hubs opened. The disparity in the objective function values for the four, five and six-hub solutions clearly underscores the importance of allowing farmers to travel directly to the central hub. We would again like to remind our readers that the values shown in figure 4- 25 are not the minimum possible ton-miles achievable. These values correspond to the capacity values that we set for the regional hubs in figure 4- 24.

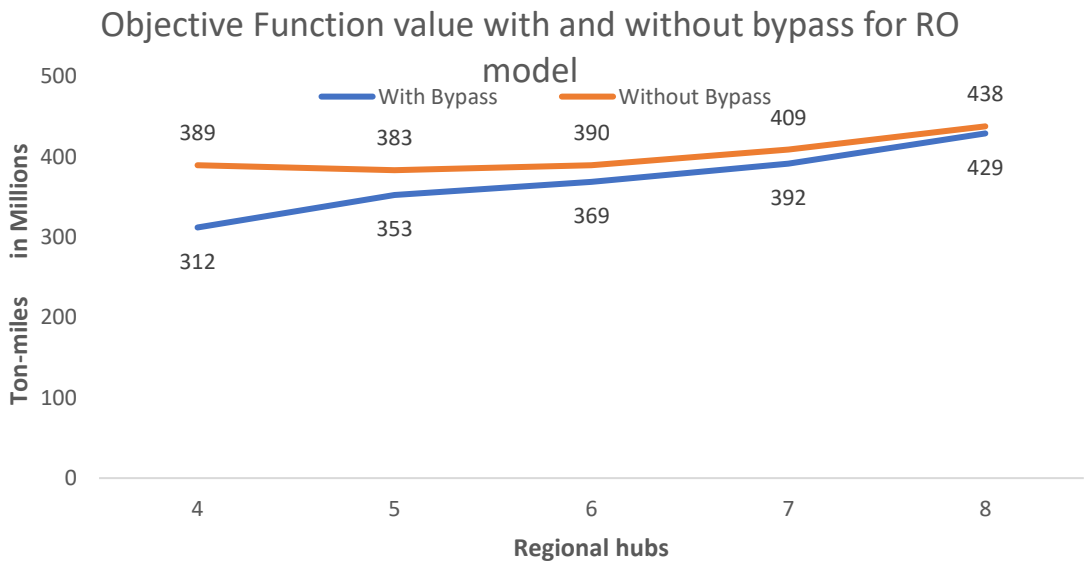

Figure 4- 25: Objective function values for RO model with all worst-case variations considered.

Table 4- 30 shows the minimum capacity values for which the model returns a feasible solution both with and without bypass and the corresponding objective function values for

the RO model. The table also shows the minimum achievable objective function values for the 4, 5 and 6-hub solutions with and without bypass.

Number of hubs opened	Bypass allowed?	Minimizing	Hub capacity	Ton-miles
4 Hubs	No	Hub capacity	**31,000**	389,308,613
		Ton-miles	50,000	**314,006,6423**
	Yes	Hub capacity	**10,100**	394,436,352
		Ton-miles	25,000	**288,876,680**
5 Hubs	No	Hub capacity	**25,000**	383,290,154
		Ton-miles	45,000	**341,912,004**
	Yes	Hub capacity	**12,050**	358,311,572
		Ton-miles	25,000	**311,407,203**
6 Hubs	No	Hub capacity	**25,000**	389,568,766
		Ton-miles	45,000	**371,548,876**
	Yes	Hub capacity	**12,050**	413,570,024
		Ton-miles	25,000	**340,367,283**

Table 4- 30: Minimum feasible values for capacity of regional hubs and corresponding ton-miles traveled for robust model.

If we look at the solutions for the 4, 5 and 6-hub configurations where we are minimizing the overall ton-miles traveled and not allowing farmers to bypass hubs, we see that the objective function values increase as we increase the number of hubs. Figures 4- 26, 4-27 and 4- 28 below show how these assignments vary for the 4, 5 and 6-hub solutions.

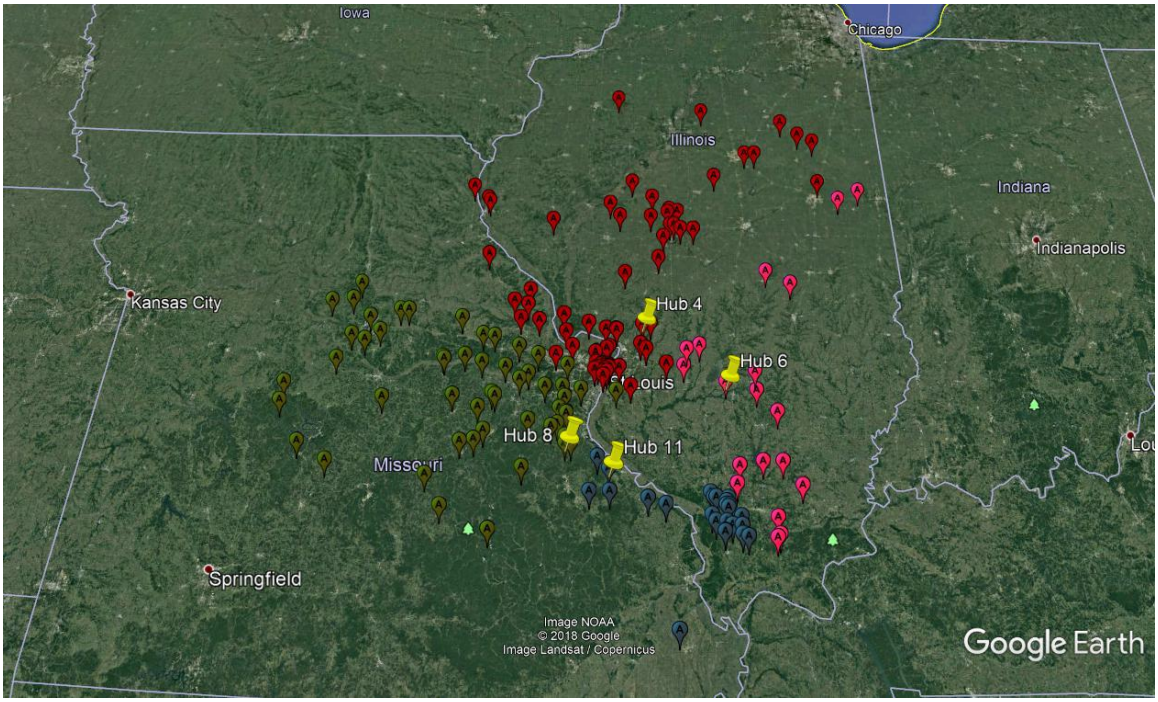

Figure 4- 26: Minimizing ton miles with 4 hubs open without bypass

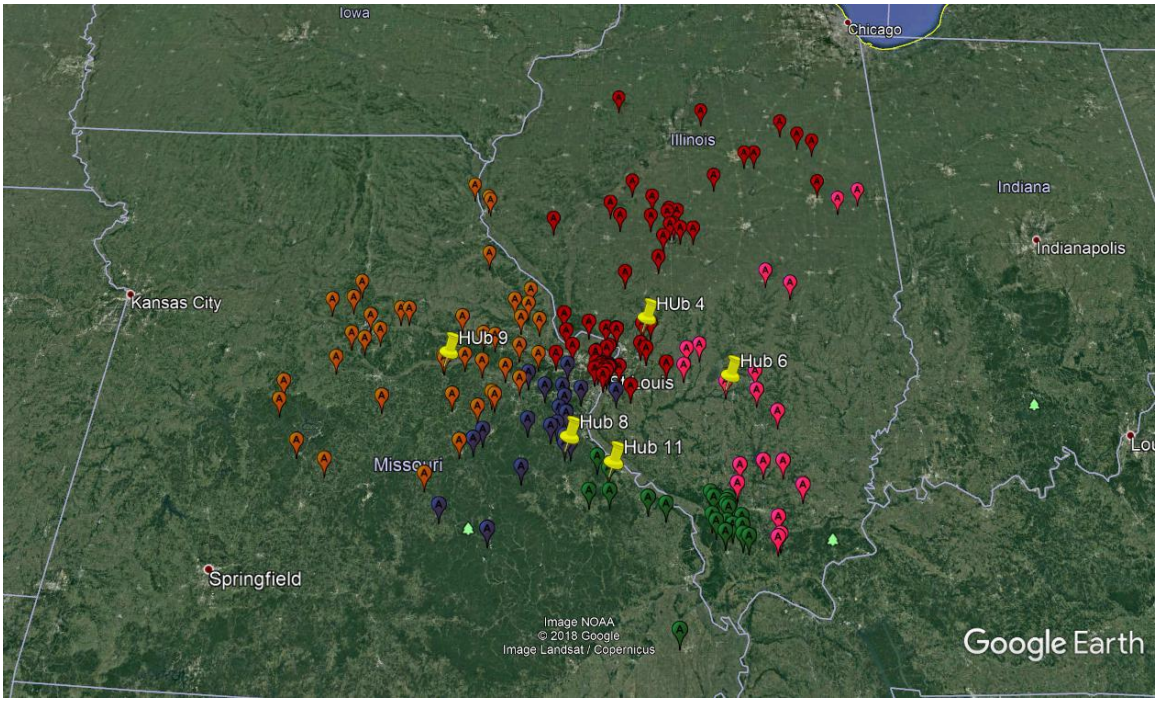

Figure 4- 27: Minimizing ton miles for RO model with 5 hubs open without bypass

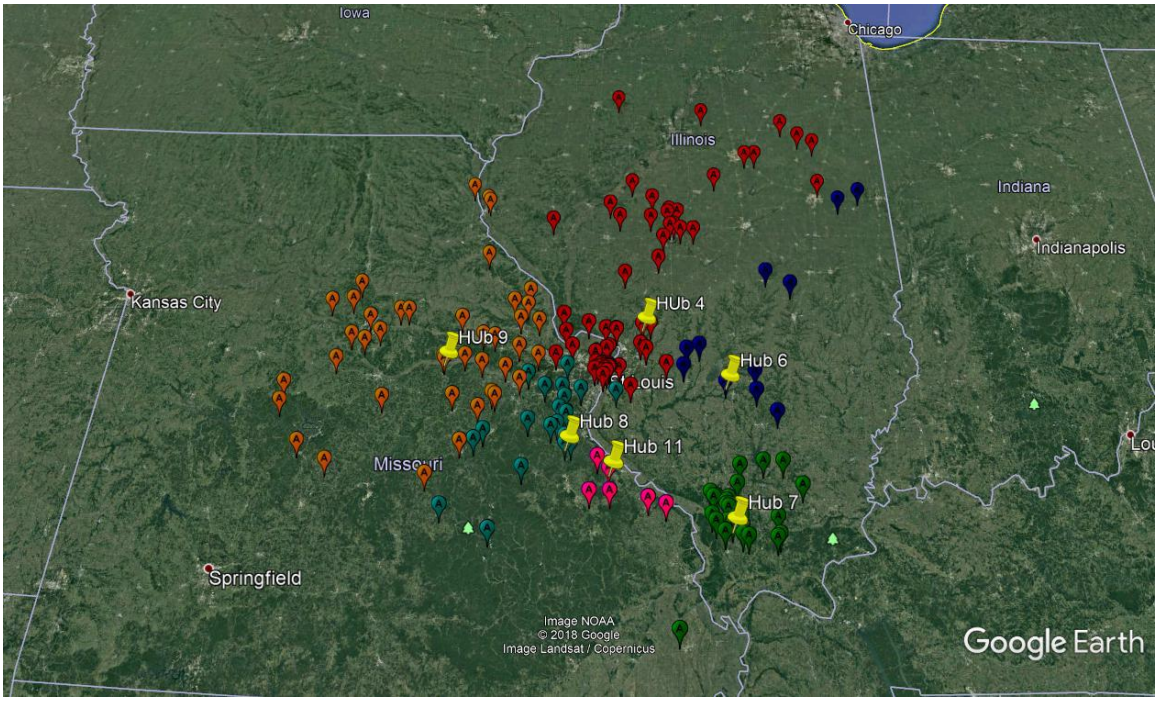

Figure 4- 28: Minimizing ton miles for RO model with 6 hubs open without bypass

As in the case of the deterministic model, for the RO model, we see that in the 5-hub solution, the model opens the same hubs as the 4-hub solution along with hub 9. Similarly

for the 6-hub solution, the model opens the same hubs as the 5-hub solution along with hub 7. Further farmer-travel decreases while MCE vehicles'-travel increases as we go from 4 to 5 to 6 hubs. However, total miles traveled by farmers and MCE vehicles decreases from 2.51 million in the 4-hub solution to 1.85 million in the 6-hub solution. Next, we compared the average number of outgoing trips for MCE vehicles from each hub as shown in the table below.

Configuration	Hub 4	Hub 6	Hub 7	Hub 8	Hub 9	Hub 11
4 hubs	4.04	1.58	-	3.13	-	1.71
5 hubs	3.67	1.58	-	1.51	2.5	1.71
6 hubs	3.67	1.32	1.66	1.51	2.5	1

Table 4- 31: Average number of vehicles trips for MCE vehicles for 4, 5 and 6-hub configuration (RO model without bypass)

If we compare figures 4- 26, 4-27 and 4- 28, and table 4- 31, it is evident that as we move from 4 to 5 hubs, some farms that were initially assigned to hubs 4 and 8 (which are closer to the central hub) are now assigned to hub 9 (which is much further away from the central hub). Since one of our model assumptions is that MCE vehicles are filled to their maximum capacity when delivering product from regional hubs to central hub, we can see how this adds additional ton-miles to the existing solution. Similarly as we move from 5 to 6 hubs, some farms assigned to hubs 6 and 11 (which are relatively closer to the central hub) are now assigned to hub 7 (which is much further away from the central hub). Once again we see that the reduction in distance traveled (and hence ton-miles) by these farmers and the reduction in ton-miles for MCE vehicles from hubs 6 and 11 is not enough to counter the increase in ton-miles that occur when these farmers are assigned to hub 7 which is much further away from the central hub. If we compare tables 4- 15 and 4- 31 we see how the average number of trips (and hence distance traveled) by MCE vehicles increases for the

RO model (except for hub 11 in the 6-hub solution) as compared to the deterministic model due to the RO model accounting for variability of production at farms.

Another observation from the results of the RO model is that when farmers are allowed to bypass the regional hubs and travel to the central hub, the minimum capacity of the hubs required increases as we go from 4 hubs to 5 hubs. This is rather odd since with more hubs open, we should be allowed to decrease the capacity of each hub. Presented are the maps of the two solutions in figures 4- 29 and 4- 30.

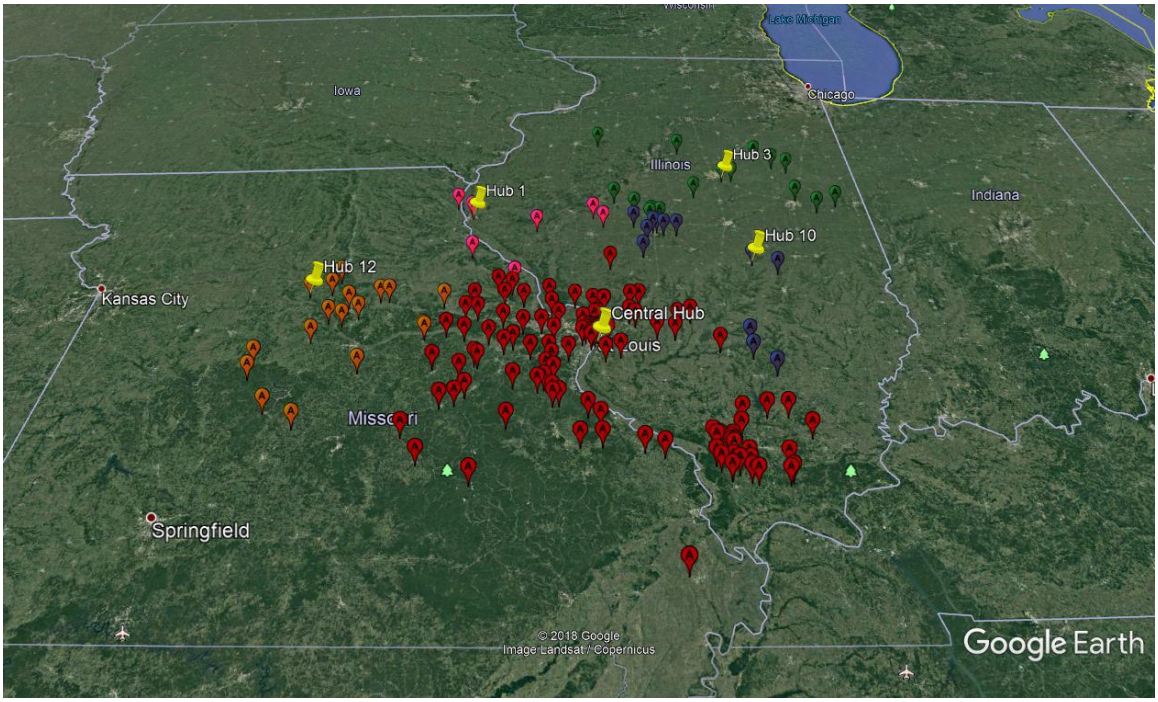

Figure 4- 29: Minimizing hub capacities for RO model with 4 hubs open with bypass

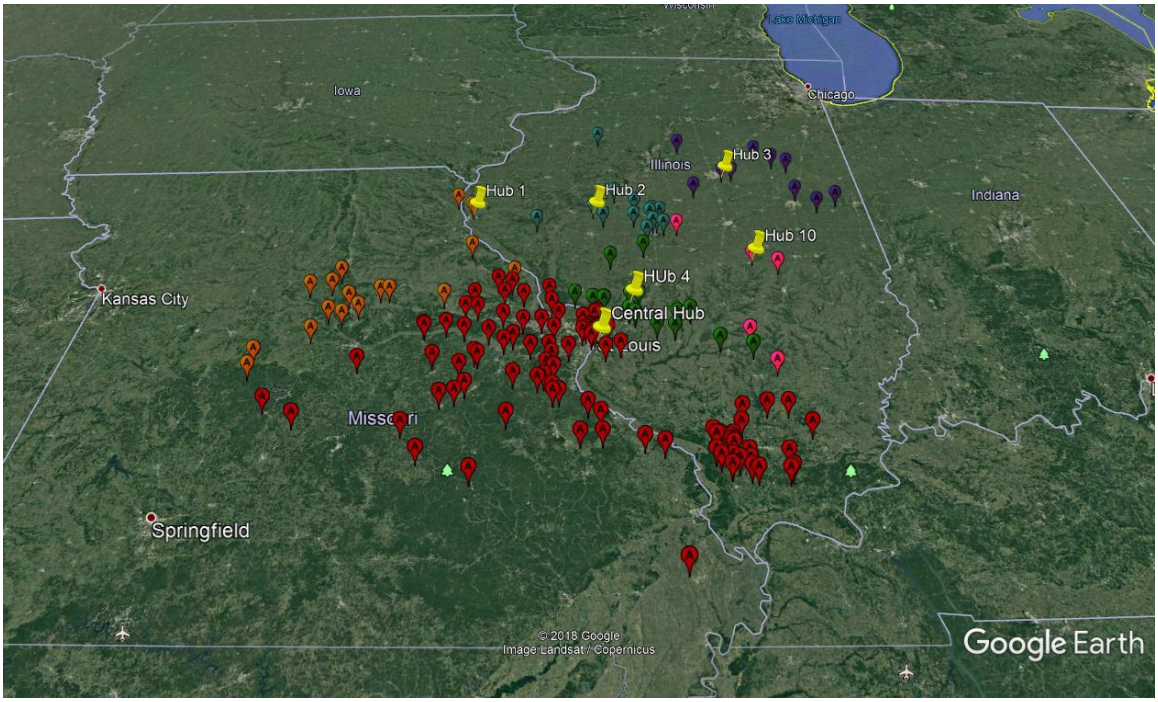

Figure 4- 30: Minimizing hub capacities for RO model with 5 hubs open with bypass

We looked at the hubs that were most utilized (excluding the central hub since there were no capacity constraints for this hub) for each configuration to understand why the model was not allowing us to decrease the capacities of hub. For the 4-hub solution we learned that hub 10 was the most utilized regional hub with an average utilized capacity of 3,712 lbs. per week while for the 5-hub solution, hub 2 was the most-utilized with an average utilized capacity of 4,439 lbs. per week followed by hub 4 with average utilized capacity of 3,970 lbs. per week. Table 4-31 shows the average capacity utilized at hubs that are opened for the respective solutions. Recall that for the RO model, we assumed a 50% variation of Plant and Animal products around their nominal values which means that under the assigned capacities of 10,100 (for the 4-hub solution) and 12,050 (for the 5-hub solution) the current solutions would be feasible even if the production at all farms increased by up to 50%.

Configuration	Hub 1	Hub 2	Hub 3	Hub 4	Hub 10	Hub 12	Central Hub
4 hubs	3285	-	2994	-	3712	3686	24735
5 hubs	3246	4439	1914	3970	2229	-	22613

Table 4- 31: Average utilization of hubs (RO model with bypass)

After looking at the utilization values in table 4-31 we see that hub 2 is the bottleneck hub in the 5-hub solution followed by hub 4. After looking at the production of farms assigned to hub 2, we discovered that in the process of reassigning farms from hubs 1, 3 and 10 from the previous solution to hub 2, the farm with the highest production in the entire network (Farm k79) got allocated to hub 2 along with other high production farms (as is evident from the outgoing vehicle trips shown in table 4- 31). The model did this because of constraint 4 that states that farmers can only travel to their nearest regional hub. When we run the model by keeping the capacity of hubs 2 and 4 fixed at 12,050 lbs. and reducing the capacities of all other regional hubs, we can decrease the capacities of the remaining hubs well below 10,100 lbs. Also, we see from table 4- 31 that the maximum capacity at any regional hub (apart from the central hub) is greater in the 5-hub solution than in the 4-hub solution. This is because the 4-hub solution can assign more production to the central hub (which has no capacity constraint). Requiring a fifth regional hub to be added forces the addition of a new hub (hubs 2 and 4 in this case) with large capacity utilization, due to the constraint enforcing farmer delivery to the nearest open hub.

In order to understand how the objective function values for the RO model with bypass allowed and hub capacities of 15,500 (for the 4,6,7 and, 8-hub solutions) and 13,000 (for the 5-hub solution) vary, we graphed the results of the model at different levels of robustness. Scenario S1 corresponds to the non-robust model where no parameters are

allowed to take their worst-case-impact values while scenario S8 corresponds to the most robust model where all parameters are allowed to take their worst-case impact values (the values of which are shown in Figure 4- 25). For scenarios S2 to S7, we varied the robustness levels which are denoted by parameters g_0 , g_1 and g_2 where g_0 corresponds to the robustness level of the objective function, g_1 corresponds to the robustness level of constraint R1 and g_2 corresponds to the robustness level of constraint R2 in increments of 20, 15 and 10. The results are shown in figure 4- 31.

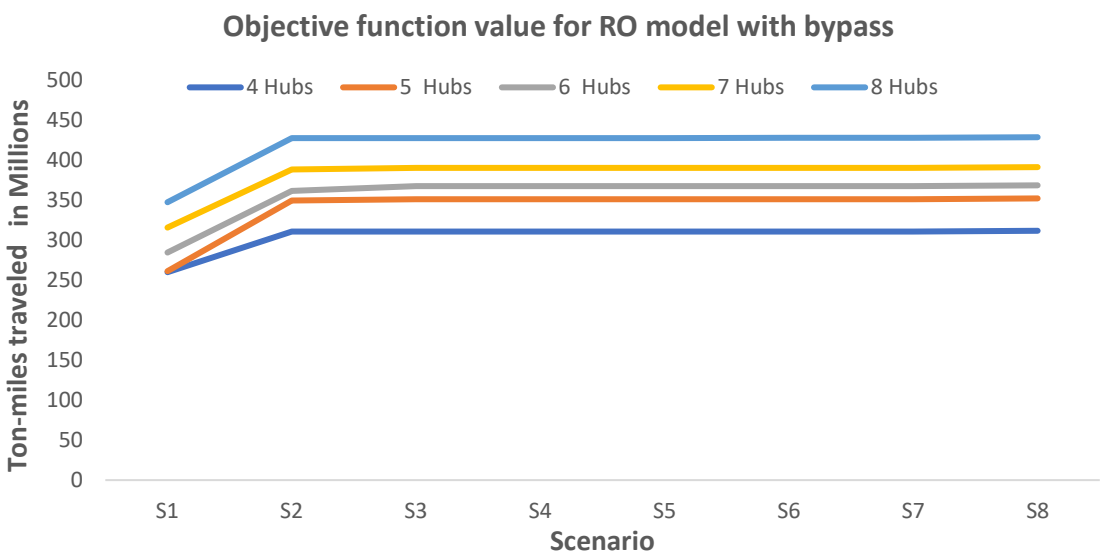

Figure 4- 31: Objective function values for modified RO model at different levels of robustness.

It was also interesting to see how miles traveled by farmers and MCE vehicles changes as the model is varied from least robust to most robust. We followed the same procedure for two configurations of the RO model and the results are shown in figure 4- 32 and figure 4- 33.

For the RO model without bypass, distance traveled by farmers and MCE vehicles levels off after scenario S3 at which point g_0 = 60, g_1=45 and g_2=40. Similar observations can be seen for the modified RO model. After analyzing the values of the robust variables when

we set g_0 equal to its maximum-possible value, we observed that only 10,400 of the 17,784 parameters in the objective function (corresponding to g_0) deviate from their nominal values. Similarly, only 44 of the 342 parameters (corresponding to g_1) deviate from their nominal values and only 66 of the 171 parameters (corresponding to g_2) deviate from their nominal values. This also explains the incremental change in the objective function values after scenario 3 as shown in figure 4- 31.

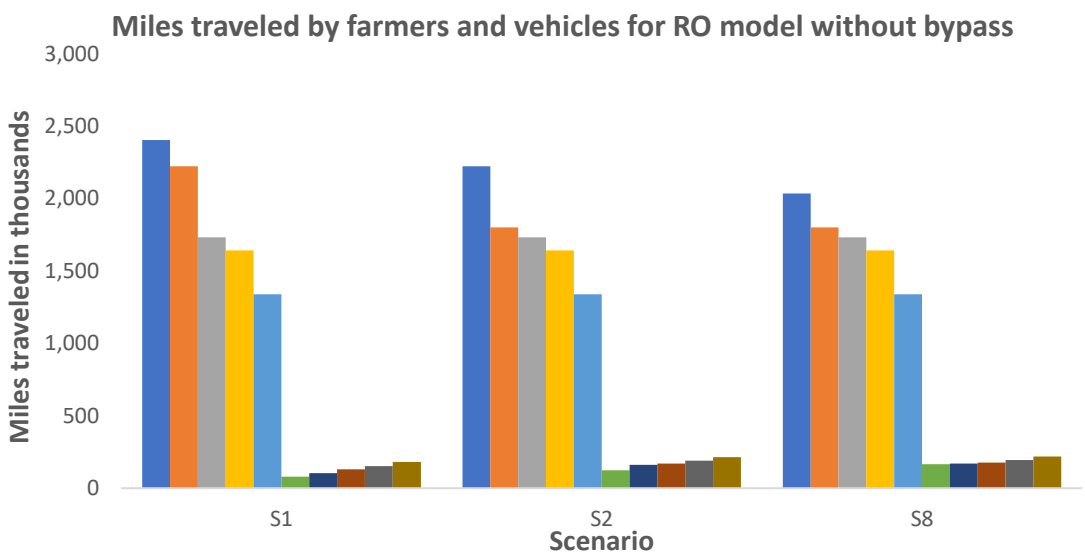

Figure 4- 32: Miles traveled by farmers and MCE vehicles for RO model at different levels of robustness.

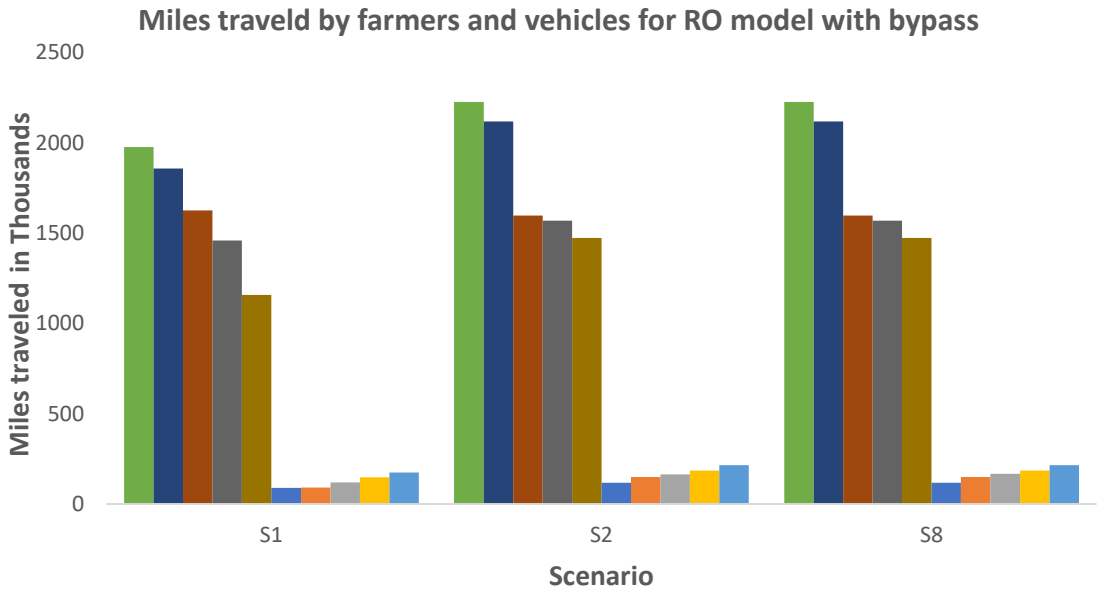

Figure 4- 33: Miles traveled by farmers and MCE vehicles for modified RO model at different levels of robustness.

Chapter 5

Conclusions and Future Work

5.1. Conclusion

In this research we assisted the Missouri Coalition for the Environment (MCE) in helping farmers from Missouri and Illinois route products from their farms to a central hub in St. Louis by developing a strategic supply chain network model. Currently, farmers do not have fixed drop-off points and end up traveling long distances to sell their products to farmer's markets, community supported agriculture (CSA's), etc. resulting in not only additional transportation cost and lost revenue because of spoilage which is a result of highly unpredictable demand at these places but also increased Greenhouse gas (GHG) emissions and Carbon Footprint (CF). In this study, a network of regional hubs is established, such that farmers transport their products a relatively short distance to a nearby regional hub, allowing products to be consolidated at the regional hubs, creating increased density and thus higher efficiency over the longer regional hub-to-central hub transport legs.

In order to serve the dual needs of low cost and sustainability, we developed a deterministic optimization model whose objective is to minimize the overall ton-miles traveled by farmers and MCE vehicles in the network. We ran the model under two configurations- one where farmers cannot bypass the regional hubs and one where they can bypass the regional hubs and travel directly to the central hub. For each of these configurations, we ran the models with 4, 5 and 6 hubs open. We utilized the CPLEX solver in the GAMS environment to solve all the models to optimality. The solutions from the models

demonstrated that it would be beneficial for both farmers as well as MCE if farmers can bypass regional hubs and travel directly to the central hub. We also calculated the minimum possible ton-miles achievable as well as minimum capacity requirements at each hub and each configuration for the 4, 5 and 6-hub solutions which would allow MCE to make the trade-off between space requirements at their hubs and distance travelled by their vehicles. We observed that as the number of hubs opened is increased, distance travelled by farmers decreases while distance travelled by MCE vehicles increases. We also observed that as the number of hubs is increased, the capacity required at each hub does not necessarily decrease. This is because of two reasons

1. We set the capacities of all hubs the same for all model configurations. When we analyzed the solutions, we realized that not all hubs were being utilized the same way and so it is possible to reduce the capacities of the remaining hubs and still get a feasible solution so long as we fulfill the capacity requirements of the bottleneck hub.
2. One of our model constraints was that farmers should travel only to their nearest regional hubs. This would cause farmers located in the same cluster to travel to one hub only which would lead to that hub being utilized more than the remaining hubs in the network thus leading to infeasibility problems.

Based on scientific studies which pointed toward significant variability in Plant and Animal production in the regions, we utilized a Robust Optimization (RO) model to account for up to 50% variability in the products grown at farms. Like deterministic optimization, our objective was to minimize the ton-miles travelled across the entire network when farmers can and cannot bypass the regional hubs. We again ran the models for 4, 5 and 6-hub

configurations. Like deterministic optimization, we calculated the minimum possible ton-miles as well as the minimum capacity requirements at each hub and each configuration for the 4, 5 and 6-hub solutions.

We mapped and compared the solutions of the respective deterministic and RO models with and without bypass to see how hubs the number of hubs opened, and capacities set at these hubs impacted, assignments of farmers to hubs, distance travelled by farmers and distance travelled by MCE vehicles.

Without Bypass:

We noticed that for the 4-hub solution, the deterministic model opens hubs located in De Soto, Missouri, Bloomsdale, Missouri, Prairie town, Illinois and Hoffman, Illinois which are relatively close to St. Louis while the RO model opens hubs located in Virginia, Illinois and Morrison, Missouri which are much further away from St. Louis along with hubs in Prairie town, Illinois and Hoffman, Illinois. For the 5-hub solution, the deterministic model additionally opens a hub in Shelbyville, Illinois which is closer to farmers in the northeast Illinois region while the robust model opens the hub in Virginia, Missouri which is closer to farms in the northwestern part of the network. For the 6-hub solution, the RO model opens the same hubs as the deterministic model. We observe that farmers travel less in the 4 and 5-hub solutions for the deterministic model than the RO model. Since we are keeping the capacities of hubs the same in both configurations, the RO model opens hubs that are closer to farmers (that is away from the central hub as stated above). This along with the fact that the RO model is accounting for variations in Plant and Animal production beyond their nominal values leads to a substantial increase in distance for MCE vehicles.

With Bypass:

For the 4-hub solution, the RO model opens hubs located in Prairie town, Missouri, Virginia, Illinois, Shelbyville, Illinois and Quincy, Missouri while the deterministic model opens hubs in Prairie town, Missouri, Hoffman, Missouri, Shelbyville, Illinois and Makanda, Illinois. Interestingly, the modified RO model with 5 hubs open does not open any of the hubs that it did for the 4-hub solution instead opening hubs relatively closer to farmers which explains the huge drop in miles traveled by farmers. The deterministic model on the other hand opens hubs closer to the central hub resulting in incremental decrease in miles traveled by farmers. For 6 regional hubs, the deterministic and RO models open the same hubs except the deterministic model opens hub 10 instead of hub 3 which leads to increased distance travelled by farmers in northern Illinois for the deterministic and hence in the network.

It is again important to note that assignments of farms to hubs depends not only on the capacity of hubs but also their location with respect to farms. Since one of the constraints in our models is that farmers can travel only to their nearest regional hub, the model sacrifices a better objective function value in order to accommodate farmers' travel requirements.

5.2. Future Work

In this research we developed a strategic agricultural supply chain network to assist MCE with transporting products from 171 farms in Missouri and Illinois to a central hub in St. Louis, Missouri. We are confident that this farm-hub network will help contribute towards a cleaner environment as well as reduce agricultural waste associated with spoilage.

First, as we mentioned in Chapter 1 and Chapter 3, we built a discrete facility location-allocation model, that is, we decided on the location of the 12 candidate regional hubs *apriori*. Future research could involve building a mathematical model which decides on the precise locations of these hubs based on the number of hubs that the user inputs to the model. This class of problems is called continuous location-allocation problems.

Secondly, we mentioned that production data on most farms utilized in the model was generated from the average production at the handful of farms for whom data was available. A mathematical model is only as reliable as the data that is inputted to it (Garbage in Garbage Out Principle). Future work could involve gathering data not just of production at each farm in the network but also about variability of production at these farms to generate better solutions from the RO model.

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