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Food Waste Management Networks: Novel Methods for Overcoming Emerging Logistics Challenges

William R. Armington
wra9936@rit.edu

Food Waste Management Networks: Novel Methods for Overcoming Emerging Logistics Challenges

by

William R. Armington

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Ph.D. DEGREE DISSERTATION

The Ph.D. Degree Dissertation of William R. Armington has been examined and approved by the dissertation committee as satisfactory for the dissertation requirement for the Ph.D. degree in Sustainability.

Dr. Thomas Trabold, Director of Ph.D. program and Department Chair & Committee Member

Dr. Anna C. Tyler, Dissertation External Chairperson

Dr. Roger B. Chen, Advisor & Committee Chairperson

Dr. Callie Babbitt, Co-Advisor & Committee Member

Dr. Brian Tomaszewski, Committee Member

Date ____________________________

ABSTRACT

The U.S. produces an estimated 63 million tons of food waste per year. Interest from state and local governments in diverting unused food from landfills to alternative treatment facilities is growing. However, this emerging food waste (FW) stream will face logistics challenges as diversion networks expand. Current methods for evaluating challenges are insufficient for providing solutions for network development because they do not explore the impacts of variability in the food waste management system. This dissertation aims to fill this knowledge gap by exploring three key research areas.

First, variability in FW generation from different types of commercial generators is characterized. Empirically collected data is combined with the prevailing FW estimation method to characterize how generator attributes, temporal variability, and spatial heterogeneity in FW generation could impact development of diversion networks. Results show that representing FW generation from commercial sources in New York State with a single annual value is likely inadequate for policy and planning purposes due to the uncertainty surrounding anticipated FW generation.

Second, two transportation models are presented to understand how variability in spatial locations and generation rates affects FW collection. Results indicate that in residential systems with uniform generation rates, increasing spatial density of participants is critical to reducing service costs. In commercial systems, the inherent heterogeneity of food waste generation rates is important to reduce costs for initial collection services.

Finally, material inputs and digestate management are incorporated into a FW treatment facility siting method. Results show that digestate transportation distance is critical for ensuring that land application of digestate does not overload nearby farm fields with phosphorus. This

dissertation contributes to the body of scientific knowledge for waste management through the creation of novel, generalizable methods that investigate the impacts of variability on logistics decisions to inform development of effective food waste management networks.

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GLOSSARY OF TERMS

FW	Food Waste
GHG	Greenhouse Gas
MSW	Municipal Solid Waste
WTP	Willingness-to-Pay
AD	Anaerobic Digester
EPA	Environmental Protection Agency
NYS	New York State
WNY	Western New York State
NYC	New York City
EU	European Union
NYSDEC	New York State Department of Environmental Conservation
CAFO	Confined Animal Feeding Operation
VRP	Vehicle Routing Problem
OD	Origin-Destination
NH	Neighborhood
HH	Household
ACO	Ant Colony Optimization
Mixed-IP	Mixed Integer Program
LP	Linear Program
ABM	Agent Based Model
GIS	Geospatial Information Systems
DH	Direct Haul
CA	Cost Objective – Collect all waste
PP	Profit Objective – Collect partial waste

CHAPTER 1

INTRODUCTION TO FOOD WASTE MANAGEMENT AND LOGISTICS NETWORKS

The production and disposal of food waste (FW) along the food supply chain is a growing global concern. In the United States alone, the amount of food wasted in the past decade has been estimated between 49 to 89 million metric tons per year (Buzby et al., 2014; Conrad et al., 2018; ReFED, 2017). Most FW in the U.S. is disposed at landfills as part of conventional municipal solid waste management, a practice that results in an estimated 115 to 160 million metric tons of CO_2e greenhouse gas emissions per year (Heller and Keoleian, 2015; Venkat, 2011). Recent research has focused on alternatives to landfilling, such as anaerobic digestion and composting to add value to FW (Ki Lin et al., 2013; Vandermeersch et al., 2014; Zhang et al., 2014). However, shifting to a new FW waste management approach requires overcoming information gaps, deployment of FW resource recovery technology, and increased voluntary participation by generators.

The increasing public desire to manage FW more sustainably than landfilling usually manifests itself in two ways. Governments at many levels have limited the landfilling of FW to reduce the release of greenhouse gas emissions (GHGs). An increasing number of local governments since 2005 have not waited for state-wide legislation or infrastructure development for FW management, supporting separate collection of FW for their residents (Yepsen, 2015, 2014). Additionally, many U.S. state governments in the Northeast have implemented policies limiting the disposal of FW from certain food waste generators unless waivers are obtained (Connecticut DEEP, 2011; Institute for Local Self-Reliance, 2016; Massachusetts DEP, 2014; New York State Senate Assembly, 2019; Vermont Agency of Natural Resources, 2019). For example, the New York State (NYS) Food Donations and Food Scrap Recycling Act specifies that FW from commercial and institutional facilities generating more than 2,000 lbs a week and are located within 25 miles (40km) must donate or recycle FW via landfill alternatives. Generators may petition the state for a one-year waiver if diverting FW will cause undue hardships, such as higher management costs from transportation and FW processing. Sparse and underdeveloped management infrastructure will ultimately cause slower adoption of FW diversion practices despite legislative initiatives. These challenges are not specific to NYS but may be encountered in other states that are enacting legislation and do not have the infrastructure in place to offer regional, cost effective solutions for FW diversion. This transition is where more research and knowledge are needed to develop FW management solutions that do not pose undue hardships upon generators in to maximize collection and diversion

Conversely, demand for FW collection has grown organically from collections of residents and businesses, creating opportunities for new or existing waste management companies to provide FW collection services (Business for Social Responsibility (BSR), 2013; Isles et al., 2011; Papargyropoulou et al., 2014). While the social pressure from both bottom-up and top-down sources is critical to ensuring separate FW management becomes a conventional practice, solutions to these pressures are often local, only considering what needs to be immediately accomplished to satisfy current demand (Levis et al., 2010). As FW management networks grow, they will inevitably encounter logistics issues that should be met in part by balancing social, environmental, and economic goals.

Alternative technologies for FW treatment generally produce fewer GHG emissions compared to landfilling (Levis and Barlaz, 2011). However, since nearly all current waste collection vehicles are fossil-fuel based (Informinc, 2012; Maimoun et al., 2013), GHG emissions from collection and transport of FW reduces the environmental benefits gained from landfill diversion. Therefore, minimizing transportation activities while collecting as much FW as possible will help to retain environmental benefits of diversion. Minimizing transportation activities is also key to reducing costs of new FW collection services. Since FW management is emerging as a new waste management stream, stakeholder values placed on participation in this new system vary. Some individuals or businesses may value environmental stewardship more than others, creating discrepancies in willingness-to-pay (WTP) for a FW collection service. It is important for collection companies and policy makers to understand the characteristics of a service network that will promote current and future development while balancing environmental benefits with economic feasibility.

There are characteristics of FW management that set it apart from current municipal solid waste (MSW) and recycling networks. Food waste, unlike other materials, is constantly degrading during transport and storage, potentially reducing the amount of energy recoverable through technological processing (Nilsson Påledal et al., 2017). Energy recovery facilities must coordinate with FW generators and collection companies to source a consistent and suitable feedstock required for effective treatment facility operation. While landfills exist to accept waste as it is delivered regardless of attributes, variability in quantity and quality of organic source material outside the control of a collection company may cause operational issues for alternative FW treatment technologies (Agyeman and Tao, 2014; Nagao et al., 2012). On the other end of treatment, any solid outputs must be managed appropriately, impacting the distribution of products or management of any resulting waste streams (Tampio et al., 2016; Westerman and Bicudo, 2005; WRAP, 2013). Facilities must ensure that there are distribution pathways for these outputs in place or have adequate storage until outputs can be managed appropriately.

New methods and insights are needed for the continued and sustainable development of FW management networks. Deeper understanding of the variability associated with different components of FW diversion will be instrumental to anticipate and mitigate future logistics challenges due to network growth. Appropriate planning based on better system understanding will help to reduce potential undue hardships and increase FW landfill diversion from all sizes of generators in the future.

DISSERTATION MOTIVATION AND OBJECTIVES

Problem Statement

Valorization of FW via existing and emerging treatment technologies promises to reduce the environmental impacts of FW disposal through diversion from landfills; however, oversimplifying logistics issues may show support for policy goals without considering environmental, economic, and social balances. Effective development of FW recovery networks requires more information on the variability that could have a considerable impact on decision making outcomes. Generation of FW is not a single annual number as often estimated and reported, but varies due to generator types, monthly seasonal patterns, and spatial heterogeneity. Consideration of spatial and generation heterogeneity within collection networks is crucial for characterizing intersections of service demand and economic feasibility. Unlike landfills, treatment technologies such as ADs convert FW into products and should consider both input and output balances when siting new treatment facilities. Three research questions are posed to characterize and address these logistics challenges for developing effective FW management networks.

Research Questions

1. How can the variability in commercial FW generation impact development of regional management networks?

Conventional waste management operations literature has emphasized the importance considering variation and uncertainty in waste generation and uncertainty for developing effective waste management networks. As new FW management systems emerge, similar problems faced by conventional waste management are likely to arise. Therefore, the goal of Chapter 2 is to assess variability of FW generation from different types of commercial generators while simultaneously characterizing temporal and spatial variables. Empirically collected data is combined with the prevailing estimation method to characterize how generator attributes, temporal variability, and spatial heterogeneity in FW generation could impact development of diversion networks. The modeling framework is suitably flexible so that future studies can continue to expand findings presented as additional data are collected

2. What are the impacts of spatial and generation heterogeneity on the economic feasibility of FW collection services?

Reducing transportation activities of FW diversion will reduce GHG emissions and help ensure environmental benefits from alternative treatment technologies. Moreover, there is a need for research to explore the network characteristics that allow collection companies to offer economically feasible FW collection services to potential participants. Chapter 3 analyzes how spatial heterogeneity in FW collection networks could impact service fees charged to residential customers for curbside FW collection. Chapter 4 presents a novel, ecologically inspired vehicle routing model to characterize the effects of FW generation variability on offering affordable FW collection services. Generalizing the effects in spatial and FW quantity heterogeneity will help plot a path for companies and planners to sustainably grow FW collection networks.

3. How are new AD siting decisions impacted when management of digestate outputs are considered in comparison to conventional material inputs?

Literature methods for siting AD facilities focus on minimizing the cost of transportation for input feedstock and maximization of revenue from energy products. AD facilities also produce digestate that is conventionally managed by application to nearby arable cropland. However, the environmental capacity for cropland to accept digestate has not been considered in the current body of spatially explicit siting literature. Chapter 5 presents a spatially explicit facility siting method that incorporates both material inputs and digestate management to identify potential facility sites from a system perspective. Phosphorus quantities in digestate are derived from material inputs and compared to crop's expected capacity to absorb phosphorus during the growing season. Areas with excess phosphorus supply or capacity are identified to re-examine the potential for new AD facilities to operate effectively.

Novel Contribution

This research presented contributes to the body of scientific knowledge through the creation of novel, generalizable methods that investigate logistical nuances to inform development of effective FW management networks.

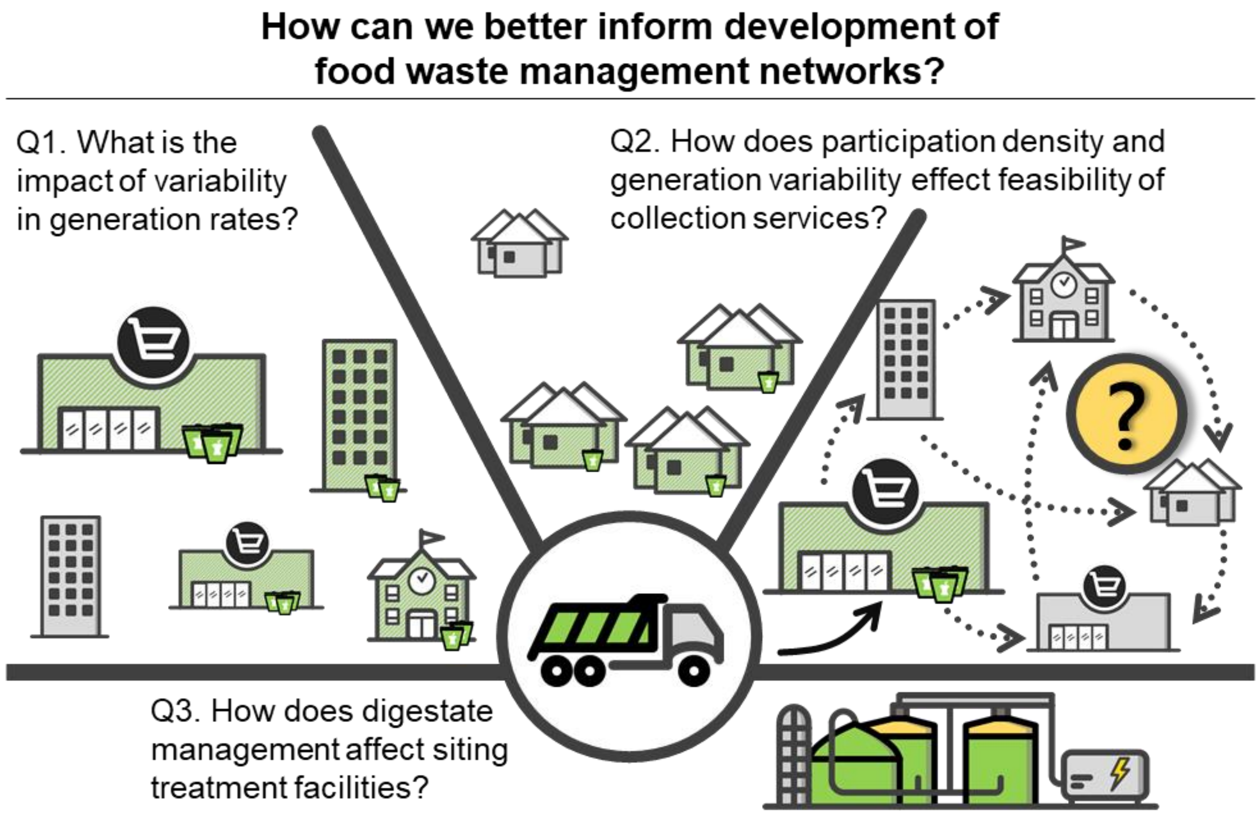

Figure 1-1: Dissertation Framework

CHAPTER 2
VARIABILITY IN COMMERCIAL FOOD WASTE GENERATION AND IMPLICATIONS FOR DEVELOPING REGIONAL MANAGEMENT NETWORKS

1. Introduction

Several U.S. states and cities are phasing in policies restricting landfills as a disposal option and mandating that larger commercial and institutional FW generators donate or recycle excess food (Manson, 2017). However, implementing this shift in FW management requires commensurate build-out of FW collection, transport, and recycling infrastructure (Iakovou et al., 2010), which in turn requires information for anticipating FW generation over space and time (Breunig et al., 2018). Empirical data collection studies have been conducted at the state level to support policy mandates (Cascadia Consulting Group, 2015; Draper/Lennon Inc., 2002, 2001; Okazaki et al., 2008; Seven Generations Ahead, 2015). Many of these studies rely on similar methods for estimating theoretical rates of FW generation from commercial and institutional facilities without the need to invest time and labor to collect data from every FW generating facility. This method is summarized as follows:

$$Theoretical\ Generation = Generation\ Activity * Generation\ Factor$$

Specific activities within each company or organization are identified as being key drivers of food being wasted ("generation activity"), and the relative amount of food wasted from that activity ("generation factor") is estimated using limited sets of empirical data collected (Draper/Lennon Inc., 2001). These terms are specific to the type of FW generator. For instance, the generation activity associated with FW in universities is student enrollment; for supermarkets, it is full time employees working in a year. Generation factors quantify the relationship between these generation activities and the expected FW quantities, where a limited number of empirical studies and waste audits have established mass of FW per residential student enrolled at a university or employee employed at a supermarket.

Within this general approach, individual studies often quantify the generation parameters using different assumptions and underlying data sets, and this variability can make it difficult to compare, develop, and apply solutions between different states and regions (Xue et al., 2017). In an effort to harmonize FW analyses, the US Environmental Protection Agency (EPA) released the Excess Food Opportunities Map, a nationwide inventory of geolocated commercial and institutional FW generators (USEPA, 2018). The goal of this database is to develop a standardized method for identifying and estimating FW sources for landfill diversion and to translate methods developed for one region to another with fewer data discrepancies. The user-friendly nature of this estimation methodology is attractive because of its accessible formulation and data inputs; however, it is limited due to lack of consideration for uncertainty or system dynamism.

In reality, FW generation is not static or homogenous. Contributions from supermarkets, for example, will differ based on infrastructure, supply chain decisions, and culturally mediated food preferences (Fernie, 1995). Relative contributions to total FW generation from different actors along the supply chain, such as retail, institutions, and food service, are not consistent between regions (Bräutigam et al., 2014). In addition, FW generation commercial sources such as supermarkets in Austria and Sweden have been shown to vary seasonally, with peaks appearing in the summer and at the end of the year (Eriksson, 2012; Lebersorger and Schneider, 2014) Furthermore, FW generation from municipal sources has been shown to vary geographically at smaller regional scales (Breunig et al., 2017) and cities (Burnley et al., 2007; Denafas et al., 2014).

Capturing these sources of variability in FW generation is critical to putting sustainable solutions into action. The total amount and spatial concentration of FW has direct implication to the costs of collecting and transporting FW, which in turn influence the cost and adoption of the overall FW management system (Gold and Seuring, 2011). The waste management operations literature has emphasized the importance of anticipating waste variation and uncertainty for system development such as siting of disposal/management facilities (Chang and Davila, 2006; Yeomans et al., 2003), logistical operations (Johansson, 2006; Mendes et al., 2013; Mes et al., 2014), and waste-to-energy product generation (Alibardi and Cossu, 2015; Cuéllar and Webber, 2010). The outcomes of these studies emphasize that waste variability should be characterized to inform planning and development, paralleling the challenges that will be faced by FW management networks.

Although several of the studies mentioned previously have characterized specific variability in FW generation, the literature generally lacks a consideration of combined effects of these dynamics in FW diversion system design and treatment decisions Therefore, the goal of this study is to assess variability of FW generation from different types of commercial and institutional generators while simultaneously characterizing temporal and spatial variables. One goal is to understand the number and type of facilities within a state that contribute the most towards FW generation, which will help inform policy targets for diversion. Another goal is to assess how FW generation varies month to month, which can inform treatment system designs that will not become overwhelmed or under-utilized. Pinpointing where FW comes from spatially can help centralize diversion operations near higher geographical concentrations of FW. To our knowledge, this is the first study to integrate real data from FW generation with a publicly accessable database of food waste estimates for explicitly considering sources and implications of these types of variability.

While the case study presented here focuses on a single region (New York State), the modeling framework is suitably flexible so that future studies can continue to expand findings presented here as additional data are collected.

2. Methodology

2.1 Methodological Framework

The methodology presented here can be used by any region with access to modest FW generation data and is useful for regions faced with the challenge of developing FW management solutions. The method is demonstrated using data collected within a specific case study region (see section 2.2). In short, the approach was to collect both real data from generators within this case study region and compare these data to estimates created using available theoretical generation quantities (Eq. 1 and described in section 2.3). FW variability was assessed across three dimensions: 1) differences in FW produced by generators of varying size or type; 2) monthly generation trends and variance from average generation per month; and 3) heterogeneity of FW generation amount and location at sub-region and county scales. Fig. 1 summarizes this framework.

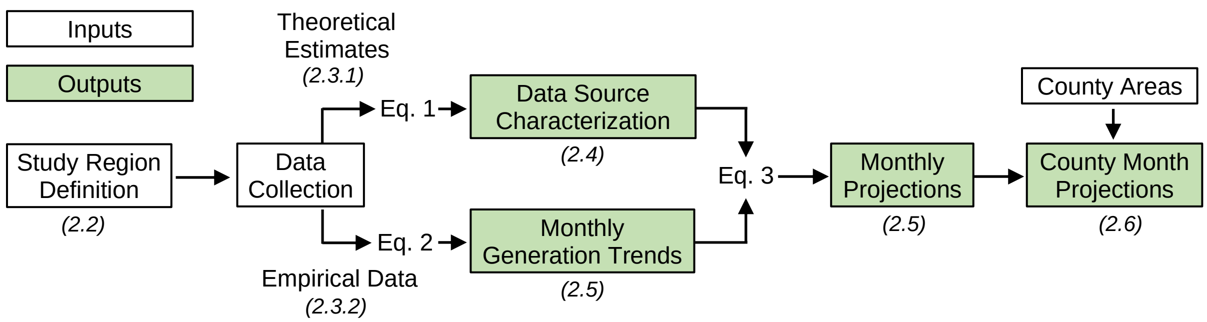

Figure 2-1. Graphical representation of the variation analysis framework used in this study. Clear boxes represent information inputs and shaded boxes represent results. Black arrow lines indicate the study steps. Numbers in parentheses and italics relate to relevant sections where the methods are described further.

2.2 Case Study Region

New York State (NYS) is chosen as a case study to demonstrate the applicability of the methods in capturing variation in FW generation. NYS has significant diversity in regional population, including the most populous city in the U.S. as well as smaller cities and rural regions over an area of 141,000 km^2. Other factors, including regional diversity in agricultural and economic activity directly impact food supply, thereby affecting food waste and creating an excellent case study on the logistical complexities of commercial FW diversion.

Due to these challenges, the state has a track record of self-evaluation and investment in FW diversion. New York City enacted its own diversion legislation in 2013 (Johnson, 2013). The NYS Energy Research and Development Authority is currently supporting established and new organics-to-energy anaerobic digestion systems (NYSERDA, 2019) after the release of a statewide benefit-cost analysis indicating that FW diversion investment is economically viable (Manson, 2017). Recently, NYS passed legislation mandating that certain categories of commercial generators expected to generate the equivalent of 94t or more of FW annually must donate or recycle their FW if nearby landfill-alternative infrastructure is available (*Bill S01508*, 2019). The focus on commercially generated FW is comparable to other states or municipalities seeking to develop management networks, just as NYS legislation mirrors that of previously enacted legislation from nearby states (e.g., Connecticut DEEP, 2011; Massachusetts DEP, 2014).

2.3 Data Sources

2.3.1 EPA Excess Food Opportunities Map

Baseline theoretical FW estimates were obtained from the 2015 EPA Excess Food Opportunities Map, which accounts for underlying activities that lead to wasted food using the method introduced in Section 1, formalized as Eq. 1 below.

$$Theoretical\ Generation_i^c = Generation\ Activity_i^c * Generation\ Factor^c \qquad (1)$$

The theoretical, or anticipated quantity of annual FW generated at a given facility i for generator type c is estimated by multiplying the value of its generation activity by its generation factor. For instance, a supermarket with 50 employees and a generation factor of 1,360kg/employee-yr would be estimated to generate 68t of FW per year.

This study focused on only those data points from the EPA database that are within NYS, representing a total of 30,009 commercial generators who produce an estimated 456,000 metric tons of food waste per year. FW generators are divided by industry code, defining their facility type within economic sectors. Generator types evaluated in this study are supermarkets, hotels, K-12 schools, prisons, universities, and other commercial generators. The EPA database provides disaggregated estimates of high, low, and edible portions of FW for some generator types. However, the low estimates are not consistently reported across generator types, and the edible portion estimates even less so. Therefore, high estimates, which are consistently provided in the database, are utilized as the baseline data for all subsequent analysis. The full EPA methodology for the Excess Food Opportunities Map is documented in Schnitzer et al. (2018).

2.3.2 Empirical Food Waste Data

Supermarkets, universities, and K-12 schools were chosen for empirical data collection due to their data availability and anticipated variability in generation rates within an annual timeframe. For example, FW generation rates from supermarkets are likely to vary along with seasonal produce growing cycles or shopper purchases coinciding with holidays centered around food. Educational institutions are expect to vary in FW generation according to when students are present during academic terms or off campus during holidays and school breaks.

Multiple years of monthly or weekly FW diversion data were obtained from three supermarkets, three universities, and two K-12 schools in NYS that currently participate in FW measurement and/or diversion efforts. Original FW diversion quantities were measured by contracted collection services and provided to respective generators. Data for this study were provided by each facility via electronic spreadsheets in units of pounds or U.S. tons, which were converted to metric tons (t). Temporal resolution of the data (weekly or monthly) varied with each facility's accounting method but were ultimately aggregated on a monthly basis to standardize time resolution for analysis. If data were provided for a single entity over multiple years, it was assumed that each data point was independent of past years.

The diversion data collected includes the mass of FW that was separated for pickup by a collection service but does not include measurements of FW that was inadvertently disposed. As such, data may omit FW that was lost to conventional municipal solid waste routes. However, the assumption was that the sources of variability being studied here would uniformly affect all FW generation, including both FW diverted, and FW lost to the conventional waste stream. For instance, a 10% increase in FW diverted from one month to the next would imply that total FW generation increased 10% for that same time period. This assumption reflects a necessary simplification in a data-scarce field, particularly since estimating that fraction of FW not captured by diversion methods would require extensive empirical measurement via waste audits and weighing, methods that are cost- and labor-intense and themselves fraught with additional uncertainties (Xue et al., 2017).

Facilities ranged in size and temporal coverage, where data for supermarkets and universities spanned multiple years, and data for K-12 schools consisted of a single year. Specific identifying information and data about the generators could not be disclosed due to confidentiality agreements, but general facility attributes are summarized in Table 1.

Facility Type	**Facility size**	**Diversion range** (t/yr)	**Diversion range** (t/month)	**Data Years**	**Location**
Supermarkets					
Supermarket 1	450-750	570 - 617	29.9 – 69.7	2015 - 2018	Western NY
Supermarket 2	employees	196 - 384	9.0 – 43.5	2015 - 2018	Western NY
Supermarket 3		216 - 323	12.6 – 36.8	2015 - 2018	Central NY
K-12 Schools					
School 1	850	9.0	0 – 1.5	2018	Western NY
School 2	students	4.8	0 – 0.8	2018	Western NY
Universities					
University 1	2,200-	82 - 85	1.6 – 13.5	2014-2017	Western NY
University 2	16,500	136 - 146	2.3 – 20.9	2015-2018	Western NY
University 3	students	173 - 175	2.1 – 23.8	2015-2018	Central NY

Table 2-1. FW generation at commercial facilities in NYS. The range in monthly FW generation, data years, and regional locations are presented. Data have been generalized to protect the anonymity of sources due to confidentiality concerns.

2.4 Variability in FW Generators

FW generation is expected to vary when looking across generators that have fundamentally different attributes, such assize, location, and economic role within the food supply chain. Baseline estimation methods (Eq. 1) assume a similarity in FW generation rates among generators within the same type, such as hotels. On the other hand, FW diversion legislation groups generators by their size, which is commonly measured in terms of annualized generation rates. For example, recently passed NYS legislation mandates that generators producing the equivalent of 94t or more FW annually are limited from using landfills (*Bill S01508*, 2019). Similar policies in other states have lowered this regulatory threshold over time, underscoring the importance of understanding how FW generation varies as an input for effective policy guidance.

FW generation in the study region is evaluated across commercial and institutional generator types and sizes. Types include supermarkets, hotels, K-12 schools, universities, prisons, and "other" generators from the EPA database. Sizes evaluated for generators include those that produce between the thresholds of 94t, 47t, and 24t of FW annually. These sizes reflect the regulatory thresholds at different stages of policy implementation in other U.S. states adopting FW diversion legislation (Connecticut DEEP, 2011; Massachusetts DEP, 2014; Oregon Metro, 2018; Rhode Island General Assembly, 2014; Vermont DEC, 2012). The number of facilities belonging to each specific generator type was also counted. Comparing the contribution in mass with the facility count reveals the degree to which FW generation is concentrated in facilities of a given size or type.

2.5 Variability by Month

Monthly FW generation trends for supermarkets, universities, and K-12 schools were calculated using the provided FW diversion data (Section 2.3.2). The annual total of each facility for each year was divided by 12 to estimate the average generation per month. The ratio of actual monthly FW diverted to the estimated average generation per month is used to determine monthly deviation. This concept is summarized in Eq. 2 where i is the facility, y is the year, and m is the month.

$$Deviation_{iy}^{m} = \frac{Recorded\ Quantity_{iy}^{m}}{Average\ per\ Month_{iy}}\ i \in I, y \in Y, m \in M \qquad (2)$$

Monthly deviations (dimensionless ratios) for each generator type were geometrically averaged to derive a single value representing the relative monthly "anomaly," or average variability in FW generation. These trends represent how FW generation rates for supermarkets, universities, and K-12 schools are expected to deviate from their average generations per month. Geometric standard deviations were also calculated to show the spread of data collected.

Since empirical data were only available for a small subset of generators in NYS, the monthly anomalies were then integrated with theoretical estimates reported by the EPA database to project average monthly generation for schools, universities, and supermarkets across the state (Eqn. 3). These projections account for the anomaly in FW trends according to generator category (c), month (m), and specific facility (i).

$$Monthly\ Projection_{i}^{cm} = \ Anomaly^{cm} * (Activity_{i}^{c} * Factor^{c})/12\ i \in I, c \in C, m \in M \qquad (3)$$

2.6 Variability by County and Region

While state-wide estimates of FW generation are useful for supporting policy development, implementation of FW management systems will occur at finer spatial scales. There are 62 counties within NYS, but not all will be responsible for the same quantities and types of FW generation. Dense urban areas, like New York City, would likely have concentrated FW generation, particularly from the retail and consumer sector. On the other hand, generation from rural counties is expected to be less spatially concentrated, but made up of agricultural, food processing, and educational FW sources. Understanding these disparities in FW generation is crucial for developing diversion management solutions that can effectively span regions with heterogeneous population and economic activity. Moreover, mapping generation estimates can assist state-level decision making for targeted FW infrastructure investment and future policy.

Development of FW diversion networks will likely stem from similarities to conventional solid waste management. Waste management solutions are developed to fulfill the needs of their local areas and, except for NYC, do not usually transport waste extreme distances (to avoid incurring unnecessary hauling costs). Thus, it is more useful to estimate FW at a regional scale to develop sustainable management solutions for individual or clusters of counties.

Esri ArcMap 10.6.1 and associated geospatial analysis tools were used to evaluate geographically explicit generation rates. Data results from Section 2.5 were combined with original facility geolocation data to estimate and map FW generation disaggregated by county. County-level FW projections were displayed on a choropleth map to illustrate temporal and spatial discrepancies. Generation rates were also normalized per 1,000 people to further interpret data relative to both population density and FW generating activities. Generation quantity classes were delineated using the default Jenks Natural Breaks method in ArcMap that classifies the data into naturally occurring categories (Esri, 2018).

2.7 Data Source Uncertainty

Most conventional applications of estimation methodology in the U.S. use only one source of industry data to estimate FW generation (Draper/Lennon Inc., 2002, 2001; NYS Pollution Prevention Institute, 2017; Oregon Metro, 2018). Although straightforward, using only a single source of data ignores the inherent uncertainty in estimating generation rates based on correlation alone. Including alternative estimates will contribute to a more complete understanding of variability to plan management solutions accordingly. Thus, two scenarios using alternate data sources were compared to the baseline data source estimates.

The first alternative data source scenario (Data Source B) depicts lower state-wide monthly projections for FW generation. The EPA database includes multiple estimates for many facility types. Many facility types include both high estimates, used as the baseline for this study's primary analysis, and lower estimates based on alternative data. Equations 2 and 3 were used to evaluate the low estimates within the database as described in Section 2.5 and compare to the baseline results from baseline data source.

The NYS Pollution Prevention Institute (NYSP2I) created the Organic Resource Locator (ORL) database prior to the release of the EPA's resource using a different activity data set but similar estimation methods described by Eq. 1 (NYS Pollution Prevention Institute, 2017). Projections from this alternate data source (Data Source C) are compared to baseline projections. The ORL does not include locations or estimates for K-12 schools; however, the methodology is still applicable and informative. The methods described in section 2.5 are applied to the ORL database and monthly projections are calculated for comparison to the baseline.

3. Results and Discussion

3.1 Variability in FW Generators

Data from the EPA database on New York State FW generators were characterized to understand how the proportion of facilities and their theoretical generation estimates contribute to FW variability by generator size and type. Size refers to the anticipated amount of FW that a facility will generate annually, while type refers to the commercial sector of business, such as supermarkets or universities. Separation of FW generation by facility size revealed the percentage of facilities in each size group compared to their percent of anticipated contribution to statewide generation (Figure 2).

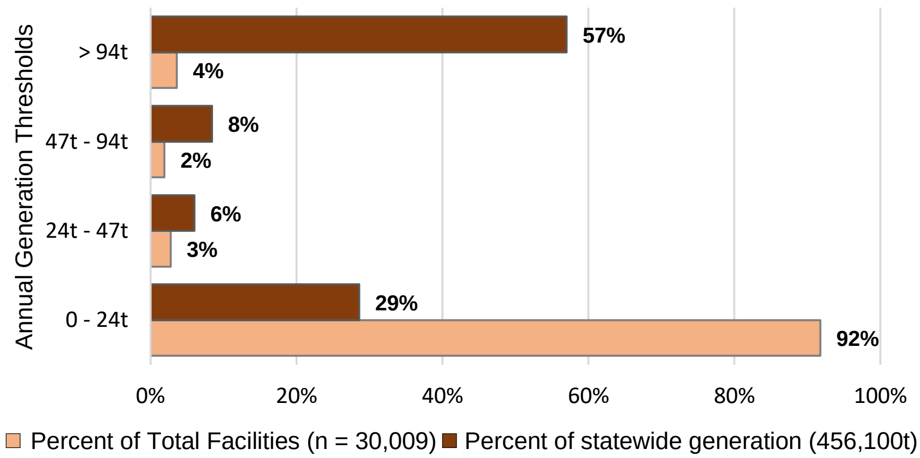

Figure 2-2. Commercial FW generators in New York State, grouped by annual anticipated FW generation threshold (y-axis). Generation thresholds correspond to the amount of FW a commercial generator must produce to be covered under regulations in NYS and nearby states. The proportional amount of facilities between each size threshold are compared to their mass contribution to total state-wide FW generation.

These results show that less than 5% of the facilities in the study region generate nearly 60% of the FW. The higher concentration of FW at these facilities supports the legislative precedents that target large facilities first and then expand to include smaller generators over time. Implementing policy focused on generators producing more than 94t/yr will result in recovery of more than half of the FW generated in the study region. As legislation phases in mandatory FW diversion for smaller facility sizes, collection efficiency will decrease due to decreasing concentrations. Collecting the remaining FW in the smallest generator group will likely require the most expense per unit FW collected. However, diversion costs will likely decrease over time as the FW management network matures and garners economies of scale (Armington and Chen, 2018).

Commercial generators were also characterized by type, including the relative representation of different types of facilities and their contribution to total FW generation (**Fig. 3**). Supermarkets are shown to be the most common type of facility and contribute the most to annual FW generation. The "other" types of generators include smaller markets, specialty food stores, retail bakeries, hospitals, and casino restaurants. While these other facilities are present across the state in high numbers, they collectively contribute less than 5% to total FW generation. The generator types that contain proportionally fewer facilities than their production of FW (supermarkets, hotels prisons, and universities) make good candidates for FW diversion policy. Mandating diversion for these generator types would affect approximately 50% of commercial facilities while capturing 85% of waste generated.

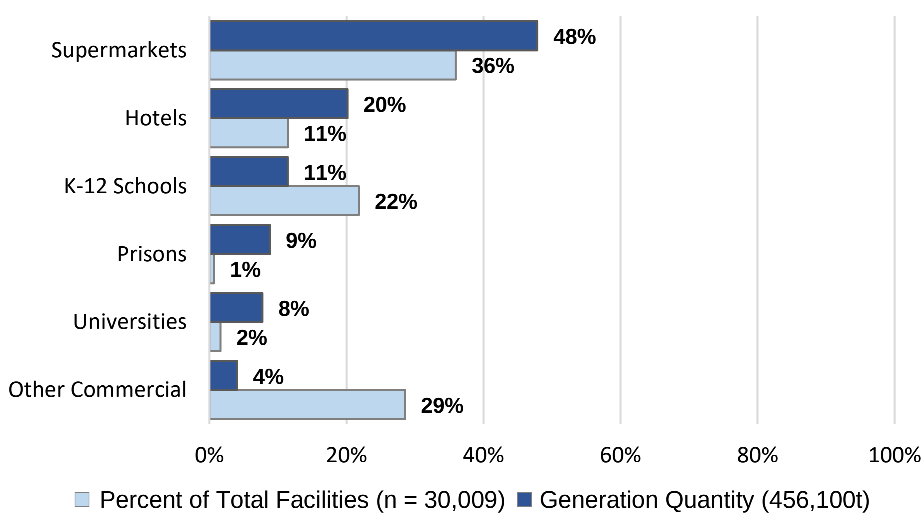

Figure 2-3. Commercial generators in NYS, grouped by generator type (y-axis). The proportional amount of facilities of each type are compared to their mass contribution to total statewide FW generation.

The comparison of FW generation by facility type and size provides valuable insights to inform policy targets over the regional system. Characterization of FW from commercial generators in the UK (WRAP UK, 2018), EU (Monier et al., 2010) and the U.S. (ReFED, 2017) have not considered both facility size and type. Other characterizations of U.S. states are similar in scope, but only consider facilities above a certain generation threshold (Draper/Lennon Inc., 2002, 2001; Manson, 2017). The recent NYS legislation mandates diversion for facilities generating over the 94t threshold but exempts hospitals and K-12 schools. Applying these legislative standards to the data predicts that 4% (1,070) of total facilities will be affected, which are responsible for 57% (260,000t) of annual FW generation.

3.2 Temporal Variability

Empirical data on FW generation and diversion were obtained from three supermarkets, two K-12 schools, and three universities from central and western NYS (Table 1). These data were analyzed as described in Section 2.5 to calculate monthly anomalies in FW generation for the three facility types (Fig. 4). Simply put, these anomalies show the ratio between actual FW generated in a given month relative to the average monthly generation (i.e., dividing a facility's total annual FW generation evenly across 12 months).

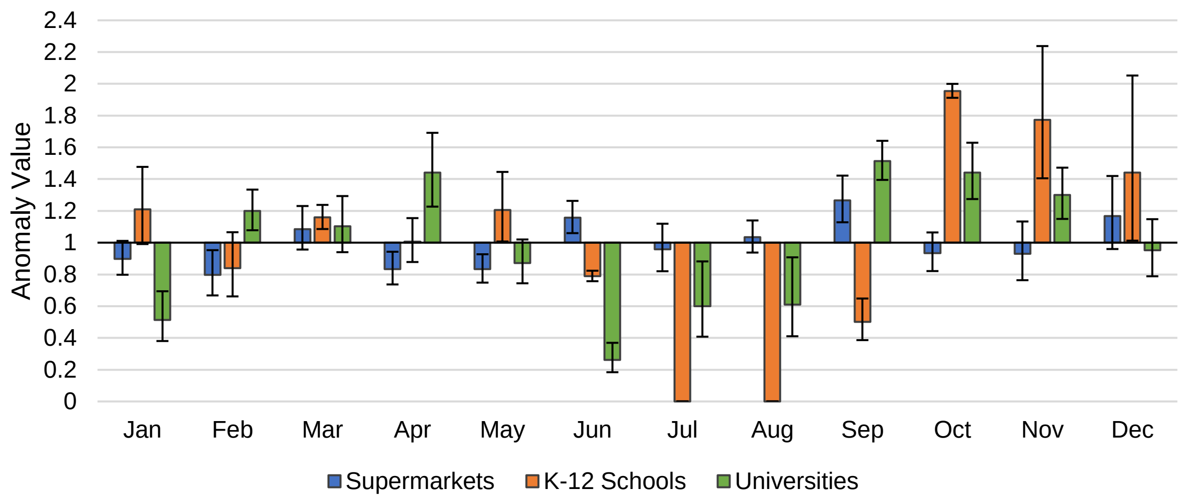

Figure 2-4. Monthly variability in FW generation relative to the average generation. Monthly anomaly values are the geometric average of monthly deviations calculated for each year. An anomaly value of 1 indicates that actual recorded FW generation in that month is equal to the estimated average generation per month, values >1 indicate actual generation that month was proportionally greater than the monthly average for the year, while values <1 indicate actual generation is less than the monthly average.

Supermarket FW generation trends are relatively consistent throughout the year, not exceeding a deviation from the mean of ± 0.2 except in the month of September. Actual FW is noticeably higher than the estimated average during June, September, and December. The observed increases are likely due to a number of interacting factors, including buyer behavior, supply chain efficiencies, summer harvest seasons for crops, and multiple food-centric holidays and observances at the end of the year (Killeen, 2016). It should also be noted that each of these “high” months represents the end of a fiscal quarter, possibly suggesting the influence of inventory management practices that do not match customer purchasing behaviors (Oliver Wyman, 2014).

Results are mixed when compared to other studies. Fresh fruit and vegetable waste generation from six supermarkets in Sweden was shown to vary throughout the year, with no discernable temporal pattern but a possibility of common generation trends among facilities

(Eriksson et al., 2012). However, supermarkets in Austria were shown to generate more fresh produce and dairy waste during the summer compared to their own average generation per month; however, data were recorded in economic value rather than mass (Lebersorger and Schneider, 2014). Comparing across studies is particularly challenging due to the wide differences in regional climate, food supply chains, and consumer behavior. Results reported herein confirm the understanding that supermarket FW generation varies throughout the year, but raise future research questions about the underlying drivers of variation between regions.

The K-12 schools included in the study are in session from September to June and recess during July and August, coinciding with generation peaks and valleys, respectively. September was expected to have higher generation rates due to starting dates early in the month. However, after reviewing data, it was found that neither school began diverting their FW until a few weeks after school began. This delay raises a limitation in choosing a month-long temporal resolution discussed later (Section 3.6). University monthly generation trends generally followed academic term (semester) cycles corresponding to when students were attending classes and residing on campus. FW generation was higher than average during autumn (Sep-Nov) and spring (Feb-Apr) semesters. Attendance in months before and after these periods varies by different university calendars, and FW generation trends differ accordingly for Aug, Dec, Jan, and May. FW generation is significantly reduced during summer break (Jun, July), but not eliminated, as university staff, graduate students, and hosted summer events still contribute to lower levels of FW generation.

Both categories of educational institutions show higher anomaly values in the autumn and approximately average generation trends in the spring, coinciding with major events in the academic year, such as student move-in, homecoming, warm weather sports and activities, commencement, and move-out. For example, increased generation for universities is seen at the beginning of the fall semesters and slowly subsides monthly. One explanation could be that at the beginning of each academic year, on-campus meal providers may be learning student preferences and behaviors and thus offering more quantity and variety of food, but more research is required to support this explanation.

The temporal variability results for the eight NYS generators for which real data were available (Fig. 4) were then combined with state-wide generator estimates presented in Fig. 3, to assess how generator types and monthly variability might interact across a calendar year. These results, specific to supermarkets, K-12 schools, and universities, are shown in Fig. 5, which also includes static estimates for prisons, hotels, and other FW sources, for which no empirical data were available to construct real temporal trend models.

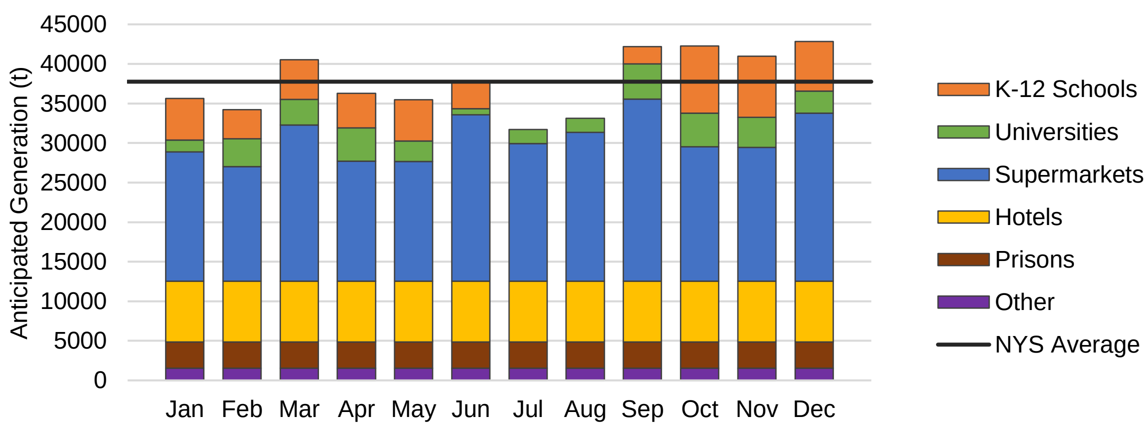

Figure 2-5. Anticipated monthly estimates of NYS FW generation. Estimates combined empirically determined monthly variations for schools, universities, and supermarkets with facility type and size data from the EPA database. Monthly variation for hotels, prisons, and other commercial generators were not empirically determined, but generic estimates from the EPA database were included to understand overall system impacts. The horizontal line indicates the estimate for statement generation without considering monthly variation.

Variability from educational institutions is expected to have the greatest impact on statewide generation (Fig. 4). While these sources only contribute about 19% to total NYS FW generation (Fig. 3), the high monthly variability, particularly between summer and fall, was enough to drive statewide estimates up or down by as much as 30% in October and November. On the other hand, supermarkets show more consistent month-to-month trends, but their contribution to net temporal variability is magnified by their significant overall contribution (48% of FW generated in NYS as shown in Fig. 3). Variable temporal effects for educational institutions and supermarkets largely offset each other during the summer, where the lowest anticipated generation rate is in July (32,000t). But additive effects are seen in later months of the year, with the highest generation rate observed in December (43,000t), a difference of 25% from low to high months.

Temporal trends can provide critical inputs for planning effective waste diversion systems. However, research must be extended to collect more empirical data on generation trends in other regions and for sources not considered here, like hotels, which could alter the monthly peaks and valleys of state-wide estimates due to seasonal trends in tourism and travel. The variability in system-wide generation revealed in these results echoes findings from past studies on generation of organic waste from several European cities, which showed a peak in the spring, generally low values in the beginning and middle of the year, and elevated waste produced at the end of the year (Denafas et al., 2014). In that study, however, changes in waste generation were different between cities, underscoring the importance of considering regionally specific FW generation trends.

Waste management companies may face operational challenges associated with seasonal and month-to-month shifts in the volume of FW requiring hauling and treatment. For instance, estimated FW generation increases approximately 20% between August and September. Such a rapid increase might require businesses to quickly expand their waste collection fleet to accommodate more generation from customers. Alternatively, rapid decreases in material availability could pose the reverse problem. In either scenario, maintaining and scheduling an incorrectly sized fleet of collection vehicles could lead to inefficient operations (Johansson, 2006), introducing instability and added costs into a collection company's operation and business plans. Understanding the variability in FW generation is critical to anticipate potential supply shocks to improve network stability and attract future investment (Iakovou et al., 2010).

On the other hand, the necessary logistics capacity may exist, but operation and utilization of treatment facilities could be impacted. Treatment facilities normally responsible for the FW management may not be sized for rapid influx of material, opting instead for onsite storage to normalize input flow. Short-term storage of organics may lead to premature degradation of material, altering biological treatment systems and affecting quality or quantity of saleable by-products (Agyeman and Tao, 2014; Lehtomäki et al., 2007). Moreover, open storage and uncontrolled degradation of organic material will ultimately release additional greenhouse gas emissions and reduce energy recovery potential, negating the original goals of FW diversion. While engineering practice usually includes a margin of safety in design, there are currently no laws that regulate treatment facilities to operate within designed capacity. Operators are free to run their facilities at maximum capacity and deal with the input fluctuations as they occur.

3.3 Spatial Variability

Results for generator type and temporal trends shown in the past two sections were then combined with spatially resolved information about the locations of commercial FW generators in NYS, disaggregated to the county level and presented for each month of the year. While results for all months are shown in the supplemental information file (Table S1), Fig. 6 highlights the months with greatest disparity between low (July) and high (December) FW estimates.

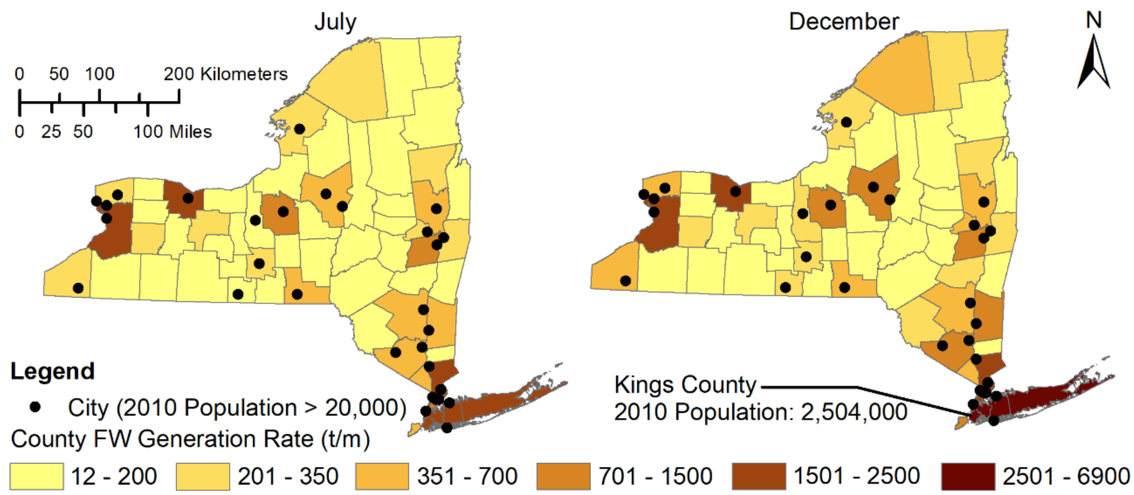

Figure 2-6. Anticipated monthly FW generation from commercial facilities within each county were summed to show geospatial variation in tons per month (t/m). Darker colors correspond to higher FW generation intensity within a county. The maps also designate cities containing populations over 20,000 people in 2010 are shown, and the most populous county in the state (King's County.

Counties with highest and most variable FW generation are those with the greatest population, typically concentrated in urban centers. However, many NYS counties are rural, and their anticipated monthly generation is both lower and more consistent between July and December than major urban regions. Nascent NYS FW donation and recycling policies are intended to affect generators across the entire state. However, the planning and implementation of such policies is carried out at the county level, allowing for development of diversion systems to treat region-specific challenges using locally available resources. For instance, siting treatment facilities in counties with higher FW generation would likely see economic benefits due to shorter transportation distances. Facilities in counties with lower FW generation might partner with diversion activities in close, more populous counties to reduce initial investments in transportation and hauling infrastructure, which may in turn translate into better overall economic performance of the diversion system (Gold and Seuring, 2011).

Without spatially resolved FW generation data, a regional diversion system developed to suit one region may be inadequate or overdesigned for use by other regions. For example, Monroe county and Westchester county are projected to generate approximately 22,000 – 23,000 tons of FW annually (Table A2). However, Westchester contains 70% more facilities than Monroe, making FW generation more aggregated in Monroe and potentially more efficient to collect (Table A3). Furthermore, a breakdown of generation by facility type shows that supermarkets generate roughly 55%-60% of FW in each county; however, generation is spread over only 220 facilities in Monroe compared to 609 in Westchester. This disparity translates to supermarkets in Monroe projected to produce on average 62 tons per year of FW compared to 20 in Westchester. A diversion system designed for Monroe county may not work effectively for Westchester county where generation rates are anticipated to be lower.

In contrast, the New York City region will require its own solutions to accommodate FW generation from the city as well as the geographically constrained Long Island region due to much higher population and generation rates. If management systems are developed in these regions separately, the transportation, infrastructure, and policy decisions made will be critical to overcoming supply chain logistics issues and implementing effective diversion systems (Gold and Seuring, 2011).

These spatial patterns change further when considering generation normalized to population in each of the counties mapped (Figure A3 and Table A4). The general spike in

December food waste production persists; however, rural counties tend to generate more FW per capita than more populated counties. While FW management systems are typically designed to manage a given total mass of material, there are instances when these normalized values may add useful insight. For example, counties with higher per capita FW generation may look to other counties with similar demographics but lower per capita generation rates to identify systems that may help reduce their per capita FW generation rate.

3.4 Data Source Uncertainty

Monthly projections from two alternate data sources were compared to the baseline analysis to understand potential uncertainty in estimating FW generation. Estimates for each data source are separated into facility types and monthly generation projections in the same way as shown in Section 3.2. Comparison of the three scenarios with nearly the same categories shows similarity in total projections (Fig. 7). While the maximum difference between highest and lowest months within the original data source is approximately 25% (Data Source A), the maximum difference in generation projections between data sources is 37% (Data Source A and B). The increase in uncertainty could exacerbate the transportation, management, and design challenges discussed previously.

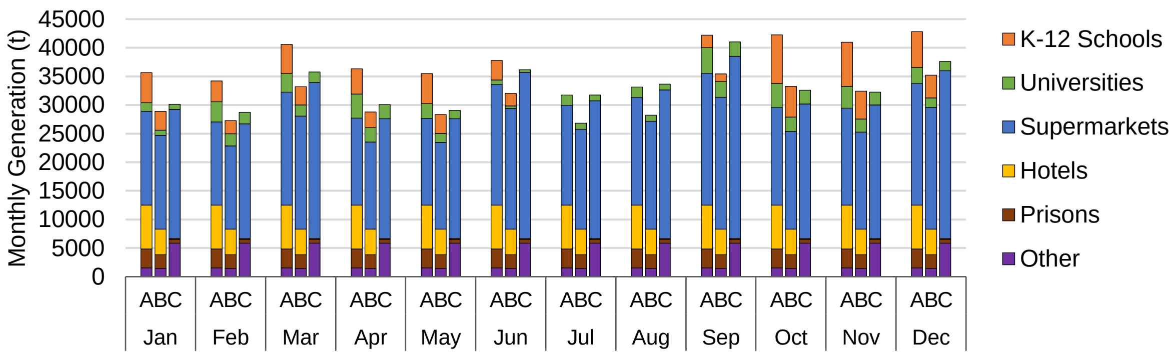

Figure 2-7. Comparison of monthly generation projections from different data sources. (A): Baseline analysis using the EPA database. (B): Analysis using lower estimates in EPA database. (C): NYSP2I ORL. The ORL does not include K-12 schools in its database, therefore no projections were shown for that category.

The comparison of data sources A and C demonstrate how disaggregated FW projections for specific generator types were considerably different despite both data sources resulting in similar FW totals. In Data Source C, supermarkets and other generator types contribute the most while contributions from hotels and prisons are negligible. Results from Data Source C have different implications for policy development, indicating that supermarkets and other types of generators are by far the best focus for FW diversion efforts. The higher supermarket estimates may also lead planners to design FW management systems in proximity to these FW sources. If, however, the distribution of FW is different than expected, then treatment systems and transportation network may be less efficient than intended. This insight is true even under the baseline scenarios but is more recognizable with a side-by-side comparison of results using differing methodologies. The best way to control for this uncertainty is to collect more data to inform decision making. However, these scenarios indicate that data source and estimation method uncertainty can have tangible effects on FW projections.

3.6 Limitations and Considerations

This study, like the broader field of FW analysis, is limited by the few real data points that were available and the associated need to rely on generic estimates from the EPA FW database, which itself has incomplete and missing information. For example, the restaurant/food service industry was not included in the 2015 values used by the EPA database, although separate estimates suggest that while these generators may have low individual FW intensity, they could collectively contribute more than 50% of the commercial FW generated in NYS (NYS Pollution Prevention Institute, 2017). Future work should expand empirical data by developing replicable measurement approaches and tools that can reliably estimate FW generation across different regions, for different types and sizes of the generators, and influenced by variable climate, food supply chain, or consumer lifestyle factors. In addition, there are key opportunities to harmonize state, federal, and private FW databases for greater comparability and comprehensiveness. Including additional data samples will create a more accurate and generalizable estimate of FW generation.

One challenge in estimating FW generation using the prevailing methodologies is that the most commonly cited generation activities may only be tangentially linked to generation rates. For example, room or employee counts are the common method for estimating annual FW generation for hotels. However, other factors such as occupancy rate, on-site restaurant, and access to food delivery services are likely to be actual drivers of FW generation. This line of inquiry was explored at a preliminary level during data collection for this study. Publicly accessible data was only available for the whole U.S. (Statista, 2019) and New York City (NYS & Company, 2019) and the average occupancy rates per month from these data are shown in the supplemental information file (Figure A4). Although slight trends towards increased occupancy during summary months are shown, these data were not included in the main analysis due to lack of regional specificity. A wide discrepancy between U.S. and NYC occupancy rates supports the need to gather regionally relevant FW generation data The activity and generation factors underlying FW generation estimates may also be difficult or expensive to collect due to the business-sensitive nature and scale of preferred data or company unwillingness to disclose waste data, which may be perceived negatively by customers.

4. Conclusions

This chapter shows that FW generation from commercial and institutional sources in New York State cannot be fully represented with a single annual value. Capturing the inherent spatial and temporal variability within this system is necessary for developing sustainable policy solutions and then deploying required FW collection, hauling, and treatment infrastructure. For example, almost 60% of estimated FW is expected to come from only those 4% of total facilities in the state that would be currently be covered under a regulation threshold of 94 t/year (2 US tons/week). Of this total, supermarkets represent the greatest contribution (48%) of facility types considered here but are also the type of generator likely to show seasonal variability in FW amount and spatial variability in location based on regional population density.

In terms of spatial heterogeneity, urban centers were demonstrated to be hotspots of commercial food generation, from the perspective of having a high and relatively consistent degree of FW generation over time. These systems-level sources of variability point to potential challenges and opportunities for optimizing future siting of FW management infrastructure. For instance, understanding how FW sources concentrate in particular locations can inform where to prioritize incentives and investment for policy implementation and how to choose treatment sites that minimize transportation costs. Reducing the economic cost to participate in FW diversion may attract additional participants beyond those required by legislative mandate. Future policy enhancements may also offer a pathway to solving FW data gaps discussed here. A requirement to report FW generation and activity factors would not only help provide valuable information for future research and applied solutions but may also help clarify the underlying drivers of FW generation. Ultimately, expanding this field of study is necessary to create more targeted and effective policies for reducing and diverting FW for environmental benefits within NYS and across the U.S. This chapter considered the challenge of variability from generation sources, but FW must also be ultimately be managed somewhere other than a landfill. Alternative management facilities need to be available for treatment of FW, which could require the construction of new treatment facilities. The actual collection of source-separated FW will likely evolve into a primary waste stream over time just as conventional recycling evolved in the U.S. in the 1960s. However, FW collection as a new waste collection network is still growing and will likely face challenges of economic feasibility. It is important to understand how the variability in FW generation identified in this chapter could affect the feasibility of collecting FW from generators and hauling it to treatment facilities.

CHAPTER 3
EFFECTS OF SPATIAL HETEROGENEITY ON EXPANSION OF FOOD WASTE COLLECTION SERVICES

1. Introduction

The spatial variability of FW generation defined in Chapter 3 will pose challenges for collection services. As companies grow their FW collection networks, they will need to identify where to expand next. Understanding how spatial variability will affect these expansion decisions is critical for maintaining an economically feasible collection service that potential customers will be willing to pay for. One category of FW generation Chapter 2 did not consider was household. While the state-level legislation mentioned previously has focused on larger consumer facing businesses, residential food waste diversion has been ignored in state-level policy and legislation. This lack of interest in diverting residential food waste from landfills is problematic if states wish to continue reducing the environmental impact of their waste management systems. Moreover, variation in residential generation is expected to be small enough that assuming a uniform generation rate will not significantly impact collection efforts (Edjabou et al., 2016; Hanssen et al., 2016), thus providing an ideal network for understanding how spatial variation effects FW collection.

As of 2014, only 200 municipalities in the US have some form of residential food waste collection in place through municipal mandates or private waste collection businesses (Yepsen, 2015). Increased costs for the addition of curbside food waste collection brings considerable challenges that have mostly been overcome by political will (Yepsen, 2014), which is unsustainable from a long-term economic perspective. In order to reduce waste collection program costs, economies of scale are critical (Bohm et al., 2010). Achieving these economies of scale may be difficult for food waste collection due to lower generation rates compared to municipal solid waste (MSW) and recyclable material (New York State Department of Environmental Conservation, 2010).

A main focus of previous waste collection models in the literature is to increase collection efficiency by optimizing routing and scheduling for networks at the urban scale (Arribas et al., 2010; Or and Curi, 1993). Urban residential waste collection poses significant methodological challenges due to the large number of individual waste bins to be collected. Also, these models neglect food waste generated by suburban areas. Larger regional networks that encompass both urban and suburban areas include many logistic dimensions such as transfer stations, time constraints, and bin types (Das and Bhattacharyya, 2015; Nuortio et al., 2006; Son and Louati, 2016). Some studies focus on specific waste materials, such as recyclables, to understand the dynamics that specific waste types confer to the collection system (Bing et al., 2014; Rousta et al., 2015). This practice may parallel dynamics seen in the food waste collection system.

Relatively few studies focus specifically on the collection of source-separated household food waste. Franchetti and Dellinger (2014) and Edwards et al. (2016) study the economic and environmental effects that an additional waste collection stream will have on the collection system. However, these studies each examine large, mature collection networks and systems, assuming all households participate in the collection service. Realistically, households in communities have varying values regarding recycling of food waste; therefore, not everyone is willing to participate in or pay for the additional service. National surveys in the US focusing on household attitudes toward food waste indicate that the majority of people still throw away food even though they feel guilty about their actions (Neff et al., 2015; Qi and Roe, 2016). Therefore, understanding the effects of participant spatial density on service cost is important for implementing collection services sustainably.

The overarching objective of this chapter is to provide system-level insights for expanding food waste collection. This objective is twofold. First, improvements to transportation costs for small start-up scale networks and the implications as service grows and more households incorporated in the network are examined. Second, the feasibility of expanding small scale residential food waste collection services is assessed by calculating travel and collections costs associated with adding new communities. As communities join the collection network, travel time and cost per household are expected to decrease, indicating positive returns to scale.

2. Analysis and Modeling Framework

2.1 Analysis Framework: Decision-making for Service Expansion

The analysis and modeling framework developed reflects the decision-making process faced by start-up food waste collection services early in development. The problem is approached by developing a model and analysis framework that solves for the vehicle routing problem (VRP) given an a priori set of households and their spatial locations over participation levels that reflect expansion scenarios. A new solution to the VRP for each network expansion level (a new collection route) is obtained as more households and communities join.

The VRP is solved using the cluster first, route second heuristic (Laporte, 2009), which helps address the high computational resources required of large networks. Under this approach, destination nodes are clustered first based on their spatial proximity and the VRP is solved for each cluster. A second VRP is performed on the network of centroids of each cluster. For this chapter, the clusters are determined (a priori) based on pre-defined neighborhood boundaries, precluding the need for a clustering algorithm. The motivation behind this assumption is behavioral. Social interaction within communities or neighborhoods likely contribute more towards behaviors such as adoption of curbside composting services (Hopper and Nielsen, 1991; McMillan and Chavis, 1986). The framework consists of two routing layers: 1) an intra-neighborhood vehicle routing and 2) inter-neighborhood vehicle routing. Figure 1 illustrates this framework.

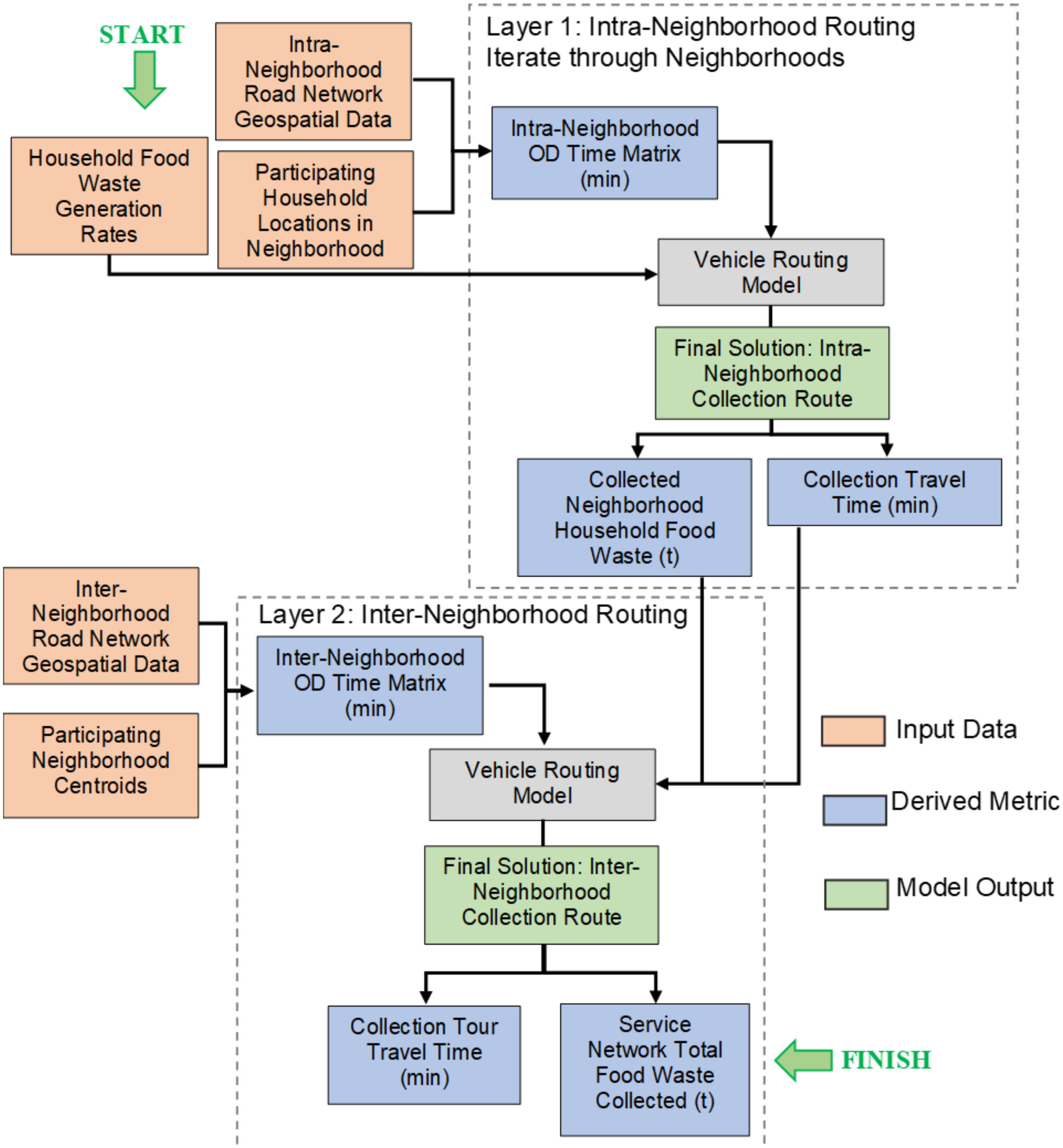

Figure 3-1: Modelling Framework

Each neighborhood represents a community seeking collection service. The first layer solves a VRP for a given neighborhood between households randomly selected to represent different levels of collection program participation. The collection vehicle must stop at each household and requires a set time duration for collecting the food waste. A solution to the first stage VRP will indicate the sequence of household stops, network links traversed, total traversal time, and quantity of collected waste is produced.

In the second layer, an inter-neighborhood VRP is solved for a network of centroids of the neighborhoods. Associated with each neighborhood centroid is a total waste collected at that neighborhood and travel time determined previously in the first (intra-neighborhood) layer. Similarly, the output to the inter-neighborhood VRP includes a collection route that indicates the sequence of stops and network link traversed between neighborhoods. This layer also produces the total time of the collection route and total quantity of food waste collected by the vehicle.

2.2 Vehicle Routing Problem (VRP) Formulation

The VRP is formulated as a mixed-integer mathematical program and solved using the cluster first and route second heuristic (Laporte, 2009). The neighborhood residential waste collection problem is formulated as a capacitated VRP where the decision variables are:

x_{hij}^{k} - The shortest path travel times nodes h, i, and j for collection truck k.

y_{i}^{k} - The total quantity of food waste in the collection truck k including node i.

w_{j}^{k} - Mass of waste delivered to recycling facility j by collection truck k.

v_{j} - The total mass of food waste delivered to recycling facility j.

The formulation has the following objective function:

$$Min = \sum_{i\in(D,N)} \sum_{j\in(D\prime,N)} \sum_{k\in K} c_{ij}\, x_{ij}^{k} + \sum_{j\in N} m_j \tag{1}$$

The objective function (1) minimizes the truck travel time between pickup $i \in D, N$ and delivery $j \in D', N$ nodes over the set of vehicles $k \in K$ mobilized in the collection network by summing the travel time c_{ij} on each traversed link x_{ij}^{k} and the collection time at each pickup node m_j.

Subject to the constraints:

$$\sum_{h\in D} \sum_{i\in N} x_{hi}^{k} = 1\ \forall\ k \in K \tag{2}$$

$$\sum_{i\in N} x_{hi}^{k} = \sum_{j\in N} x_{jh\prime}^{k}\ \forall\ k \in K, h \in D, h' \in D' \tag{3}$$

$$\sum_{h\in(D,N)} x_{hi}^{k} = \sum_{j\in(N,D\prime)} x_{ij}^{k}\ \forall\ k \in K, i \in N \tag{4}$$

$$\sum_{i\in N} x_{ij}^{k} = \sum_{h\prime\in D\prime} x_{jh\prime}^{k}\ \forall\ k \in K \tag{5}$$

$$\sum_{k\in K} \sum_{j\in(N,F)} x_{ij}^{k} = 1\ \forall\ i \in N \tag{6}$$

Constraints (2-6) provide the minimum cost flow constraints that simulate the behavior of the collection truck. The truck can only leave the depot once, all households or neighborhoods must be visited by only one truck, food waste must be dropped off at the recycling facility, and the truck must return to the vehicle depot.

$$y_i^k \geq y_h^k + (q_i + Q)x_{hi}^k - Q\ \ \forall\ h \in (N, D), i \in N, k \in K \tag{7}$$

$$w_j^k \geq y_i^k - Q(1 - x_{ij}^k) \forall\, k \in K, i \in N, j \in D' \tag{8}$$

Constraints (7-8) are modeled after the Miller-Tucker-Zemlin constraints to prevent subtours for collection vehicles (Miller et al., 1960). These constraints track the total food waste in the collection truck at each stop, ensuring that the sum of the current quantity of food waste in the truck and quantity picked up at the household q_i do exceed truck capacity Q.

$$\sum_{j \in F} w_j^k \leq Q \;\forall\, k \in K \tag{9}$$

$$\sum_{j \in F} \sum_{k \in K} w_j^k = \sum_{i \in N} q_i \tag{10}$$

Constraint (9) ensures the capacity of the collection truck is not violated. Constraint (10) ensures waste dropped off equals the total amount of waste collected.

$$v_j = \sum_{k \in K} w_j^k \;\; \forall\, j \in F \tag{11}$$

$$P_j^{quo} \leq v_j \leq P_j^{cap} \;\forall\, j \in F \tag{12,13}$$

Constraint (11) tracks the total amount of food waste delivered to the recycling facility $j \in F$, and Constraint (12,13) ensure that recycling facility quotas P_j^{quo} are met and capacities P_j^{cap} are not violated.

$$\sum_{i \in (D,N)} \sum_{j \in (N,D')} c_{ij} x_{ij}^k + m_j = B^k \;\forall\, k \in K \tag{14}$$

$$B^k \leq B^{k,Lim} \;\forall\, k \in K \tag{15}$$

Constraint (14) equates the travel time between nodes and the pickup time at each node to the total travel time for the collection route B^k. Constraint (15) ensures that the total travel time does not exceed the maximum travel time set $B^{k,Lim}$. All VRPs across scenarios considered in this chapter were solved using the IBM CPLEX solution algorithms with a MATLAB interface.

2.3 Model Assumptions, Data Sources, and Limitations

Assumptions regarding collection and transportation time, household food waste generation rates, and operational costs are summarized in Table 1 and discussed.

Item	**Value**	**Unit**	**Description**	**Reference**
Collection time for food waste bins	0.5	min	Time taken to collect food waste bins at households	Model baseline
Travel Speed	Variable/ Speed Limit	km/hr	Time taken to travel along road segments	Speed limits from road network information. NYS GIS clearinghouse
Food Waste Generation				
Low Generation (LG)	.002	t/week		
High Generation (HG)	.007	t/week		
Vehicle Operating Cost				
Low Cost (LC)	60	$USD/hr		
High Cost (HC)	100	$USD/hr		

Table 3-1: Assumed Model Parameters

Road network links, nodes and signed speed limits are obtained from the transportation network data available at the New York State Geographic Information Systems Clearinghouse (NYS Office of Information Technology Services, 2017). ESRI ArcMap is to compute the shortest path travel times between nodes, constituting the travel time matrix used in the VRP formulation. Other parameters such as vehicle acceleration and stopping times at intersections were not considered. Thus, the results may underestimate the travel time and costs per household.

In 2010, a residential and commercial solid waste audit was performed in Monroe county, NY and included in their Local Solid Waste Management Plan Update (Barton & Loguidice. D.P.C., 2015). An average MSW generation rate of 26 kg per household per week was identified by this waste audit, with a 6.8% fraction of that MSW identified as food waste equating to approximately 2 kg of food waste generated per household per week. Conversely, the New York State Department of Environmental Conservation has estimated that food waste generation rates are higher, at 20% of the MSW generated by households, equating to 5.2 kg of food waste per week based on total waste generated found in the regional waste audit. However, an upper bound of 7 kg of food waste per household per week is used to represent increases or spikes in food waste generation during the holiday or summer seasons (Lebersorger and Schneider, 2014). All households are assumed to generate the same quantity of food waste in each scenario. Food waste generation rates vary across households weekly because estimating actual household generation rates poses additional challenges not considered in this chapter.

Transportation costs are estimated in $USD per hour, which is the industry standard (personal communications with Waste Management, Inc. and Natural Upcycling). True operation costs will vary with fuel prices, weather, salary, and other vehicle maintenance costs not considered in this chapter. To account for some cost variability, upper and lower costs are derived from correspondence with two local waste collection companies. The current model only comprehends a homogeneous vehicle fleets with pre-defined capacities. If preliminary routing solutions indicate that smaller vehicles may be more desirable than larger vehicles due to time constraints rather than capacity, those parameters must be changed manually. Realistically, some collection vehicles are more suited to residences that produce only a few kilograms of food waste a week, while others can pick up larger quantities of food waste from multi-family households.

2.4 Study Area

The study area is the Town of Penfield, a municipality located near Rochester, NY. Regional data for Penfield was used for this chapter, including geocoded household locations and traffic road network links. Only single-family households are considered for analysis, constituting 98% of the total residential parcels in Penfield. The collection vehicle starting depot and delivery location are the same facility located just south of the City of Rochester. A map of neighborhoods considered within Penfield is shown in Figure 2 and characteristics of the study area are shown in Table 2.

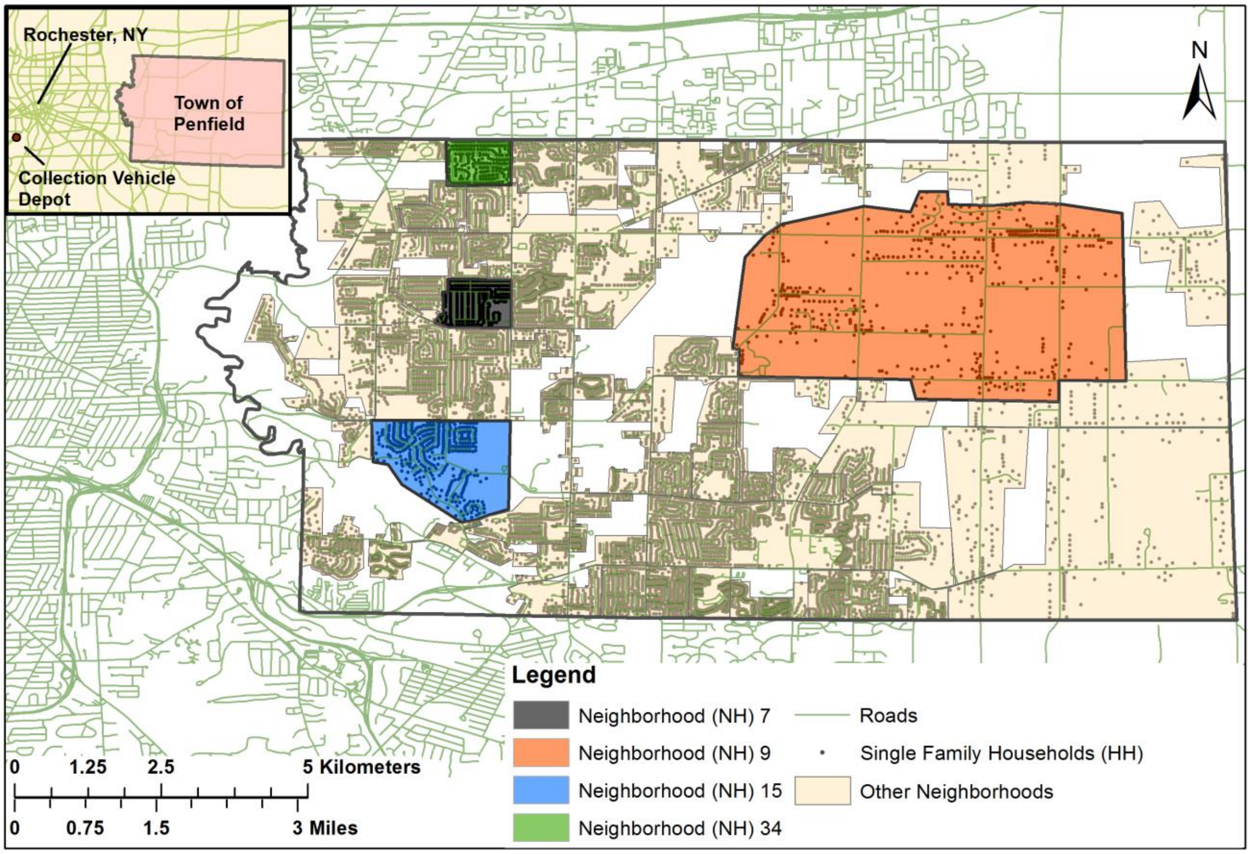

Figure 3-2: Study Area Penfield, NY

Name	Area (km^2)	Total Households	50 Randomly Selected HH (% Total)	Depot to Centroid TT (min)
Penfield, NY	97	12450	N/A	N/A
Neighborhood 7	0.70	280	17.9%	17.4
Neighborhood 9	14.53	469	10.7%	24.53
Neighborhood 15	1.95	386	13.0%	14.74
Neighborhood 34	0.62	221	22.6%	17.94

Table 3-2: Neighborhood Characteristics

2.5 Evaluation Steps

First, participation from Neighborhood 7 (NH7) and Neighborhood 15 (NH15) are evaluated independently to understand characteristics from each neighborhood. Participation levels from 5 to 50 households per neighborhood are considered for each neighborhood. Second, NH7 and NH15 are combined to create the base service network for the collection program. The time for the collection routes for participating households in NH7 are evaluated from 5 to 50 participants. Then, more participating households from NH15 are added to the network and collection times are evaluated. Third, households from NH9 and NH34 are independently added to the base network and the collection route times are compared. Comparing the addition of NH9 to the addition of NH34 indicates how adding neighborhoods with different spatial characteristics effect the collection route time. Finally, high/low operational costs in conjunction with high/low waste generation rates are applied to the collection service network route solutions to assess potential collection costs per ton of material.

3. Results

3.1 Travel Time in Individual Neighborhoods

Comparing the final objective function (Eq. 1) values at convergence from NH7 to NH15 show an increase in total route time and intra-neighborhood time as households are added to the network.

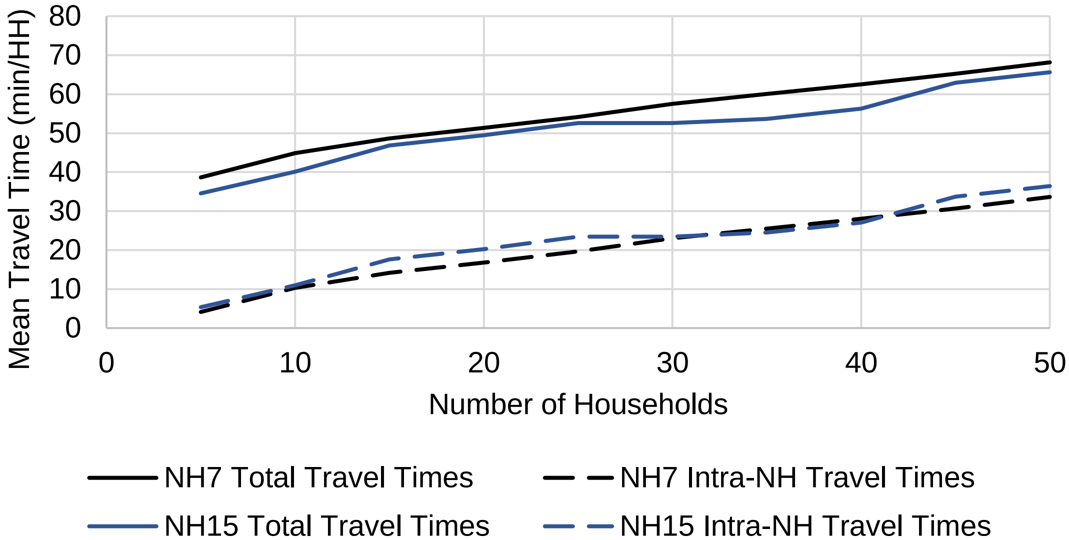

Figure 3-3: Comparison of Total Route and Intra-HH Travel Times for NH7 and NH15

Figure 3 suggests that increasing the number of participating households increases intra-neighborhood travel times. The total travel time experienced (intra and inter neighborhood travel times) also increases with more participating households. The similarity in mean travel time (min/HH) increase between total and intra-household travel times suggests that the rate of increase for total travel time is due largely to adding more participants to the network. This is illustrated also in Figure 4.

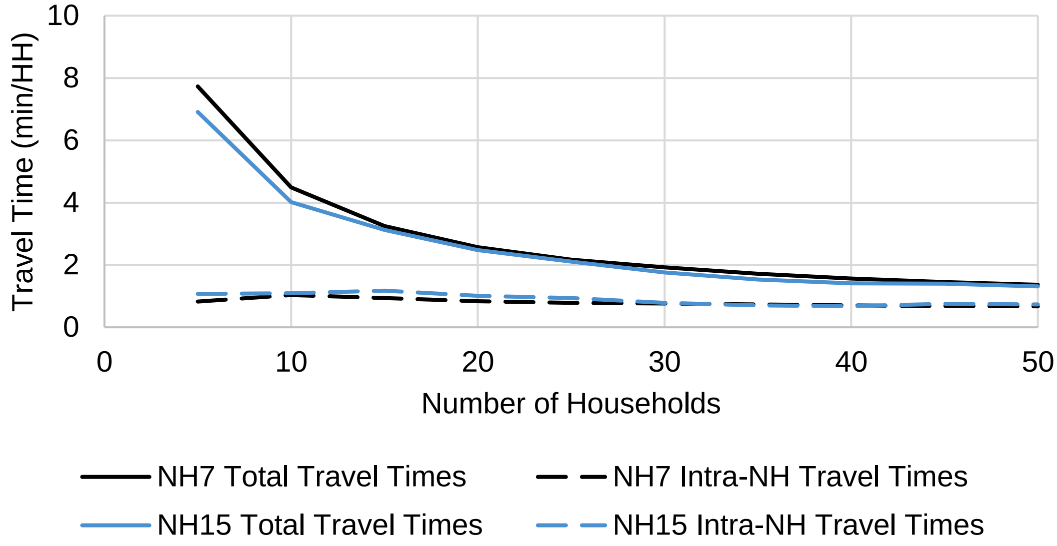

Figure 3-4: Comparison of Mean Household Route Times for NH7 and NH15

Figure 4 points to economies of scale as program participation increases. The intra-neighborhood route time per household remains relatively constant, while the inter-neighborhood travel time per household (not shown) decreases, subsequently decreasing total travel time. Each neighborhood is a static defined area with fixed boundaries; therefore, as program participation continues to increase in any given neighborhood, the participation density also increases. Figure 5 considers the impact of increasing participant density on travel time per household.

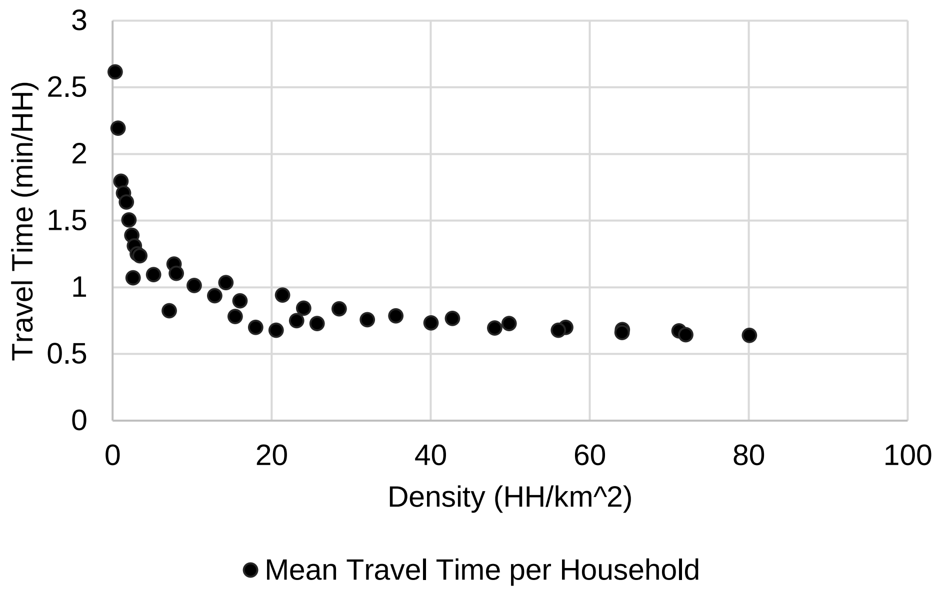

Figure 3-5: Travel Time vs Household Density

Graphing the travel time per household against household density in neighborhoods, a similar trend emerges indicating reduction in travel time per household as participation increases and households are added to service network. Variations in the trend are due to the different road networks and collection routes for each scenario. A drastic decrease in travel time per household is seen increasing from 0 to 10 participants per km^2, showing a "knee" in the curve between 10 to 20 participants per km^2. Including additional participants beyond 20 per km^2 marginally reduces the travel time per participating household in the neighborhood. Collection trucks require a minimal time for waste collection at destinations and therefore are only able to improve route travel times up to that limit, which is 30 seconds in this chapter.

3.2 Travel Times in Expanding Service Networks

Although assessing the travel times for single neighborhood networks independently yield insights into neighborhood routing performance characteristics, waste collection services consider networks of neighborhoods jointly, building out through an expansion process. To represent and model this expansion, once NH7 reaches 50 participants, 50 participants from NH15 are introduced to the network incrementally. This expansion scenario continues the trends in for increasing overall travel times (Figure 6), but reducing travel time per participant (Figure 7).

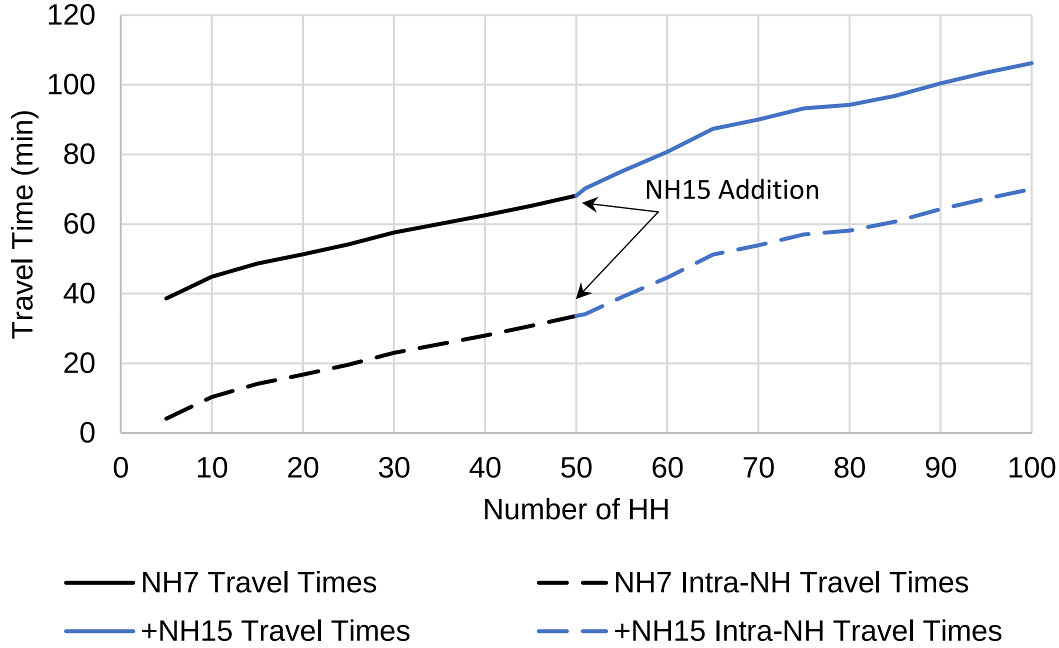

Figure 3-6: Total Collection Route Times for the NH7 and NH15 Collection Network

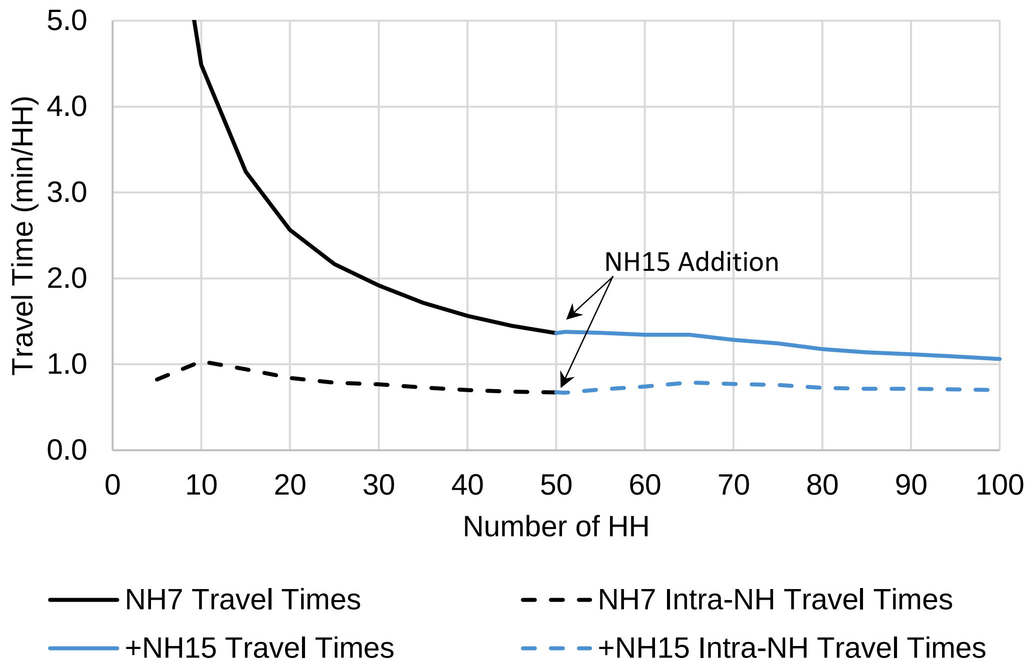

Figure 3-7: Mean Collection Route Times for the NH7 and NH15 Collection Network

The total travel time of the collection vehicle per participant decreases and the intra-neighborhood travel time per participant remains consistent as participating households from NH15 are added to the service network. The decrease in total travel time per participant indicates economies of scale that continue as participants are added from NH15 and consistence in intra-neighborhood travel time suggests a uniformity in the distribution of households within each neighborhood.

As the food waste collection service grows, these services will consider including more neighborhoods. Deciding which neighborhood routes to incorporate into the service may have a large impact on the total travel time for collection, ultimately affecting route travel time and subsequently operation cost. Densely populated neighborhoods closer to the existing network are more desirable for expansion relative to neighborhoods where travel time between houses is larger and the neighborhood center is further away from the existing service area. However, advantages of considering these different additions is unclear if potential participants are willing to pay the cost for the collection service. A comparison of adding NH9 and NH34 to the base service network are compared for total travel time and mean travel time per participating household.

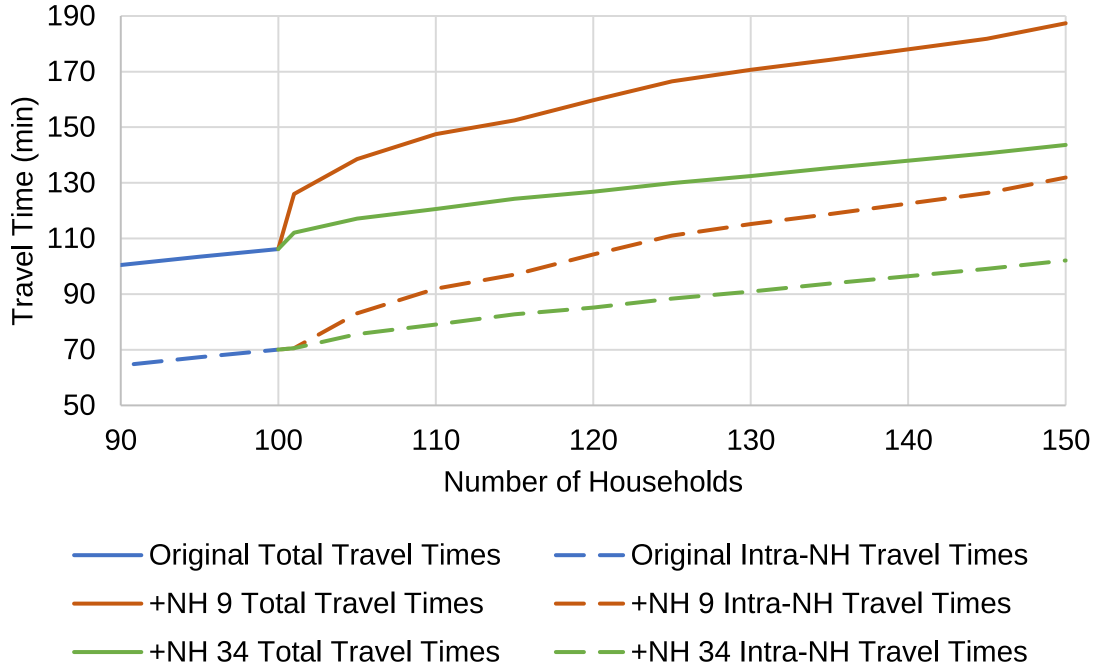

Figure 3-8: Total Collection Route Times of the Expanded NH9 and NH34 Collection Network

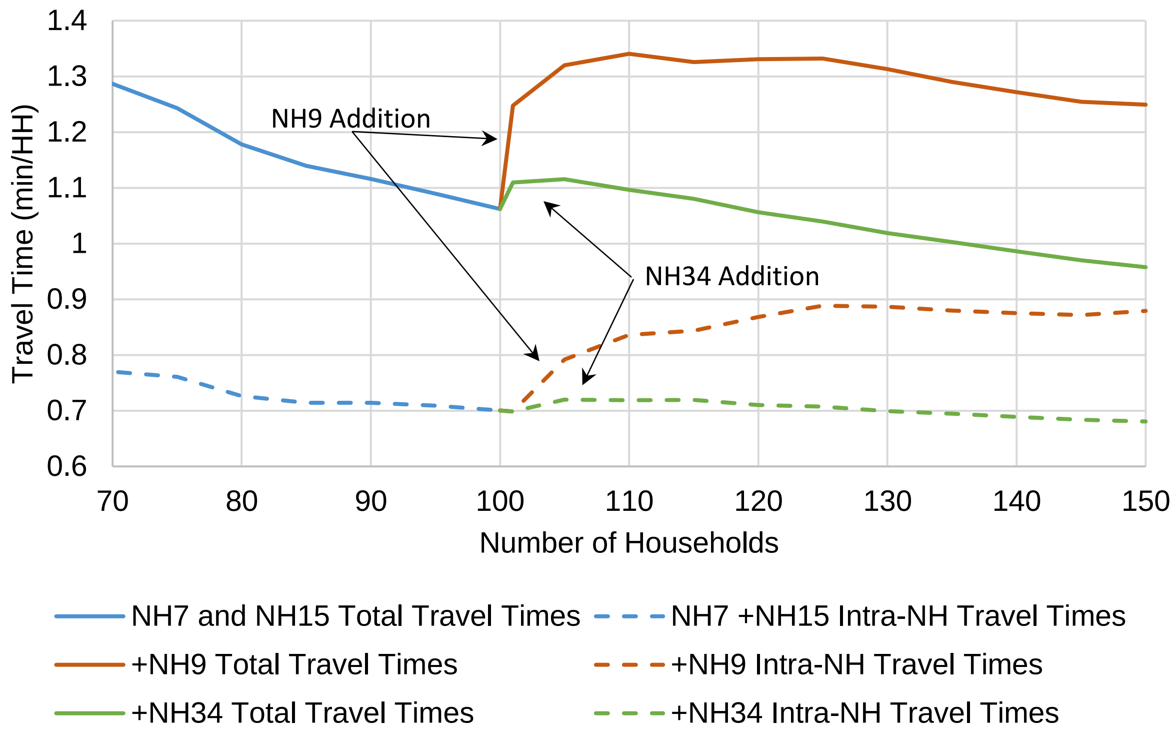

Figure 3-9: Mean Collection Route Times of the Expanded NH9 and NH34 Collection Network

The addition of NH9 or NH34 to the network have very different effects on both total and per participant travel times for the final routes. Spikes in total travel time are shown when NH9 and NH34 are initially added to the network. The spike for NH9 is larger than NH34 because it is a further distance from the base service network. The rate of increase for collection time increase for NH9 is also higher than NH34 due to the lower density of households in NH9 causing increased travel times between households.

Adding NH9 initially increases travel time per participant, due to the longer distances traveled by the collection truck to the neighborhood, then slowly decreases with the addition of participants. After an addition of 50 households, the travel time per household does not return to the previous level of pre-NH9 addition. Alternatively, adding NH34 to the collection network continues the travel time reduction trends seen previously. After the addition of approximately 20 participants from NH34, travel times per participant are equivalent to pre-NH34 addition, and more participants lead to further route time reductions. Figure 8 and Figure 9 shows that it is possible to temper the initial shocks of adding new neighborhood service areas by recruiting more households into the program to justify the longer distance traveled.

3.3 Cost Assessment

Collection cost is also important to assess from a feasibility standpoint, especially when considering potential participants' willingness to pay for service. However, the variability of food waste generation and operational costs present barriers to generalizing costs per ton to a specific value. Therefore, upper and lower bounds for generation and operational costs are considered to encompass a range of variability in food waste generation and operational costs (Table 2). The high-cost scenario combines the high operation cost parameter with the low food waste generation parameter, producing the highest cost per ton of food waste collected. The low-cost scenario combines low operation cost with high food waste generation, producing the lowest cost per ton of collected food waste. Low cost/low generation and high cost/high generation parameter combinations are omitted because the cost per ton of food waste collected are intermediate to the evaluated high and low-cost scenarios. Regardless of the values of cost and generation parameters, collection costs per ton of material are expected to follow decreasing trends as the number of participants in the network increase.

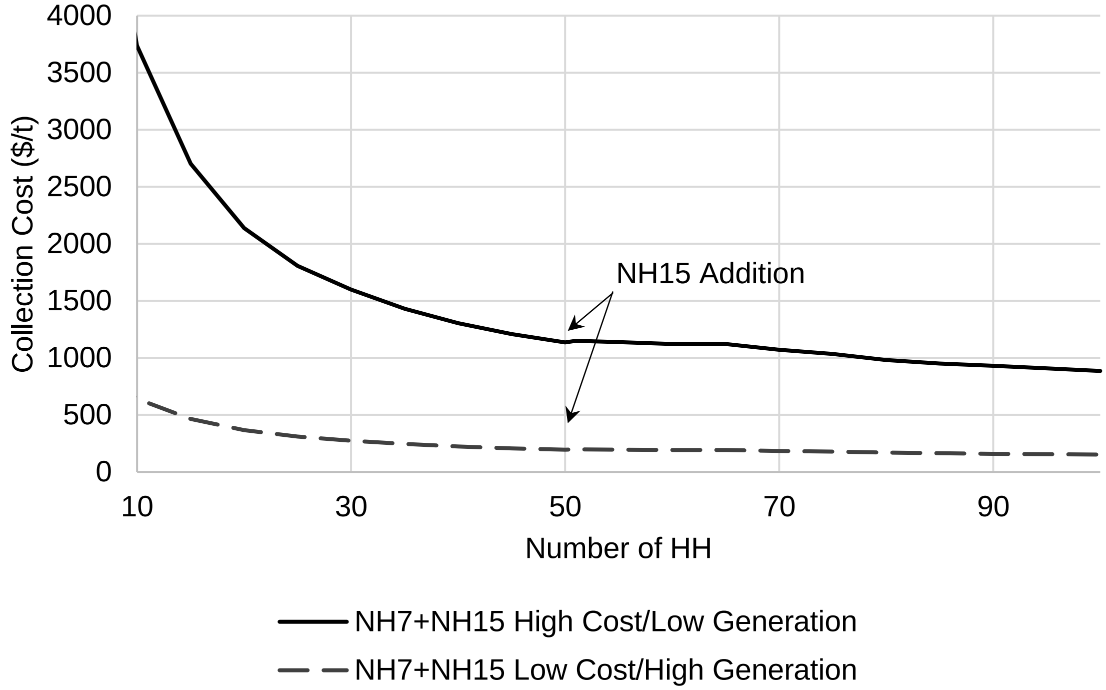

Figure 3-10: Transportation Costs for the NH7 and NH15 Network

Trends in collection costs per ton of material ($/t) are shown to decrease similarly to reductions in mean per participant travel times in the network for NH7 and NH15 but show the wide range in potential collection costs. These high and low cost scenarios are extended to 50 more households from NH9 or NH34 to show how the addition of these neighborhoods effect total cost.

Cost Scenarios	100 HH from base network	+50 HH from NH9		+50 HH from NH34	
($/t)	Total ($/t)	Total ($/t)	Change ($/t)	Total ($/t)	Change ($/t)
(HC,LG)	708	832	+124	638	-70
(LC,HG)	142	167	+25	128	-14

Table 3-3: Cost Scenario Values for Expansion to NH9 or NH34 Network

Even under the best scenarios of high food waste generation and low operating costs, inclusion of NH9 in the collection network increases the collections cost per ton. However, the marginal cost of providing service will continue to decrease as participants are added. Alternatively, the inclusion of NH34 in the collection network decreases the total collection costs in each scenario. Under higher cost scenario, the additional cost or savings are more pronounced in the additional neighborhoods than the lower cost scenario. Therefore, if operating costs and food waste generation rates are unfavorable, the company can capitalize on potential savings by extending service to neighborhoods that are close and dense to reduce the overall collection costs. Inversely, demand for service in in a more rural neighborhood will increase overall costs, but these increases can be minimized with low operation costs and high food waste generation.

4. Discussion

4.1 Effects of Household Density of Neighborhoods

Results indicate a relationship between the decreases in travel time per household in collection routes with increasing household density in neighborhoods. Although this relationship is intuitive, there are two interesting insights revealed.

First, there is a clear trend in the decrease in travel time per households as more households are added to the collection route within a given neighborhood. More extensive modeling and study is required to further corroborate this result. However, if future work finds consistency across similar networks, the relationship can be used to estimate the cost of waste collection without solving a VRP for large-scale network with many nodes, which is computationally prohibitive. Additionally, the estimation method could be applied to other food waste collection scenarios, most notably to a commercial facilities context. Current policy reports that quantify the cost of performing food waste collection from large commercial sources considers only the cumulative cost of traveling from each individual generator of waste to the final depot (Manson, 2017). This method both models unrealistic waste management behavior and overestimates the cost of transportation. Clustering generators together as we did in this chapter and applying a travel time relationship to estimate costs is an approximation, but it is more accurate than transportation costs estimated in reports like Manson (2017).

Secondly, reductions in travel time per household are significant up to a critical threshold as participants are added to the collection route. At this threshold of participant density, the improvements in cost reductions are only marginal compared to the initial growth of the service. In the scenarios presented in this chapter, the threshold of participant density appears to be between 10 and 20 households per km^2. After that, decreases in travel time per participant show diminishing returns, approaching a stable travel time per participant.

4.2 Effects of Spatial Separation between Neighborhoods in a Service Area

In the scenarios presented, a system shock occurs as neighborhoods are added to the collection network. When initially adding neighborhoods with a few households to the collection network, the total travel time and cost per household will spike. The distance of the newly added neighborhood from the base network influences the magnitude of the spike, and the density of potential customers in the neighborhood influences how quickly the system recovers. Moreover, this model reveals a critical mass of participating households that are needed before the collection times and costs will return to pre-shock levels. Customers added after this critical mass is reached will only continue to reduce the travel time per participant in the network, hypothetically reducing the collection costs for all participants in the program.

Identifying the critical mass of new participants in each neighborhood will help inform program expansion decisions. A company could administer a survey to a neighborhood community, and if participation interest reaches the critical mass identified by the routing trends, then it would be economical to provide service in that area. After the participant mass is reached, revenue generated per customer from additional participants will remain relatively stable. The stability allows a startup company to decide if it is worth spending resources on attracting new participants in the same neighborhood or focusing on service expansion to other neighborhoods

5. Conclusion

While past studies have examined residential waste collection and variants of this pick-up and deliver problem, none to the knowledge of the authors have considered the network build-out of these systems. This chapter presents a residential food waste collection model focusing on the impacts of expanding and growing the network both in terms of additional households and additional communities for a service provider in the early stages of its development and growth.

The increases in the overall collection time are most affected by the increases in household participation within neighborhoods rather than travel time between neighborhood clusters. Increases in household participation lead to an increase in spatial density of participants, subsequently reducing the collection time per participant if distributed equally. When household density is low (less than 10 households/km^2), addition of more participants quickly reduces the per household travel time. At higher participant densities, the rate of travel time decreases less quickly, indicating diminishing returns on collection time after approximately 10 households/km^2.

Economies of scale are clearly visible as participants are added to the collection network of individual and multiple neighborhoods. Decreases in travel time as well as decreases in program cost are visible as more households participate and more food waste is collected. This trend should be leveraged by start-up collection programs to assess how economic feasibility will be maintained while satisfying service demands from customers.

Since food waste constitutes a fraction of residential solid waste generation and voluntary participation is limited, collection methods will be different compared to municipal solid waste. This chapter focused on spatial properties of small collection programs, but there are other unanswered questions that should be addressed in future research. The optimal size of collection vehicles for food waste programs should be studied because smaller collection vehicles might be more suitable for food waste collection due to decreased operation costs and environmental impacts. Ultimately, the goal of residential food waste recovery is to reduce the environmental impacts of food waste degradation in landfills by diverting food waste to other recycling facilities. However, the energy, emissions, and economic balance that includes in-depth transportation modeling should be researched to understand these balances more completely.

Additionally, this analysis does not consider how variability in the quantity of FW generation could affect feasibility of collection. At commercial scale, this type of variability could present an additional challenge for building out collection networks. Many existing transportation estimates of FW collection at this scale simplify transportation behavior to estimate transportation costs. However, it is important to model collection networks more realistically so that results are more relevant to stakeholders such as collection companies and policy analysis. Chapter 5 addresses this challenge by presenting a new vehicle routing model to differentiate the effects of heterogeneous FW generation from homogenous generation on emerging commercial FW collection networks.

CHAPTER 4
ADAPTING ECOLOGICAL MODELS TO INFORM SUSTAINABLE EXPANSION OF COMMERCIAL FOOD WASTE COLLECTION BEHAVIOR

1. Introduction

Chapter 3 characterized how spatial variability in FW generation is important for growing early stage service networks. While residential sources are a major contributor to the total FW generation, commercial generators are responsible for an equally large portion of FW generation (ReFED, 2017). Increasing interest in commercial FW collection is seen in state legislation, where commercial collection is perceived to be economical due to higher concentrations of FW discussed in Chapter 2. Unlike residences, FW generation from commercial sources vary with activity level and facility type. This heterogeneity needs to be assessed and incorporated into FW diversion decision-making such that emerging collection networks and policy assistance are most effectively implemented to maximize FW collection.

Decades of VRP operations research and methods have been produced, beginning with "The Truck Dispatching Problem" (Dantzig and Ramser, 1959), and extended to create complex waste collection routing methods that consider capacity, time-windows, and even lunch breaks (Beliën et al., 2012). This literature focuses primarily on cost minimization of mature service networks and feasible solution approaches for large-scale networks. However, methods based on linear programming for large-scale networks may face exponentially longer convergence issues in the final solution as the networks grow (Beliën et al., 2012). Heuristic approaches circumvent the need to arrive at exact solutions, shortening the computation time for arriving at sensible routing solutions for larger networks (Laporte, 2009). Many of the methods developed focus on obtaining final solutions for well-established networks that provide flexibility for exploring numerous ways to tackle routing specific scenarios. However, these methods face methodological challenges for understanding or informing contexts where network learning is important, such as emerging FW collection networks. Solving network routes using a computerized algorithm gives little information about how network characteristics influence service decisions. Therefore, a new modeling perspective sensitive to these issues may prove useful, given its comparability in solution accuracy to existing heuristics methods.

2. Theoretical Framework

Inspiration from ecological systems may be able to provide such a starting point for model development. Traditional central place foraging concepts (Bell, 1990), specifically, are notably similar to the conventional VRP: the truck (foraging animal) begins at a single location, searches the area collecting waste/food, and returns to its depot/nest to deliver its collection. Literature on optimal foraging behavior is frequently based on marginal value theorem to characterize foraging dynamics, which assumes that animals will optimize their own foraging behavior and energy budgets (Charnov, 1976a). For example, observations of central place foraging behavior in starlings reveals that they not only minimize energy expenditure while foraging, but also maximize energy gains from food collected (Brito e Abreu and Kacelnik, 1999; Kacelnik, 1984; Tinbergen, 2002).

The application of ecologically inspired heuristics solutions, such as those based on marginal value theory and central place foraging, depend on achieving an acceptable accuracy in the final solution. The accuracy of ecological models relies on rigor in their collected empirical data for informing effective conservation efforts. (Boyd et al., 2014; Godley et al., 2002; Russo and Jones, 2003). Likewise, vehicle behaviors and network parameters in FW collection models should be calibrated using data from existing collection services to produce acceptably accurate results, which will help make well informed logistics decisions as service networks expand.

Few waste collection models characterize the effects of variability from waste generation on vehicle routing decisions. However, in ecological modeling, observations of foragers can reveal how their behaviors are impacted by characteristics and variability of their foraging environment (Carvell et al., 2012; Ford et al., 2007; Godley et al., 2002; Olsson et al., 2008). Extending these concepts to FW collection can make collection network decisions more robust. Collectively drawing vehicle routing inspiration from ecological foraging models can help early FW collection responses to variability in FW generation and key governmental policies that may apply outside pressures to collection decisions.

Social insect foraging behavior in particular offers a unique perspective on vehicle routing. Just as fleets of vehicles may work for a single company, many individuals make up a colony of bees or ants. Social insects will cooperatively use communication to maximize their foraging behavior in the face of imperfect information of food availability and quality (Detrain et al., 1999; Harkness and Maroudas, 1985; McIver, 1991; Seeley, 1986; Traniello, 1989). Similarly, a waste collection company conceivably coordinates individual truck routes to maximize profits gained, while faced with uncertainty on availability and quantity of waste. In fact, as an alternative to solving waste collection systems with Mixed-Integer Programming (IP) methods, the communication between ants through pheromones has inspired a new class of VRP algorithms based on “ant colony” optimization or ACO (Colorni et al., 1992). Under this class of optimization trucks are analogous to ants. As trucks continue traveling, “pheromones” are “laid” along their travel route, with profitable routes receiving higher levels. Trucks make routing choices based on the strength of “pheromones” on paths based on the perceived cost of traveling to the next location.

When trucks return from their routes, truck routes are compared, and more weight is given to "pheromone trails" with better solutions.

Unfortunately, current ant colony optimization (ACO) research has followed a similar path as conventional VRP methods, exploring better or faster ways to meet the collection demand of mature networks (Bautista et al., 2008; Bell and Griffis, 2010; Bell and McMullen, 2004; Mazzeo and Loiseau, 2004; Rizzoli et al., 2007; Schyns, 2015; Xiao and Jiang-qing, 2012). Observational foraging models have been developed to characterize how food distance and availability relate to energy maximization and tradeoffs made by bumblebees (Carvell et al., 2012; Cresswell et al., 2000). Similarly, economic tradeoffs between travel cost and collection revenue can be applied in FW transportation models to maximize profit in emerging collection networks.

The goal of this chapter is to introduce an ecologically inspired waste collection model to understand the effects of heterogeneous FW generation on decisions made in emerging collection networks. Current literature on ACO is leveraged to build an agent-based modeling (ABM) approach to simulate routing decisions and economic tradeoffs for a fleet of collection vehicles. First, the approach is used to emphasize the importance of modeling collection networks with the inclusion of collection and travel time. Next, waste collection solutions heterogeneous and homogeneous FW generation networks are compared to understand the impact of variability in generations. Results from this analysis can be used to inform FW collection in other systems where learning processes are important and the evolution of collection routes are of interest.

3. Methods

3.1 Methods framework

The methods presented in this paper introduce an ecologically inspired ABM approach to solving a VRP for a network of commercial FW generators. The model framework is inspired by ecological principles and leverages previous work of ACO methods to determine agent decision rules. Monroe County in NYS is chosen as a case study to test the new formulation for a hypothetical emerging FW collection service. Solutions to preliminary routing scenarios are benchmarked against solutions from a traditional mixed integer program (Mixed IP) formulation to ensure the efficacy of solutions.

3.2 Data Collection and Assumptions

Commercial FW generators in the study area were identified from the US EPA Excess Food Opportunities map described in Chapter 2 (USEPA, 2018). Generators estimated to produce 80kg/day or more were chosen for analysis. This is equivalent a single, 64-gallon tote bins given a FW density of 330kg/m^3 (Environment Protection Agency Victoria, 2015; U.S. Environmental Protection Agency, 2016). In all, generation rates of 588 commercial generators were extracted from the database. The analysis uses three different sized networks randomly generated from among the 588 generators. For the smallest test network, six generators were chosen at random as a proof of concept for the modeling. A larger network that includes 14 additional generators (20 in all) were then chosen to test model concepts at a larger scale. Additionally, a separate 100-generator network is chosen at random to compare FW generation rates. The 6 and 20 generator network sizes were chosen to allow the benchmark Mixed-IP formulation to find a solution within a reasonable amount of time (less than three days). Collection is assumed to occur twice a week, equating to 3.5 days of FW generation available for pickup at each commercial generator.

In this study, truck depots where vehicles begin and end their collection tours also serve as the treatment facilities were trucks deliver FW diverted from the landfill. A hypothetical depot was chosen at an existing industrial park in the City of Rochester from feasible sites identified in Chapter 5. The location is relatively central to many of the generators in the county. An alternative depot for a comparison analysis. This location was also identified from the proceeding chapter and is in a rural farmland location at the southern edge of the county.

All trucks in this study are assumed to travel along roads and use road attributes to calculate cost. Road network data was obtained from the NYS GIS clearinghouse (NYS Office of Information Technology Services, 2017) and contain distance in meters and travel time in minutes based on posted speed limits as attributes inherent to each road segment. Travel arcs, the shortest path identified between each pair of nodes in the network, and their costs in both distance and time were obtained using Esri ArcMap Network Analyst. An origin-destination (OD) distance-cost and a time-cost OD matrix were generated for the county-wide network.

Waste collection trucks vary considerably in capacity and configuration. This study assumes a truck capacity of 6 metric tons for Mixed-IP and ABM scenarios. The direct-haul (DH) approach uses a different truck capacity based on a method described in section 3.3. For scenarios using time as a cost estimator, loading and unloading times of 15 minutes each are assumed at FW generators and depots.

Cost per distance of hauling was assumed to be $2.48/km ($4/mi) based on the method of FW transportation used in statewide estimation of FW transportation costs (Hooper and Murray, 2017; Manson, 2017). Cost-per-hour of truck operation time for waste collection can vary considerably depending on regional factors, but common estimates range from $70/hr to $110/hr (Adler, 2004; Bumpus, 1993; James, 2010; Kessler Consulting Inc., 2015; NewGen Strategies and Solutions and Louis Berger Group, 2014; River, 2016; RRS, 2017; SHAW Environmental, 2012). This study assumes an operational cost of $85/hr. Tipping fees for FW delivery at treatment facilities are not included in the analysis. While the combination of hauling cost and tipping fees contribute towards the total cost for collection, tipping fees in this study are assumed to pass through the hauling company directly to the generator, and therefore do not affect transportation behavior. Decoupling the tipping fee from the actual transportation cost presents a clearer representation of how FW collection costs change with respect to network characteristics.

3.3 Ecologically Inspired Agent Based Model (ABM)

3.3.1 Model Overview

The ABM was constructed as an alternative to existing heuristic formulation for solving the VRP. The truck agent is the main actor for FW collection, with other agents such as generators and treatment facility acting simply to provide an environment for trucks to function. The behavior of truck agents is inspired by behaviors in ants and is based on existing ACO methods (Bell and McMullen, 2004). Additionally, individual truck memory of facility generation rates is introduced to simulate how foraging animals would gather information about a foraging area to make future decisions. The model was developed in Python. Figure 1 illustrates a simplified flow of behavior each truck agent follows.

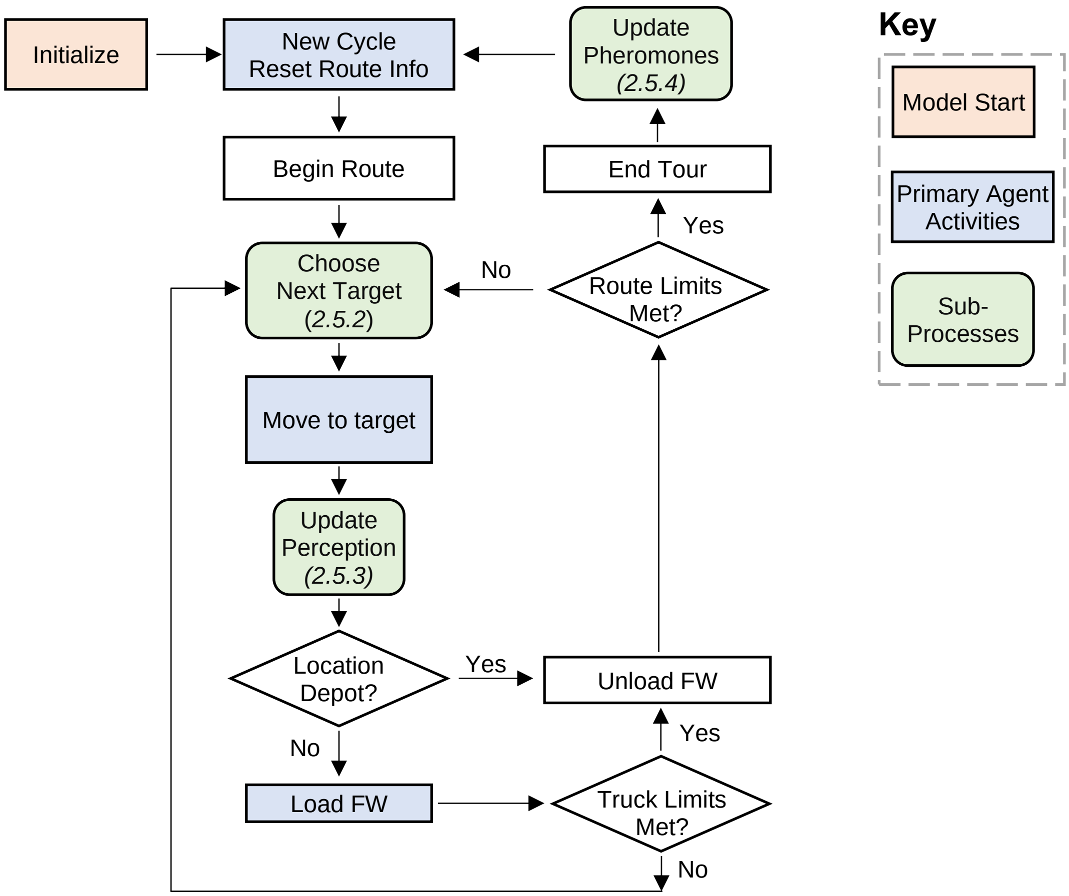

Figure 4-1: Basic ABM formulation behavior of a truck agent. Trucks search out new FW sources to collect and return to the depot for delivery. Pheromone trails and truck perceptions of generation quantity are updated to reflect influx of new information about FW sources.

At every cycle, a truck travels a collection route to pick up FW from commercial generator nodes. Each cycle consists of a series of steps. Each step begins with choosing the next target for the truck, as explained in Section 3.5.2. After a target is chosen, the truck moves to the target. If the target is a generator, FW is loaded onto the truck and the truck's perception of FW generation at that generator is updated (Section 3.5.3). If the capacity of the truck or operational time limit (time curfew) is exceeded, the truck returns to the depot. Otherwise the truck surveys the network to identify the next target for collection.

When the truck returns to the depot, it decides whether to ends its route or attempt another collection tour. If the route is finished, pheromones along the traveled route for that day and current best-known route are updated to reflect laying pheromones along arcs traveled on those routes. Pheromone updating is explained in Section 3.5.4. At the end of the cycle after all trucks have completed collection routes, generation quantities and truck capacities are reset to their starting values, but pheromone levels remain. Cycles are continued until the user specified input is reached, then the best solution is chosen.

This model can be run with different system objectives and constraints, including a cost-minimization objective, profit-maximization objective, collect-all FW constraint, and return to depot constraint. Combinations of these options allow for different scenario assumptions.

2.3.2 Choose Next Target

The Choose Next Target sub-model uses the existing level of pheromones along the arcs in combination with the cost of along the arc to decide which locations to travel to next. Figure 2 illustrates the individual pieces of the sub-model.

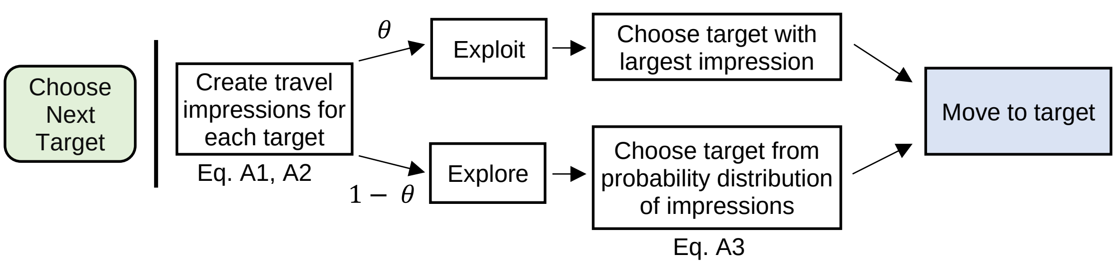

Figure 4-2: "Choose Next Target" sub model. Travel impressions are created for each possible target. The truck decides whether to exploit the best arc or explore other potential arcs and moves to the target chosen.

First, the truck surveys possible generators u from its current location i that demand FW collection. Then, travel impressions of possible path arcs are created based on the pheromone level of connecting arc τ_{iu} and the inverse of travel arc cost η raised to a weight β for that arc (Eq. A1).

$$Impression_{iu} = (\tau_{iu})(\eta_{iu})^{\beta} \; \forall \, Arc_{iu} \qquad \text{A1}$$

In scenarios where revenue is introduced in addition to cost, travel cost is scaled with maximum revenue, and then the true revenue is subtracted. (Eq. A2).

$$\eta = \frac{1}{Maximum\ Revenue + Travel\ Cost - Actual\ Revenue} \qquad \text{A2}$$

This step is performed to ensure the denominator is never a negative value in cases where revenue exceeds cost. In scenarios where only travel cost is considered, no scaling occurs.

Next, the truck decides to exploit the arc with best impression or explore alternative arc choices given the probability of exploitation as Θ and exploration as 1- Θ. If exploitation is chosen, the arc with the maximum impression is chosen from all arcs identified. If the truck chooses to explore, a generator is chosen from a probability distribution of arc impressions generated using Eq. A3. After the target is chosen, the truck moves to the target.

$$Probability_{iu} = \frac{Impression_{iu}}{\sum_{iu} Impression_{iu}} \; \forall \, Arc_{iu} \qquad \text{A3}$$

3.3.3 Updating Generation Perception

Individual perceptions and working memories of truck agents are modeled to simulate retention of FW generation knowledge gained from visiting facilities. This is only implemented under profit-seeking scenarios, since cost-minimization disregards FW quantity when determining collection routes. The goal of this novel addition is to further simulate information gathering when exploring a new environment. For example, first impressions foraging for food in a new area might be mediocre, but worth exploring. As different foraging patches within the environment are explored, some patches may be remembered as good and others as bad. Over time foraging in the same area, good and bad food patches are solidified in memory and foraging habits should lean toward exploiting good patches.

Each truck agent first assumes that generators in the network produce similar quantities of FW, set to a normal distribution around the average generation rate of the network. The mean generation of each individual perception is used to generate anticipated revenue for travel impression and target choices (Eq A1, A2, A3). When the truck visits a generator, it updates its generation perception based on the actual quantity of FW available. The new perception remains in memory when creating network travel impressions and is updated after every visit to a generator (Figure 3).

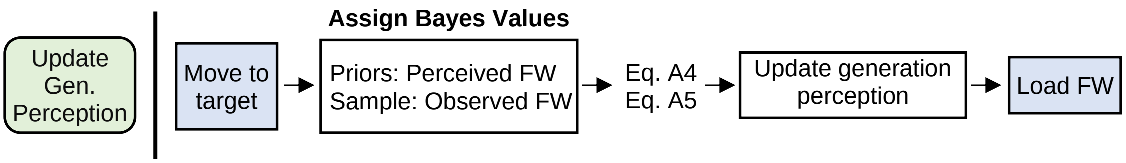

Figure 4-3: Food waste generator perception update

Generation perceptions are updated using Bayesian inference for a normal distribution with unknown mean and known variance. The initial perceptions of each generator constitute the prior distribution. A posterior distribution is generated with the real quantity of FW revealed to the truck upon visiting the generator. Equations A4 and A5 describe the Bayesian inference process.

$$\mu_{,,} = \frac{v_{\emptyset} * \mu_{,} + v_{,} * \ Sample_{\emptyset}}{v_{\emptyset} + v_{,}} \qquad \text{A4}$$

$$v_{,,} = \frac{v_{\emptyset} * v_{,}}{v_{\emptyset} + v_{,}} \qquad \text{A5}$$

Where:

$'$	Information from prior distribution (μ, σ)
$\emptyset$	Information from known distribution (μ, σ)
$''$	Information of posterior distribution (μ, σ)
μ	Mean
v	Standard Deviation
Sample	Sample point used for updating prior distribution (currently the mean of true dist.)

No information was available for estimating the variance of the true generation distributions; therefore, standard deviation of FW generation was assumed to be 10% of the mean, then converted to variance. Idealistically, variance would be determined based on real FW data collected over a period.

2.3.4 Pheromone Update

After all trucks have returned to the depot and completed their routes, the objective value of the total solution is compared to the previous best solution, and pheromones are updated accordingly. Figure 4 illustrates the pheromone updating processes.

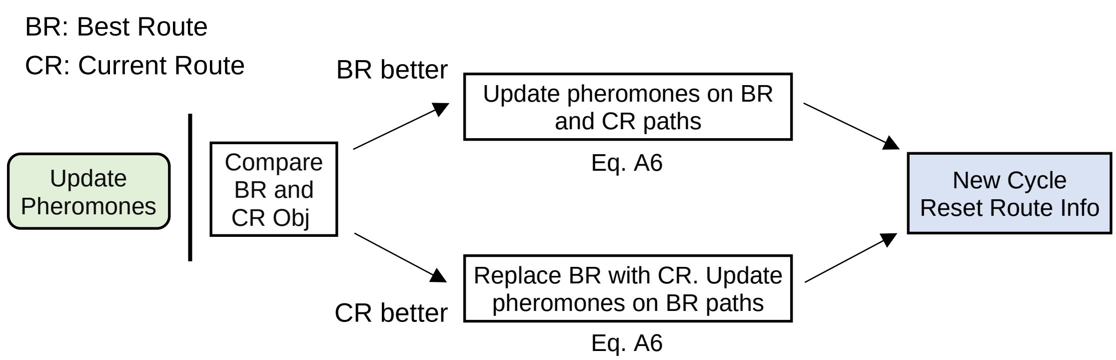

Figure 4-4: Pheromone trail updating. Current route and best route objective values are compared. Pheromones are updated using Equation A6.

Since the goals is to minimize cost, if the objective for the current set of routes is lower cost than the objective from the best-known set of routes, the best-known routes are replaced, and pheromones updated. If the current objective is higher than the best objective, pheromones are updated for the best routes at full strength, while pheromones for the current route are updated less than full strength. The purpose of updating both current and best routes is to enforce the influence of the best-known routes while still providing the ability to explore alternative routes, so the simulation can continue to search for less-costly route combinations. Pheromones are updated according to Eq. A6.

$$\tau'_{ij} = (1 - \alpha)\tau_{ij} + (\alpha * \gamma)L \qquad \text{A6}$$

Pheromones are chemical trails prone to decay from environmental conditions. This environmental condition is approximated by the decay rate α of pheromone trails during updating. A majority of existing pheromone remains on the arc, while decayed pheromones are replaced with new pheromones based on the inverse of the best-known objective value. The parameter γ is set to 1 for updating the best routes, while it is given a specified value between 0 and 1 for updating current routes. The value L is the inverse of the best objective value identified so far in the simulation. Updated pheromones levels are used to evaluate travel decisions on subsequent cycles.

3.4 Benchmarking: Mixed Integer Program (Mixed IP) Baseline

A Mixed IP VRP formulation was constructed for this study to solve for the best available solution in each scenario for the test networks. The formulation is based on the traditional capacitated VRP formulations from literature with the extension that a truck can complete multiple tours provided that total travel does not exceed 10 hours for a standard working day based on reports of commercial waste collection in municipalities (Houssaye and White, 2013; NewGen

Strategies & Solutions, 2016) and discussions with local FW hauling practices. While the municipal operations usually limit collection Shifts to 8.5 hours, the private hauling companies observed will operate until their scheduled routes are completely collected from, often 10 or more hours per day depending on route conditions. Thus, 10 hours was chosen to reflect the workday of private hauling services in an emerging network. The Mixed IP solutions serve as benchmarks for the ABM formulation. Arc costs identified in Section 3.2 between a pair of nodes are equal regardless of direction of travel. The formulation was programmed in MATLAB and scenarios were solved using optimization solvers in CPLEX. The remainder of the section will describe the objective function and constraints of the basic formulation.

Objective Nomenclature:

x_{ij}^{k} - The decision by truck k to travel arc i, j. {Binary}

y_{i}^{k} - The decision by truck k to collect a quantity of FW from generator i. {Continuous}

z_{j}^{k} - Total load of FW on truck k at node j. {Continuous}

w_{j}^{k} - Mass of waste delivered by truck k to delivery point j. {Continuous}

Formulation Nomenclature:

$n \in N$	Set of generators
$d \in D, D'$	Set of vehicle depots, prime indicates delivery location equivalent
$u \in U$	Set of intermediate depot delivery points. Shares locations with depots.
$k \in K$	Set of trucks
Q_k	Capacity of truck k
q_n	Quantity of waste produced by generator n
A	A large number
c_{ij}	Cost of travel arc ij

Objective Function:

$$Min\ Cost = \sum_{i \in (D,N,U)} \sum_{j \in (D',N,U)} \sum_{k \in K} c_{ij} x_{ij}^{k} \qquad \text{M1}$$

Where *c* is cost in dollars for traveling arc *ij* based on distance or time specified by inputs. *D* represents the depot for the beginning of the tour, *D*' represents the depot for the end of the tour, *N* represents generator nodes, and *U* represents intermediate delivery locations. For this study, intermediate delivery locations share the same location as the start and end depot.

Cost-flow constraints:

$$\sum_{j \in N,U,D'} x_{ij}^{k} \le 1 \ \forall\, i \in (D,N,U), k \in K \qquad \text{M2}$$

$$\sum_{i \in U} \sum_{j \in N} x_{ij}^{k} - A \sum_{i \in D} \sum_{j \in N} x_{ij}^{k} \le 0 \ \forall\, k \in K \qquad \text{M3}$$

$$\sum_{i \in D,N,U} x_{ij}^{k} = \sum_{i \in N,U,D'} x_{ji}^{k} \ \forall\, k \in K, j \in N, U \qquad \text{M4}$$

$$\sum_{j \in N} x_{ij}^{k} = \sum_{j \in N} x_{ji}^{k} \ \forall\, k \in K, i \in D \qquad \text{M5}$$

These constraints constitute important continuity of travel rules throughout the network. The constant *A* represents a large number to ensure constraints hold true under specified conditions. Constraint M2 dictates that each truck can only traverse an arc once in any route. Constraint M3 ties visiting an intermediate facility to leaving the starting depot. Constraint M4 ensures continuity of travel for nodes other than depots. Constraint M5 ensures that if a truck leaves a depot at the beginning of the tour, it must finish its tour at a depot.

Collection constraints:

$$y_j^k - \sum_{i \in D,N,U} q_j \, x_{ij}^k \le 0 \;\; \forall, j \in N, k \in K \qquad \text{M6}$$

$$\sum_{k \in K} y_j^k \le q_j \;\; \forall\, j \in N \qquad \text{M7}$$

$$\sum_{i \in N} q_j x_{ij}^k - y_j^k \le 0 \;\; \forall, j \in U, k \in K \qquad \text{M8}$$

$$-Q \le y_j^k \le 0 \;\; \forall\, j \in U, k \in K \qquad \text{M9}$$

These constraints describe the behavior of the truck for collection of waste from generators. Trucks are not required to load all FW available at a generator in a single stop. The load capacity of the truck is denoted by Q, and the quantity of FW for pickup at an individual generator is represented by q. Constraint M6 ensures that if a truck visits a generator, it cannot collect more than is generated. Constraint M7 limits the total amount of FW collected from a generator across all trucks to the generated quantity. Constraint M8 allows for a truck to unload FW at an intermediate delivery facility to allow it to make more trips. Constraint M9 ensures that the truck cannot drop off more than its capacity and cannot collect FW from an intermediate facility.

Tour continuity constraints:

$$Ax_{ij}^k + z_i^k + y_j^k - z_j^k \le A \;\forall\; k \in K, i \in (D,N,U), j \in N,U \qquad \text{M10}$$

$$z_i^k = 0 \;\forall\; k \in K, i \in D,U \qquad \text{M11}$$

$$z_j^k - \sum_{i \in D,N,U} Q x_{ij}^k \le 0 \;\forall\; k \in K, j \in N \qquad \text{M12}$$

Tour continuity constraints enable the truck to traverse the network in a logical route order. Constraint M10 is a sub-tour elimination constraint that combines arc routes with truck load to make sure the current load of the truck plus FW collected at the next location is equal to the trucks load at the next location. Constraint M11 dictates that the truck load upon leaving the depot or intermediate facility is 0. Constraint M12 limits the load of the truck so that it does not exceed the stated capacity at any given node.

Waste Tracking constraints:

$$\sum_{i \in N} y_i^k - w^k = 0 \; \forall \; k \in K \qquad \text{M13}$$

$$w^k - Q \sum_{i \in D,U} \sum_{j \in N} x_{ij}^k \leq 0 \; \forall \; k \in K \qquad \text{M14}$$

$$\sum_{k \in K} w^k = \sum_{i \in N} q_i \qquad \text{M15}$$

Waste tracking constraints make sure that waste delivered to the treatment facility remains within the bounds of truck capacity and facility generation. Constraint M13 ensures that the total quantity of FW delivered to the treatment facility by a truck is equivalent to the waste it collects along its route. Constraint M14 limits the total delivered load to the truck capacity multiplied by the number of deliveries it makes to depots and intermediate facilities. Constraint M15 requires that the total amount of FW delivered to treatment facilities equals the total generation of generators in the network.

3.4.1 Mixed-IP Profit Model Modifications

The original Mixed-IP formulation presented was constructed with the ability to switch between objective functions and collection constraints, explaining why many constraints deviate from traditional formulations that only consider satisfying collection demand. First, a term was included in the objective function to account for revenue gained from charging a service fee for FW collection. For the objective value, revenue is treated as a negative cost.

$$Min\ Cost = \sum_{i\in(D,N,U)} \sum_{j\in(D',N,U)} \sum_{k\in K} c_{ij}x_{ij}^{k} - \sum_{k\in K} f \cdot w^{k} \qquad \text{M1'}$$

The new terms *f* is the unit revenue in $/ton charged for collection of FW. To reiterate:

x_{ij}^{k} - The decision by truck k to travel arc i, j. {Binary}

w_{j}^{k} - Mass of waste delivered by truck k to delivery point j. {Continuous}

D and D' are the starting and ending depot, U represents the delivery facility, N are generators, K are the set of trucks, and C is the cost for each travel link.

Additionally, constraint M15 is updated to reflect the new collection constraint where q is the generated FW at each commercial facility.

$$\sum_{k\in K} w^{k} \leq \sum_{i\in N} q_{i} \qquad \text{M15'}$$

3.5 Defining Collection Behavior

Defining and modeling FW collection as appropriately as possible is necessary for results to be applicable for stakeholders. Some stakeholders may not have the resources to perform a thorough analysis using software that implement a mixed IP formulation of the routing problem, and thus may use a simpler heuristic when attempting to estimate FW transportation costs. Two conventional rules in these heuristics are: 1) assuming vehicles directly haul FW one way from a generator to a treatment facility, and 2) use of distance as a cost basis. While this approach is more useful for long-haul freight transportation (Demir et al., 2014), using the direct hauling (DH) approach to waste collection does not account for realistic practices such as trip-chaining, where trucks collect waste from multiple customers in a single tour to reduce hauling costs. Additionally, estimating cost by distance does not capture the time required to collect waste, or travel speed of vehicles along roads. Cost estimation by time is more appropriate for waste collection and is commonly used by municipalities and organizations attempting to accurately estimate collection costs (NewGen Strategies & Solutions, 2016; NewGen Strategies and Solutions and Louis Berger Group, 2014; RRS, 2017; SHAW Environmental, 2012). Therefore, Trip-chaining and time cost basis are compared against potential shortcuts to understand the importance of considering realistic behavior in models.

3.5.1 Value of Trip-Chaining vs Direct Haul

This scenario is designed to illustrate the value of chaining pickup destinations instead of assuming trucks haul FW directly from each generator to the treatment facility. The DH approach is a quick and conceptually simple way to estimate transportation costs for large networks. The method instance used for comparison in this study was taken from a NYS economic analysis on the impact of implementing FW diversion legislation (New York State Senate Assembly, 2019). The report's method obtains estimated FW generation rates from commercial generators in a similar manner to this study, obtains the road distance from each generator to an existing or proposed treatment facility, and calculates the cost of transportation given collection rates of twice per week given social acceptability for odor control. Long-haul, 20-ton capacity trucks are assumed to transport FW, and more trucks are added if the generation rate exceed truck capacity. A hauling cost of $4/mile ($2.48/km) is used based on a long-haul transportation cost estimated for an analysis of FW collection in New York City (Houssaye and White, 2013). The cost is applied per truck regardless of how much capacity a truck has utilized. Each truck begins their trip at the generator and takes the shortest path to the closest treatment facility where FW is delivered. For full description of the methods, please refer to “Benefit-Cost Analysis of Potential Food Waste Diversion Legislation” (Manson, 2017).

Routing solutions from DH and ABM approach using trip-chaining are compared on the 6 generator and 20 generator networks as proof-of-concept. Total hauling distance is the primary cost attribute used for each network since distance is the base transportation cost used in the DH approach. Transportation estimates vary considerably with network characteristics such as depot location. Therefore, this scenario is tested using two separate depot locations, one near the cluster of generators in an industrial park, and one at the southern edge of the study area (Section 3.2). Each model’s objective is to minimize the cost of transportation while collecting all FW available in the system. This represents the most basic collection case to illustrate discrepancies between DH and trip-chaining.

3.5.2 Cost Based on Time

As stated previously, cost estimates for transportation based on operation time are more in line with municipal and industry practices. Therefore, the cost attributes of models are changed to be based on operation time of trucks. Operation time consists of time traveled along arcs between nodes with additional collection time of FW at generators. Trucks are assumed to travel at the road’s posted speed limit and loading/unloading time is fixed at 15 minutes, representing some automation in the system that does not scale with quantity of FW collected. A time limit for each truck is also introduced to simulate the number of hours in a workday which the truck must adhere to simulate a workday.

$$\sum_{i \in D,N,U} \sum_{j \in N,U,D'} t_{ij} x_{ij}^{k} + m_j \leq T \;\forall\; k \in K \qquad \text{M16}$$

The travel time of arc ij is denoted as t_{ij} and the collection/delivery time of each node is m_j. T indicates the time limit of the route that cannot be exceeded.

Solutions for the 6 generator and 20 generators test networks with the industrial park depot are presented ABM formulations and loosely compared to solutions from Section 3.5.1. Again, all FW available in the network must be collected each day.

3.6 Comparing Collection of Variable and Uniform Food Waste Generation Sources

Characterizing transportation decisions through an ecological lens requires two fundamental changes to conventional VRP models to observe the decision-making behavior of trucks. First, the introduction of a profit seeking function is required to mirror how animals forage to accumulate a net gain of energy. Second, animals are not scheduled by a third party to eat all the food present in the area. Thus, this constraint in conventional models must be relaxed to allow trucks to choose which destinations to include in their routes to accumulate profit. The introduction of these two changes allows observation of truck decision-making under various environmental conditions set by the model user.

To first illustrate proof of concept and model efficacy, the ecological model is tested on the same 6 and 20 generator networks and solutions are benchmarked against the baseline Mixed IP formulation.

Next, the model is applied to the 100-generator network using the estimated, heterogeneous FW generation rates identified in Section 3.2. The network is first solved using the cost objective and collect-all constraint as a reference point to calculate the compensation or material value required to break even between cost and revenue. Compensation values are decreased in increments of $10/ton until no FW is collected and increased at the same increments until all the

FW is collected. In a case where the cost of collection exceeds the reference point cost, but all FW is not collected, the reference solution is used and that increment's compensation value applied to calculate profit. This is done because the user can infer that using the reference point solution will yield a higher profit than the profit-seeking alternative approach. These analysis steps are repeated assuming that each generator in the network produces a uniform quantity of waste, set to the average of the heterogeneous network.

4. Results and Discussion

4.1 Realistic Collection Behavior – Trip-chaining

DH vehicle behavior is compared to FW collection via more realistic trip-chaining behavior. Figure 5 illustrates the visual differences between solutions using these two methods for both 6, 20, and 100 generator test networks assuming the depot is located at the industrial park location. Table 1 and Table 1a show numeric data that accompany these routing solutions.

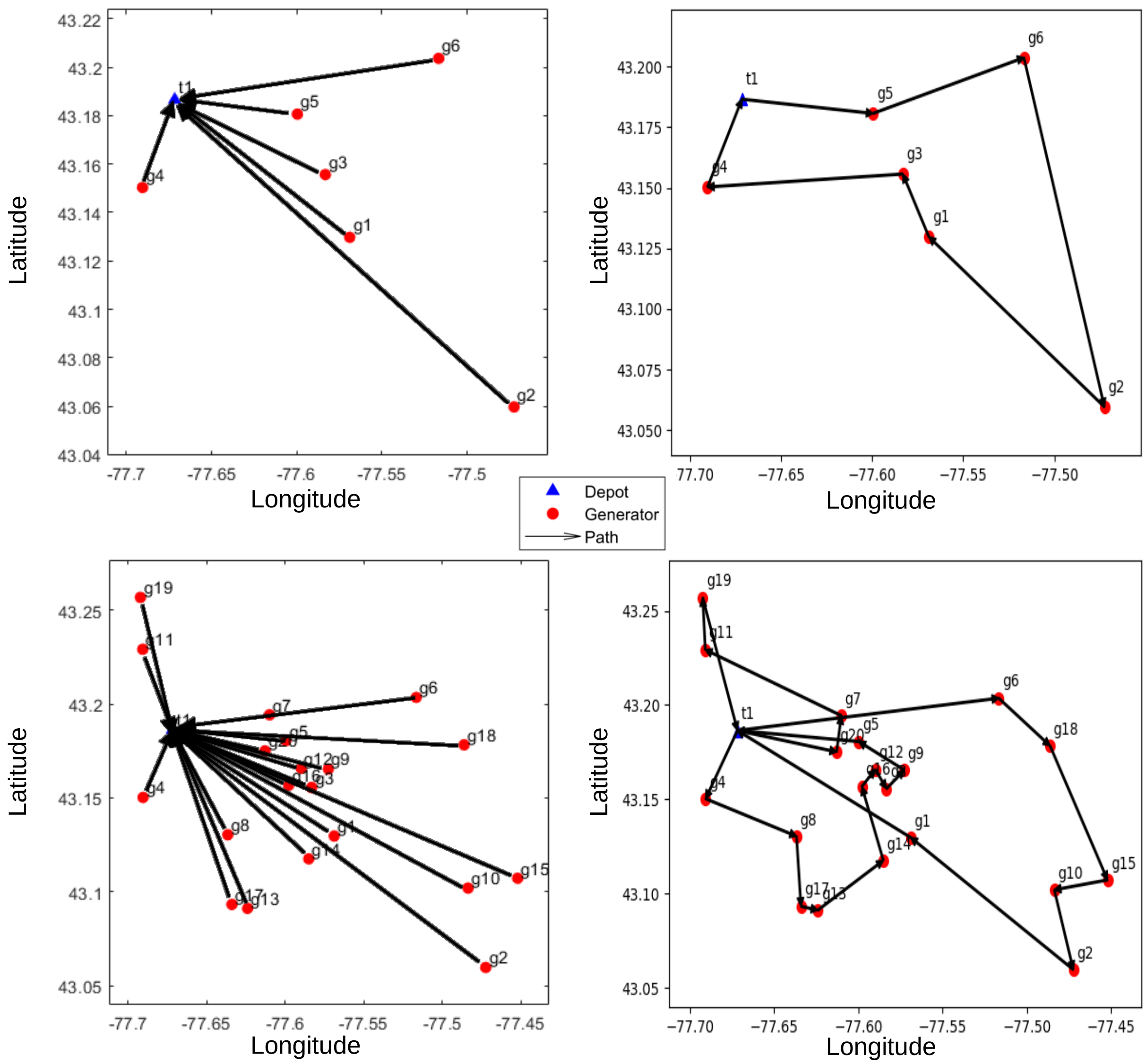

Figure 4-5: Visual comparison of direct haul (left) vs trip-chaining solved using the ABM (right) collection estimate approaches for the 6 generator (top) and 20 generator (bottom) test networks with the industrial park depot location.

Approach	Gen #	Cost ($/km)	Objective ($)	% Diff from Bench	Distance (km)	Collected FW (t)	Solve Time (s)
Benchmark	6	2.485	168.2	--	67.7	3.2	0.2
ABM	6	2.485	168.2	0.0%	67.7	3.2	4.7
DH	6	2.485	181.3	7.8%	73.0	3.2	--
Benchmark	20	2.485	360.0	--	144.9	13.4	84271.5
ABM	20	2.485	366.3	1.8%	146.6	13.4	57.7
DH	20	2.485	591.9	64.4%	238.1	13.4	--
ABM	100	2.485	1520.0	--*		60.2	1110.7
DH	100	2.485	2970.0	107.8%*	1194.9	60.2	--

Table 4-1: Comparison of DH, Mixed-IP, and ABM approach results for distance-cost scenario where the depot/treatment facility is located in an industrial park. A * indicates disparity from ABM solution since benchmark could not be applied to this scenario.

Approach	Gen #	Exploit Probability	Alpha	Beta	Gamma	Initial Pheromone	Random Seed	Cycles
ABM	6	0.85	0.1	0.95	0.5	0.000459	1552576418	600
ABM	20	0.85	0.15	0.95	0.5	0.000159	1552576418	2000
ABM	100	0.75	0.15	0.85	0.5	0.000249	1552576418	10000

Table 4-1a: Parameter settings used to find the routing solutions in Table 1 using the ABM approach.

Results show that using the DH approach for the 6, 20, and 100 generator networks generates a higher cost estimation. As the network of collection participants grow, the cost disparity will also continue to increase. Planning for FW collection based on assumptions of inaccurate collection behavior could lead to over budgeting and poor planning decisions. Differences in cost estimates due to generation variability if the DH model was used for future scenarios may not be identified.

One challenge in forecasting transportation costs is that estimates are dependent on the spatial characteristics of the network. Specifically, the depot location can contribute considerable variability in the final transportation costs and solution. Figure 6 illustrates collection routes between DH and trip-chaining approaches when the depot is moved further away from the cluster center of generators. Table 2 and Table 2a show numeric data that accompany these routing solutions.

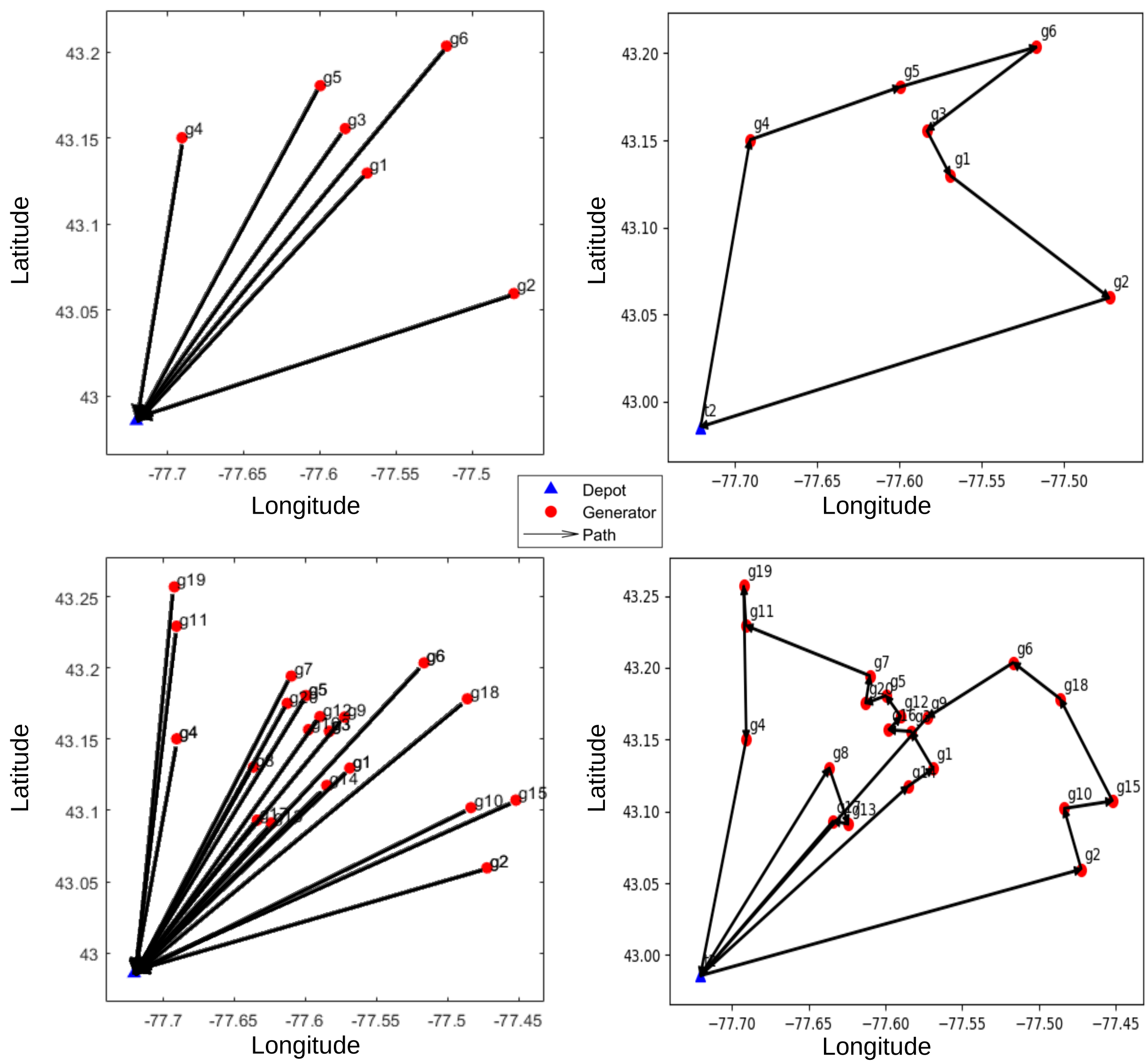

Figure 4-6: Visual comparison of direct haul (left) vs trip-chaining solved using the ABM (right) collection estimate approaches for the 6 generator (top) and 20 generator (bottom) test networks using the farmland depot location.

Approach	Gen #	Cost ($/km)	Objective ($)	% Diff from Bench	Distance (km)	Collected FW (t)	Solve Time (s)
Benchmark	6	2.485	248.2	--	99.9	3.2	0.1
ABM	6	2.485	248.2	0.0%	99.9	3.2	4.7
DH	6	2.485	435.8	75.6%	175.3	3.2	--
Benchmark	20	2.485	550.8	--	221.7	13.4	96304.1
ABM	20	2.485	574.2	4.2%	223.0	13.4	58.5
DH	20	2.485	1321.5	139.9%	531.7	13.4	--
ABM	100	2.485	2092.3	--*	840.3	60.2	1112.5
DH	100	2.485	6128.6	193.5%*	2465.8	60.2	--

Table 4-2: Comparison of DH, benchmark, and ABM approach results for distance-cost scenario where the depot/treatment facility is located at a farm field at the edge of the study area. * indicates disparity from ABM solution since benchmark could not be applied to this scenario.

Approach	Gen #	Exploit Probability	Alpha	Beta	Gamma	Initial Pheromone	Random Seed	Cycles
ABM	6	0.85	0.1	0.95	0.25	0.003384	1552576418	600
ABM	20	0.85	0.15	0.95	0.5	0.000143	1552576418	2000
ABM	100	0.75	0.15	0.85	0.5	0.000249	1552576418	2000

Table 4-2a: Parameter settings used to find the routing solutions in Table 2 using the ABM approach.

Results from this second analysis indicate the importance of depot location in determining transportation costs. Assuming a DH collection approach shows even greater disparity in cost estimates compared to the previous scenario where the depot was located in a city space. This is relevant for planners who are trying to site new treatment facilities. As will be shown in Chapter 5, it may be difficult to site treatment facilities in or near cities due to digestate management concerns. A more likely location for treatment facilities would be rural areas, away from the majority of commercial FW generations. Figure 7 summarizes these findings by illustrating the objective values between scenarios.

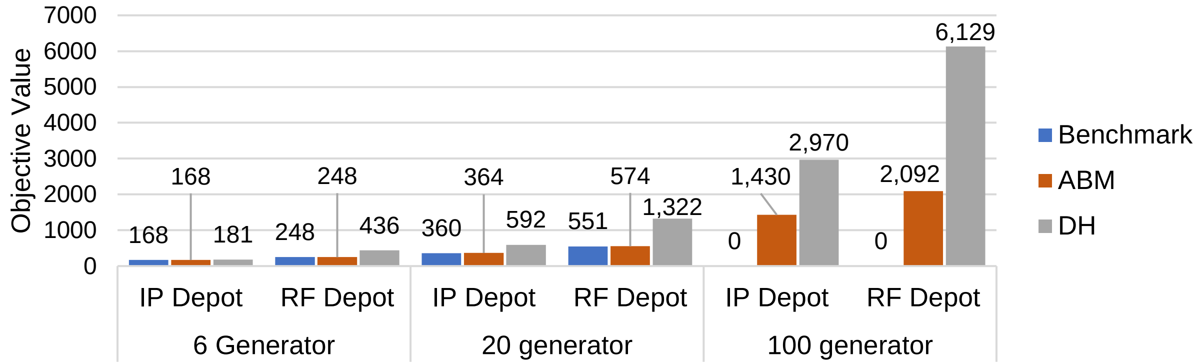

Figure 4-7: Comparing objective values of routing solutions to for 6, 20, and 100 generator test networks. IP: Industrial Park Depot. RF: Rural Farm Depot

4.2 Realistic Collection Behavior – Time as a Cost Basis

The cost basis of collection was changed from distance to time. A simulated collection time of 15 minutes was added at each generator. There is no logical way to model this estimate based on distance. Figure 8 compares the resulting objective values cost-by-distance scenarios from Section 4.1 and cost-by-time scenarios. Table 3 and Table 3a report relevant numeric results and parameters. DH is not used in this analysis.

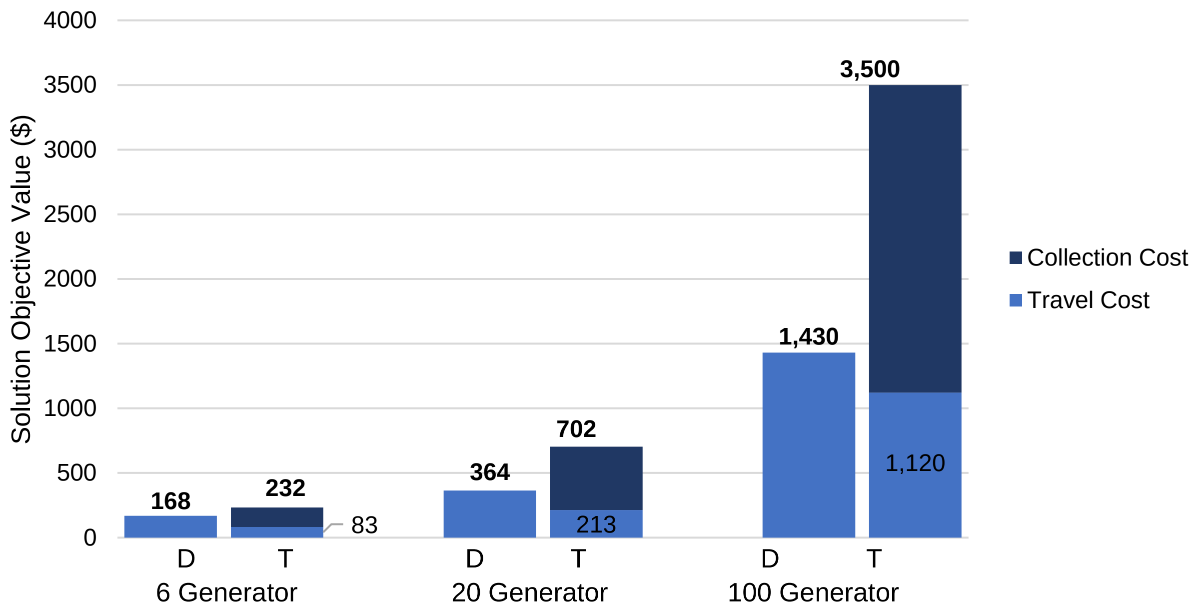

Figure 4-8: Comparison of distance and time ABM route solution objective values for 6, 20, and 100 generator networks. Time cost objective values is separated into travel time of vehicle on the road and collection time incurred at commercial generators. D: Distance cost basis, T: Time cost basis

Approach	Gen #	Cost ($/hr)	Objective ($)	% Diff from Bench	Operation Time (hr)	Collected FW (t)	Break Even Value ($/t)	Solve Time (s)
Benchmark	6	85	232.1	--	2.73	3.2	72.6	0.1
ABM	6	85	232.1	0%	2.73	3.2	72.6	4.9
Benchmark	20	85	700.6	--	8.24	13.4	52.2	17977.8
ABM	20	85	716.9	2.3%	8.26	13.4	52.3	62.7
ABM	100	85	3564.8	--*	41.18	60.2	58.2	389.2

Table 4-3: Comparison of benchmark and ABM formulations for time-cost scenarios where the depot/treatment facility is located in an industrial park.

Approach	Gen #	Exploit Probability	Alpha	Beta	Gamma	Initial Pheromone	Random Seed	Cycles
ABM	6	0.85	0.1	0.95	0.5	0.000394	15525764181	600
ABM	20	0.85	0.15	0.95	0.5	0.000128	15525764181	2000
ABM	100	0.75	0.15	0.85	0.5	0.000256	15525764181	2000

Table 4-3a: Parameter settings used to find the routing solutions in Table 3 using the ABM approach.

Although results of distance and time-based solutions are shown side by side in Figure 9, only observations can be made about differences between both models because there is no direct or common basis for comparison. Unit costs for each model are informed by costs of real systems, but they can be altered to reflect other scenarios. However, based on the specific unit costs used in these models, solutions show that the overall cost of collection increases substantially when time is used as a cost basis.

Assessment of only the time basis transportation estimates reveals that costs attributed to FW collection at commercial generators constitute 64% - 70% of the total collection costs. The collection time at each generator regardless of waste quantity is set at 15 minutes in the model. This assumption is likely to be low based on personal experience. Because FW is messy, the collection bins usually need to be cleaned to satisfy the customer, which takes extra time. However, even with the conservatively low collection time estimate, the contribution to overall cost is high. This finding presents an opportunity to FW companies to invest in processes to reduce the collection time at generators, potentially by employing more automated collection technologies. It is also likely that travel time between generators is underestimated due to the modeling approach. Trucks are assumed to have instantaneous acceleration, travel exactly the speed limit, and are unaffected by traffic. However, even if travel time increased by 100%, collection time at generators would still contribute a considerable portion of costs and present an opportunity for savings.

Observations of truck collection time and travel time appear similar to animal foraging activities such as prey handling time and search time (Charnov, 1976b; Olsson et al., 2008). Commercial FW can come in many forms, just as prey are not a single size or species of animal. The type of prey may determine a specific handling activity by a predator, such as octopuses choosing to pull apart mollusks or choose to expend more energy by drilling through shells (Fiorito and Gherardi, 1999; Steer and Semmens, 2003). Likewise, different truck collection methods and technologies are used to collect FW in tote bins, larger bins, or liquid containers (Bernstad and la Cour Jansen, 2012; Hesselgrave, 2017).

Drawing parallels between search time in animals and collection vehicles is more difficult because of how each of these systems function. The concept of foraging implies imperfect information about the system: where food is, what its quality might be, or how much exists (Stephens et al., 2007). On the other hand, mature waste collection networks likely have contracts with their customers identifying their location, how often waste should be collected, and the size of their collection bin. While there might be some variation in how much waste is generated, there is little left to "discover", thus operations literature has focused on faster ways to solve a specified system (Beliën et al., 2012). Depending on routes identified, different vehicle types are allocated to service those routes. There may be no need to send a conventional MSW collection vehicle to collect the residential FW as was assumed in Chapter 3 since generation rates are smaller. Assigning a smaller, more agile vehicle may be able to reduce fuel and labor costs. Therefore, current waste collection models may want to allow for assignment of different collection vehicles to efficiently collect FW depending on the situation, just as animals may adapt foraging and other activity patterns to use energy more efficiently (Asensio et al., 2007; Dell'Omo et al., 2000; Thiel et al., 2006; Wikelski and Trillmich, n.d.; Zielinski et al., 1983).

4.3 Effects of food waste heterogeneity on collection decisions

Combinations of objective functions and collection constraints were assessed on the smallest test network to understand how flipping these model switches effect FW collection. Figure 9 visually illustrates these effects. Table 4 reports the numeric results.

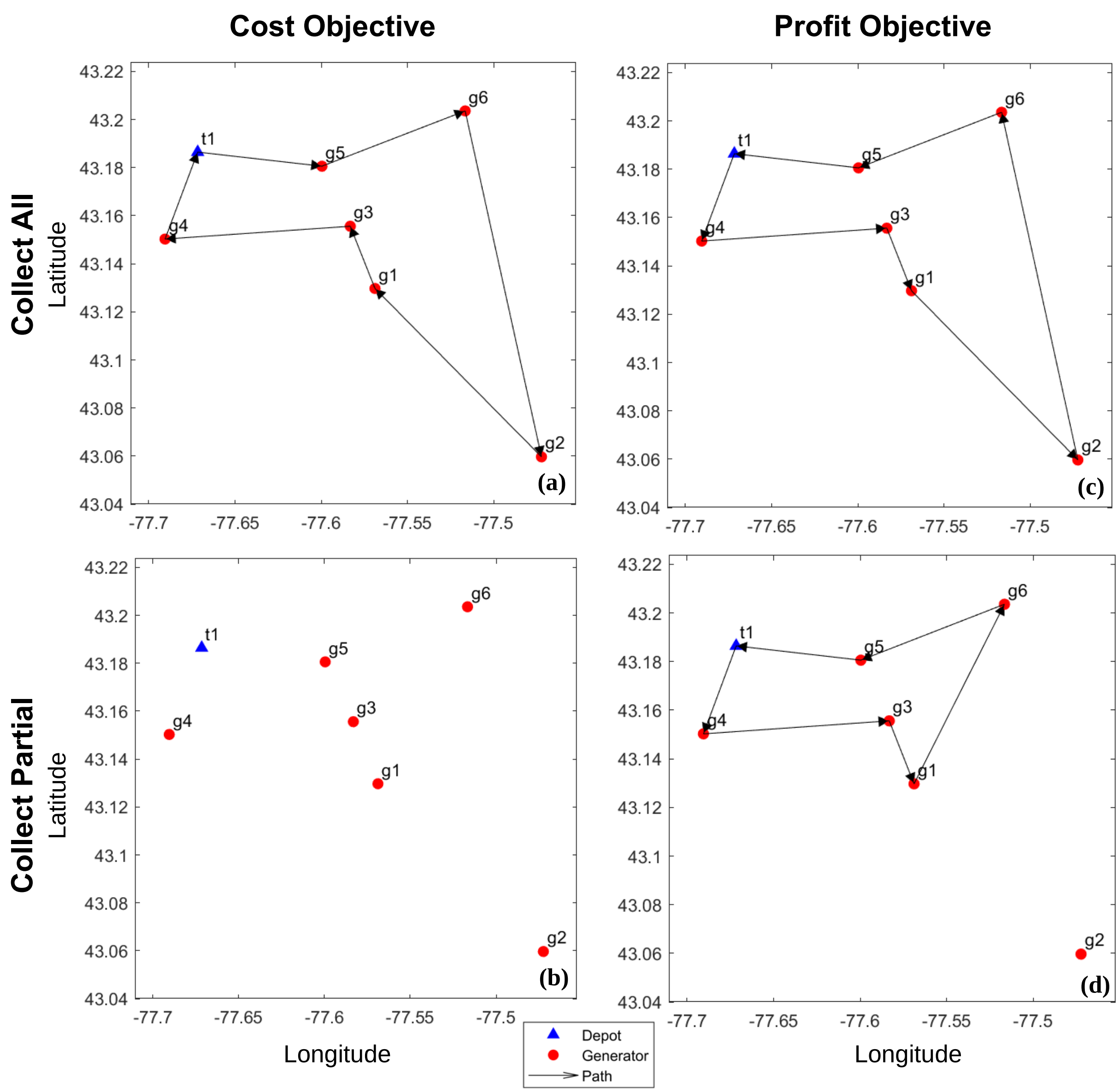

Figure 4-9: Comparison of objective functions and collection constraints on a 6-generator test network.

Appr.	Gen #	Obj. Type	Collect. Const.	Cost ($/hr)	Fee ($/ton)	Obj. ($)	Break Even Fee ($/t)	% Diff from Bench	Travel Time (hr)	FW (t)	Solve Time (s)
Bench	6	Cost	All	85	0	232.1	72.6	--	2.7	3.2	0.1
ABM	6	Cost	All	85	0	232.1	72.6	0%	2.7	3.2	4.9
Bench	6	Cost	Partial	85	0	0.0	0	--	0.0	0.0	0.1
ABM	6	Cost	Partial	85	0	0.0	0	0%	0.0	0.0	4.4
Bench	6	Profit	All	85	72.6	0.0	--	--	2.7	3.2	0.1
ABM	6	Profit	All	85	72.6	0.0	--	0%	2.7	3.2	4.7
Bench	6	Profit	Partial	85	72.6	-4.0	--	--	2.2	2.7	0.2
ABM	6	Profit	Partial	85	72.6	-4.0	--	0%	2.2	2.7	5.1

Table 4-4: Comparison of solutions between benchmark and ABM approaches under multiple objective and FW collection constraints.

Objective Type	Collection Constraint	Exploit Probability	A	B	G	Initial Pheromone	Random Seed	Cycles
Cost	All	0.85	0.1	0.95	0.5	0.000394	15525764181	600
Cost	Partial	0.85	0.1	0.95	0.5	0.000394	15525764181	600
Profit	All	0.85	0.1	0.95	0.5	0.000394	15525764181	600
Profit	Partial	0.85	0.1	0.95	0.5	0.000343	246780520	600

Table 4-4a: Parameter settings used to find the routing solutions in Table 5 using the ABM approach.

From this example, two formulations of model parameters, cost-collect all (CA) and profit-collect partial (PP) approximate two different policy scenarios that could be implemented. The CA formulation is similar to a collection mandate, where all FW from identified generators must be collected, while the PP formulation allows for FW to be collected in order to maximize service profit and may be more similar to an incentive-based policy. Additionally, the CA formulation is akin to conventional vehicle routing methods with a cost minimization objective, whereas the PP formulation can draw parallels to ecological models. The collection vehicle tries to maximize profit over its cycles, just as an animal tries to optimize its foraging behavior to maximize net energy (Charnov, 1976a). At a compensation value of $72.6/t in this example, the collection company would break even if all FW was collected, but when the collection constraints are relaxed, the best collection route excludes one generator to maximize profit. Calculations revealed that if the skipped generator produced at least an additional 56kg FW during the cycle, the collection vehicle would visit the generator to add to its profits. A small but fundamental effect of generation heterogeneity is illustrated on this test network. As the network of potential participants grows, this effect is expected to be more pronounced.

The PP formulation of the model was applied to the 100-generator network to observe effects of heterogeneity in FW generation compared to the same network assuming homogeneous generation rates. The effects of collection compensation rates on total waste collected are compared (Figure 10).

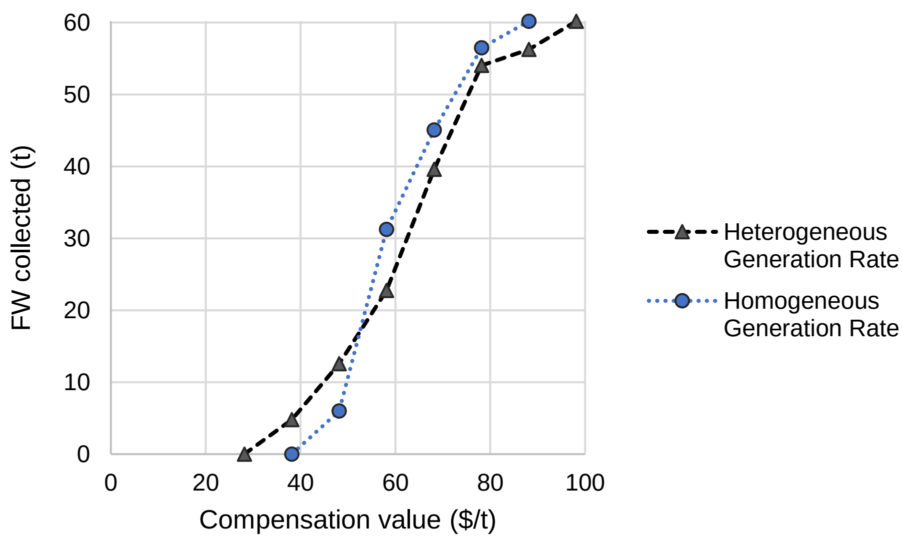

Figure 4-10: Tons of FW collected resulting from compensation rates used to find routing solutions using the profit-seeking ABM formulation. Solutions from the same network assuming “natural” heterogeneous generation and homogeneous generation are compared.

Immediately noticeable is the S shape of collection curves indicating distinctive collection trends. At lower compensation rates, collection of FW from the network is less efficient. As compensation values increase, so does the FW that can be economically collected. At some compensation rate, an inflection occurs where the economic feasibility of FW collection diminishes. While this trend is apparent in both models, generation assumptions change the collection behavior. At lower compensation values, more FW from the heterogeneous network can be collected than if generation is assumed to be uniform. Moreover, the initial entry point where any FW collection is feasible is lower. Upon inspection of the numerical results, it was found that these initial collection locations produce the most FW and are critical for providing initial collection targets. Without these key participants, distance from the depot is the only deciding factor in economic feasibility. Identifying key participants for collection has similarities to keystone species in ecology. Although there is considerable debate in the ecological community on the implications of this concept (Cottee-Jones and Whittaker, 2012), identifying key species are essential to understanding ecosystem effects upon their loss (Power et al., 1996). Similarly, the removal of these "keystone" generators does not result in the collapse of the collection network, but more compensation is required to facilitate FW collection that is economically feasible to the collection company. In summary, assuming a uniform distribution of FW to make initial planning efforts easier will be detrimental for identifying early collection opportunities.

The cluster-first, route-second heuristic currently employed in operation literature as a class of heuristic for partitioning larger problems into smaller, more easily solvable problems. Capacitated clustering creates clusters of generators centered around the median of its individuals while keeping the total generation within a given capacity constraint (Negreiros and Palhano, 2006; Zare Mehrjerdi and Nadizadeh, 2013). This method uses only two parameters for clustering:

quantity and density of resources. Quantity of the cluster is constrained, while the spatial size of the cluster is minimized to reduce potential transportation costs. The results show that this method may not be adequate for determining economic feasibility. Although uniformity of food patches in the environment is also usually assumed by researchers (Arditi and Dacorogna, 1988; Naef-Daenzer, 2000; Rozen-Rechels et al., 2015; Steingrímsson and Grant, 2008), additional attributes such as quality and distance from the central place are generally important for understanding foraging behavior (Olsson et al., 2008). Thus, inclusion of quality in service area clustering may also be beneficial.

If profit for collection companies is treated analogously to net-energy gained in animals, then potential revenue gained from offering collection services to generators could be interpreted as the quality of FW. Circling back to differences in individual values placed on FW collection, the WTP of individuals for separate FW collection combined with the quantity could be utilized as a quality metric. Clusters or patches of generators could then also be produced based on this quality metric and compared to the compensation required (or energy expended) to collect FW from that cluster. If the cluster quality exceeds the expenditure required for collection based on network properties (Figure 9), then providing service is likely to be economically feasible. Alternatively, if the quality does not support initial feasible collection, the disparity could indicate the level at which policy intervention or incentive is needed to make collection economically feasible.

3.4 Discussion Summary and Considerations

This study has presented a novel agent-based modeling formulation inspired by ecological systems for solving VRPs for FW collection networks. Results from this study show that modeling

FW collection considering realistic transportation behaviors alters estimates considerably. By considering trip-chaining behaviors rather than simple point-to-point assumptions, cost estimates are much lower on the same network. Altering cost estimates based on distance to estimates based on time also changes resulting outcomes, even when both estimation methods are rooted in real data. Moreover, the heterogeneous generation of FW is important for early adoption of economically feasible collection services and assumptions of homogeneity can be detrimental to planning efforts. An ecological perspective to modeling approach contributes to understanding how to improve FW collection.

Many additional expansions to the ABM could be considered for future work due to its flexibility over Mixed-IP methods in terms of capturing and modeling learning and adaptation processes. Exploring and improving the fundamental formulation for ant-colony optimization may also yield more consistent simulations. Further refinement of the presented ABM method so that solution convergence is more likely would be a considerable improvement over choosing the best solution from a series of simulations. One important assumption of these methods is the generation and collection of FW occurs on a specifically defined cycle of twice per week. A more likely scenario is that weekly collection schedules differ among commercial facilities based on their FW generation rates. The ABM model could be extended to simulate daily generation and subsequent collection of FW to form a weekly schedule for collection that reduces cost or maximizes profit. These and future transportation models can help connect and inform transportation of FW via collection services, but currently do not holistically consider what type of treatment facilities may be receiving FW from various sources. The models presented in the previous two chapters are treatment facility neutral but managing FW sustainably will require the development and siting of treatment technologies that provide landfill alternatives.

The allure of alternative treatment technologies is the ability to recover energy and resources from what was once considered waste. However, unlike landfills, these facilities are not designed to sequester material, but rather to convert the material from one form to another. Mass reduction of inputs can be low for processes like wet anaerobic digestion that produces a liquid output called digestate with some nutrient properties. Understanding the transportation service costs associated with locating new facilities will inform overall costs and potential business opportunities of future treatment facility siting. Likewise, knowing the locations and economics of new treatment facilities will feed back into the transportation models presented to help inform collection decisions. The following chapter will consider where to locate treatment facilities considering both simple proximity to FW generation, additional organic resources, and the capacity to manage the resulting digestate from treatment processes.

CHAPTER 5
CONSIDERATION OF ANAEROBIC DIGESTATE MANAGEMENT TO REDUCE ECOLOGICAL RISK IN FACILTY SITING

1. Introduction

The FW diversion policies enacted by state governments will not only effect generators of waste, but also influence the buildout of infrastructure to treat the new FW waste stream. These diversion policies each consist of a spatial component stipulating that the targeted generators are limited from landfill disposal if an alternative option is within a specified maximum transportation distance, which currently ranges from 15 miles (Institute for Local Self-Reliance, 2016) to 25 miles (New York State Senate Assembly, 2019). Maximizing the diversion of FW in NYS will require construction of many new facilities to accommodate FW treatment in addition to any other pre-existing organic material management such as composting of yard waste or management of animal manure. Thus, it is important consider the ramifications of statewide infrastructure development and the subsequent effects on local municipalities who will ultimately facilitate the construction and operation of new facilities.

Many technologies are available for converting organics to recover resources and energy. Anaerobic digestion (AD) technology has gained attention as an option to convert commercial FW to value added energy products. Recovery of energy products through AD of commercial FW has shown promising recovery rates for economic viability (Banks, 2017; Chiew et al., 2015; Zhang et al., 2014) and even greater yields when particle size (Agyeman and Tao, 2014) and synergistic effects of co-substrates (Ebner et al., 2016) are considered. The bio-methane produced in AD can be used as a replacement for fossil natural gas in electricity generation or compressed and cleaned to be used as a fuel.

However, the underlying biochemical processes within in AD systems also result in secondary waste or byproduct streams. Namely, when organic material breaks down in the absence of oxygen, a nutrient-containing liquid residue typically called "digestate" is produced. This liquid digestate may have potential for further use as a soil amendment or fertilizer replacement but may also represent a waste stream that the AD operating company must bear costs to manage. To maximize the economic and environmental benefits of deploying AD for FW treatment, these facilities should be sited near sources of commercial FW and near energy or digestate co-product markets (Iakovou et al., 2010).

Many studies have considered siting AD facilities, and biomass-to-energy facilities more broadly. The basic method used for finding potential facility sites is to first excludes sites that do not meet minimum land use criteria due to environmental and social concerns. For example, areas near wetlands and residences are to be excluded from available locations. Then, feasible sites are weighted by preferential factors such as proximity to transmission lines, natural gas pipelines, and roads for product distribution (Ma, n.d.; Villamar et al., 2016; Zubaryeva et al., 2012). Further economic analysis is completed outside of the method on a site-by-site basis

On the other hand, studies have also factored in economics from the generator and hauler perspective by performing a location-allocation analysis in Esri ArcMap. This operation locates a specified number of facilities while simultaneously minimizing the transportation distance from the biomaterial or FW source (Delivand et al., 2015; Sultana and Kumar, 2012; Thompson et al., 2013). Alternatively, custom mixed integer programs have been built that function similarly to location-allocation but can consider additional economic criteria for facility placement (Chen and Fan, 2012; Mayerle and Neiva de Figueiredo, 2016; Mukherjee et al., 2015). Not all location-specific methods use optimization algorithms to site facilities. Another method characterizes

Euclidean distances of potential sites from input resources, roads, and farmland, then greedily selects economically advantageous locations until no potential sites meeting minimum siting requirements exist (Sliz-Szkliniarz and Vogt, 2012). While many of these studies consider the economics of bringing FW to a treatment facility and then exporting energy products to appropriate markets, , the authors know of no studies that specifically consider the downstream management of digestate, and the attendant economic or ecological implications, when constructing spatial models to inform AD siting decisions.

This knowledge gap is particularly critical when the scale and potential impact of digestate management is considered. Liquid and solid mass of inputs are mostly conserved in AD systems; thus, large quantities of digestate must be managed appropriately. Currently, a common management practice is to land-apply digestate on arable farm fields, which has the joint benefit of avoiding costs of treating this liquid effluent while displacing some degree of chemical fertilizer that would have been otherwise used. Some literature suggests that digestate substitution performs as well as chemical fertilizers (Nkoa, 2014), but others note that performance is dependent on the nutrient content of digestate and characteristics of applicable farmland (Dahlin et al., 2015; Delzeit and Kellner, 2013; Lukehurst et al., 2010; Peng and Pivato, 2019).

Another barrier to digestate land application is the transportation that may be required to move this heavy, high-water content material from the AD facility to a field that can accept this nutrient input. It has been reported that digestate management via land application is not economically viable if digestate transportation distance exceeds a maximum of 16-32 km from an AD facility (Mouat et al., 2010; WRAP, 2013). It is likely that this distance may be even lower if the digestate's nutrient composition and fertilization quality is not sufficient to fully displace fertilizer use and thus does not offset transportation and field application costs. Therefore, digestate management often becomes a bottleneck for increasing biogas and energy production (Fuchs and Drosg, 2013).

Further complicating digestate management are the uncertainties surrounding environmental impacts of digestate storage, transport, and field application compared to chemical fertilizer use and alternate digestate treatment methods. While global warming potential of utilizing digestate is less than chemical fertilizers (Chiew et al., 2015; Ebner et al., 2015; Rehl and Müller, 2011), evidence suggests that eutrophication potential could be worse largely due to digestate handling (Chiew et al., 2015). Operators seek to minimize these impacts by following nutrient best management practices such as applying digestate during months of highest crop uptake (Lukehurst et al., 2010; WRAP, 2013). Evidence suggests that managing nutrients based on phosphorus content can reduce soil nutrient buildup over multiple years (Maguire, 2009; Maguire et al., 2008), thus reducing the risk of phosphorus leaching into surface runoff and increasing eutrophication risks of local water resources (Carpenter, 2005; Heckrath et al., 1995; Sharpley and Rekolainen, 1997; Smith et al., 1999).

Since the nutrient content of digestate is directly related to the input material sourced for operation (Provenzano, Logan), the capacity of crop fields in the region to accept digestate should be directly compared to potential FW inputs to the AD process. Current research and industry practice shows FW is often co-digested with animal manure to improve process stability (Xu et al., 2018; Zhang and Jahng, 2012), considerably increasing the total quantity of digestate produced and complicating it’s potential as a fertilizer replacement. Multiple materials may be sourced to optimize biogas yield, leaving the nutrient content of digestate as an afterthought (Mayerle and Neiva de Figueiredo, 2016; Nghiem et al., 2017), making digestate’s potential as a fertilizer replacement more complicated. Ignoring the potential economic and environmental impacts of digestate management when siting an AD facility could lead to unforeseen future challenges that impede short-term operations and long-term strategic business goals.

Therefore, the goal of this study is to evaluate how digestate management constraints may influence spatial AD siting models, the ecological tradeoffs of AD deployment, and the broader decision-making process on infrastructure buildout for increased FW management. A GIS siting model is created to consider multiple scenarios of the FW and manure management system within a region. The capacity and eutrophication risks associated with land applying the resulting digestate are evaluated to determine effects on AD siting decisions. A system perspective is used to include both source material and digestate management for informing developers of potential environmental risks. These methods use the best available current data in the study region to characterize the balance of inputs and outputs associated with AD facilities.

2. Methods

2.1 Methods Framework

The methods presented in this study are intended to identify potential sites for AD facilities sourcing organic material (commercial FW). Esri ArcMap 10.6 was used to complete the environmental assessment in the study region using the projected coordinate system UTM Zone 18N. Analyses are performed on a raster grid of 30 m x 30 m cells covering the study region. In short, the model evaluates the magnitude of material inputs available within a sourcing radius of each cell and the capacity to subsequently land-apply resulting digestate on crop fields within a disposal radius from each cell (Figure 1). Phosphorus is used as the currency for this modeling approach because of its necessity for crop growth and potential for environmental impact.

First, available facility sites were identified through an exclusionary land assessment process (Section 2.3). Next, mass of FW and manure inputs for co-digestion (Section 2.4), the resulting digestate phosphorus supply (Section 2.5), and crop field capacity to accept the available phosphorus (Section 2.6) are calculated within each specified transportation radius. Finally, the availability of nutrients from material supply and the field acceptance capacity are compared to generate an environmental information layer for siting consideration (Section 2.7). The baseline co-digestion scenario is compared to an AD "process improvement" scenario where digestion of FW-only is possible to identify the impacts to locating potential AD facilities (Section 2.8). Due to the current economic and infrastructure difficulties of digestate transportation and application, two transportation ranges are compared throughout.

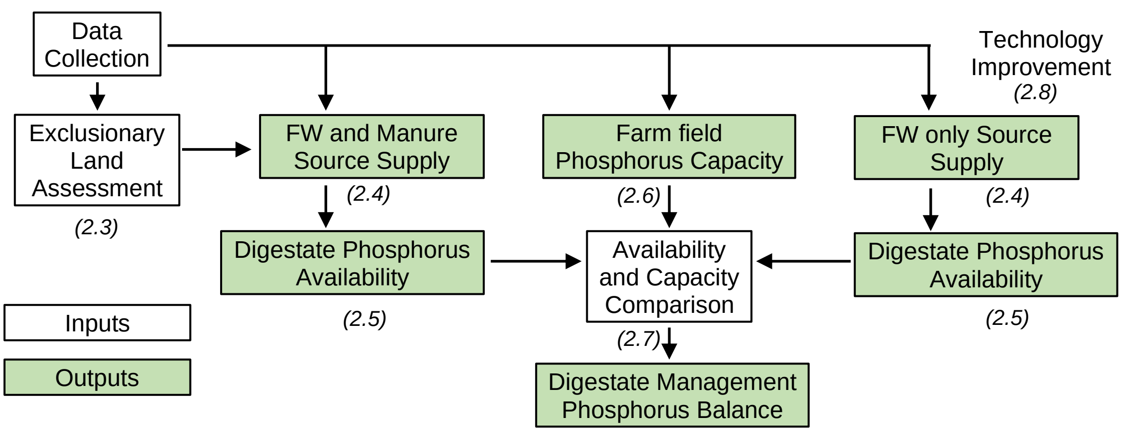

Figure 5-1: Methods Framework

2.2 Case Study Region

New York State (NYS) was chosen as the case study region due to recently passed legislation on commercial FW diversion. This analysis zooms in on Western NYS (WNY), where many AD facilities intended originally for manure management exist (NYS Pollution Prevention

Institute, 2016), and some already source FW to increase biogas yields. The region contains the second two most populous cities in NYS and multiple collection companies already source FW for established AD facilities. Moreover, the WNY region, comprised of NYSDEC Regions 8 and 9 (NYSDEC, 2019a), contains approximately 46% of harvested cropland and 38% of dairy cow inventory in the state (U.S. Department of Agriculture, 2017). Interest in infrastructure expansion, proximity of urban areas to farmland, and availability of resources makes this region an excellent test case.

2.3 Siting Exclusions

2.3.1 Assessment

The availability of suitable land for constructing new AD facilities was determined by combining multiple exclusionary constraints, such as setback distances to residential locations or wetlands, slope grade, and proximity to road access in order to restrict placement of AD facilities based on previous literature (Table 1).

Feature Type	Setback in Literature	Setback in study	Literature
Wetlands	33m – 200m	33m	(Khan, 2015; Ma, n.d.; NYSDEC, 2019b; Sultana and Kumar, 2012; Thompson et al., 2013)
Protected Land	100m – 1000m	100m	(Delivand et al., 2015; Khan, 2015; Ma, n.d.; Mukherjee et al., 2015; Sultana and Kumar, 2012)
Open Water	50m – 300m	50m	(David et al., 2013; Delivand et al., 2015; Khan, 2015; Ma, n.d.; Mukherjee et al., 2015; Sliz-Szkliniarz and Vogt, 2012; Sultana and Kumar, 2012; Thompson et al., 2013)
Residential	200m – 1000m	400m	(David et al., 2013; Khan, 2015; Ma, n.d.; Mukherjee et al., 2015; Sultana and Kumar, 2012)
Commercial	300m – 1000m	400m	(David et al., 2013; Khan, 2015; Sultana and Kumar, 2012)
Highways		50m	
Schools		400m	
	Inclusion in Literature	Inclusion in study	
Roads	300m	1000m	(Mukherjee et al., 2015)
	Slope Criteria in Literature	Slope Criteria in study	
Slope	2% - 15%	15%	(David et al., 2013; Khan, 2015; Ma, n.d.; Sultana and Kumar, 2012; Thompson et al., 2013)

Table 5-1: Setback distances, inclusionary distances, and slope criteria for exclusionary features.

Although schools were not included in literature, they are prominent in the study region with the potential to affect siting locations. A setback distance for schools equivalent to commercial and residential locations were assigned. Instead of a setback distance, roads were given an inclusion distance, where potential digesters had to be sited within 1000 m of a road to ensure reasonable transportation and construction access.

2.3.2 Data Collection and Use

The National Land Cover Dataset (NLCD) for 2016 was downloaded to extract wetland and open water areas for the study region (MRLC Consortium, 2016). The slope of NYS was obtained from Cornell University's Geospatial Information Repository (CUGIR, 2019). Remaining data–including political boundaries, protected land, roads, schools, and parcel types–were downloaded from the NYS GIS Clearinghouse (NYS Office of Information Technology Services, 2017). Data were extracted and clipped to the extent of the study region, and converted to raster format comparable with the NLCD data to ensure common analysis geometry.

Exclusionary features were imported into ArcMap and Euclidean distances of each cell to the closest feature were calculated for each data layer. Cells for each data layer that were deemed suitable for site selection were assigned 1, otherwise 0. Data layers were overlaid to align cells within the study area, and cell columns were multiplied to calculate a data layer indicating cells suitable for development. The land footprint of the smallest standalone AD facility in the study region was approximately 120 m x 90 m (10,800 m^2) and was designed to process 23,000 metric tons of organic material annually (Maringer, 2013). Therefore, groups of cells with a combined area less than 10,800 m^2 were removed from consideration.

2.4 Food Waste and Manure Sourcing for Co-Digestion

2.4.1 Assessment Method

The supply of commercial FW within a Sourcing Radius of each 30 m x 30 m cell was calculated to determine available input materials. A radius of 40km (25mi) was selected based on the transportation distance set forth by recently enacted FW diversion legislations (New York State

Senate Assembly, 2019). Each cell was evaluated for the annual generation (t/yr) of commercial FW within the Sourcing Radius using the Focal Statistics tool in ArcMap.

Animal manures are currently considered important for maintaining operational stability of AD systems (Zhang et al., 2014). Indeed, many existing AD facilities in the study region already co-digest manure with FW sourced from commercial and industrial generators. To reflect the potential for co-digestion, a transportation distance for manure of 20km from confined animal feeding operations (CAFOs) was used as a base case for co-input material based on the maximum distance of manure transport (U.S. Department of Agriculture and Natural Resources Conservation Service, 2003).

2.4.2 Data Collection

Locations and annual estimates of FW generation rates for commercial generators and manure generators for registered CAFOs were obtained from the NYS P2I Organic Resource Locator (NYS Pollution Prevention Institute, 2017). Facilities included higher education, restaurants, retail, wholesale, hospitality, and corrections facilities from the NYSP2I ORL database (NYS Pollution Prevention Institute, 2019). Addresses were geocoded to provide latitude and longitude coordinates for analysis.

2.5 Phosphorus Availability

Phosphorus was identified as a key nutrient for plant growth and eutrophication risk due to run-off from farmland into local water systems. The phosphorus content of inputs was obtained for each input material to understand the availability of the nutrient entering the digestion process and post-digestion utilization. Phosphorus content of mixed commercial FW was obtained from literature (Table 2).

Source	Value	Units	Solids Content	kg/ton @ 28% Solids
(Zhang et al., 2007)	0.52	% dry mass	30%	1.56
(Banks et al., 2011)	1.90	kg/ton	28%	1.90
(El-Mashad and Zhang, 2010)	4.83	g/kg TS	28%	1.35
(Chiew et al., 2015)	0.32	% dry mass	28%	0.90
			Average	1.43
			SD	0.36

Table 5-2: Values and sources for phosphorus concentrations of mixed commercial FW from literature.

Supply of FW calculated in Section 2.4 was multiplied by the literature value identified in Table 2 to convert FW (t/yr) to phosphorus (kg/yr). Phosphorus content of dairy manure was obtained and calculated similarly (Table 3).

Source	Value	Units	Solids Content	kg/ton @ 10% Solids
(Agyeman and Tao, 2014)	0.78	g/L	17%	0.46
(Lukehurst et al., 2010)	0.50	kg/m3	6%	0.83
(El-Mashad and Zhang, 2010)	8.38	g/kg TS	14%	0.84
(Laboski and Peters, 2012)	3.52	lb/1000 gal	10%	0.42
			Average	0.64
			SD	0.20

Table 5-3: Values and sources for phosphorus concentrations of dairy manure from literature.

Phosphorus in the digestate is assumed to be equivalent to the phosphorus calculated from input material. Phosphorus and related compounds are stable, remaining in solid form unlike other nutrient, such as nitrogen that is more transient (Maguire, 2009). Although there is some conversion of solid mass to the gaseous state like CO_2 and CH_4, this will not diminish the phosphorus quantity in digestate.

2.6 Nutrient Capacity of Farmlands

2.6.1 Crop Nutrient Uptake and Data Collection

Estimating nutrient uptake of crops requires knowledge of the crops grown in the region. Different crop types have different yield estimates and nutrient requirements. Spatial data and yield of crops grown in the region were obtained to estimate crop-specific P uptake. A raster dataset of crop locations and types from 2018 was obtained from the CropScape (U.S. Department of Agriculture and National Agriculture Statistics Service, 2018). The dataset was clipped to the study region, and field and vegetable crop types with a total land area of more than 200 acres (81 ha) were extracted from the dataset. CropScape data originates from satellite imagery and cropland designation is not always logical (*e.g.*, wheat growing in a public park); to correct this, CUGIR's database of registered agricultural districts are used to retain only crops within registered areas. CUGIR maintains a database of registered agricultural districts for permitting and legislation (CUGIR, 2019).

Applying fertilizer to crop fields is a complex process that includes consideration of many factors such as anticipated erosion, existing soil phosphorus, and expected crop uptake (Ketterings et al., 2003). Phosphorus capacity of crop fields is assumed to be equivalent to the removal of crops when harvested. A nutrient steady-state is assumed where erosion and dissolved run off are zero and soil phosphorus optimally maintained such that new phosphorus must be applied each year for crop growth. While these assumptions considerably simplify fertilization estimates, expected phosphorus uptake provides a minimum estimate to replace lost nutrients after harvest. Expected phosphorus uptake was obtained from University of Wisconsin Cooperative Extension assuming average yield for each crop type (Laboski and Peters, 2012). Crop types were assumed to remain the same for the year following the CropScape dataset collected for Section 2.3.3 to estimate phosphorus demand required the following year (Table B1). Anticipated phosphorus capacity (uptake) for a hectare of crop per year from Table B1 was multiplied by 0.09 to convert ha to 30m cell and the crop specific values were applied to the cropland data layer.

2.6.2 Digestate Transportation and Application

Digestate must be transported to fields for application. The total phosphorus capacity of fields within a 10 km Transportation Radius from each cell was calculated using the focal statistics tool and available fields. This distance is economically feasible in current industry practice (Mouat et al., 2010; WRAP, 2013). Since the Transportation Radius considerably impacts the ability to manage digestate, sensitivity analyses are performed on this variable. Increasing digestate transportation distance means the more potential land available for application.

2.7 Comparison of Digestate Phosphorus and Land Capacity

Availability of phosphorus in digestate and capacity of fields to accept phosphorus were compared to determine where digestate can be applied without exceeding field capacity to minimize potential environmental impacts of digestate land application. Potential digester sites are assumed to source all material within the specified Sourcing Radius and have access to all fields within the Transportation Radius for digestate application. Phosphorus field capacity is subtracted from digestate availability for each cell in the region. A resulting positive value indicates there is excess available phosphorus compared to the capacity of fields within the digestate transport radius. A negative value indicates remaining capacity of fields.

2.8 Economic and Technology Uncertainty

Although current AD technology typically relies on animal manure as a stabilizing material, future AD processes may no longer rely on the stability of manure and digest FW alone. Separating the two systems allows each to focus on processes improvements that increase efficiency or specific product goals. Therefore, the siting implications of a FW-only AD technology were considered. Even though the two processes are now split, manure management must still be considered as farm fields within transport distance from manure-producing facilities will first utilize manure as a soil amendment. In this scenario, manure is assumed to be either directly applied to farm fields or digested in a system co-located with each CAFO and land applied. Both management practices currently exist and result in equivalent land application impacts. The closest fields to CAFOs that cumulatively have the capacity to accept the application of raw or digested manure are removed from the field data layer. It is assumed that the applied manure will satisfy those fields' annual phosphorus requirements and are no longer available for application of digestate derived from commercial FW.

3. Results and Discussion

3.1 Land Exclusion Assessment

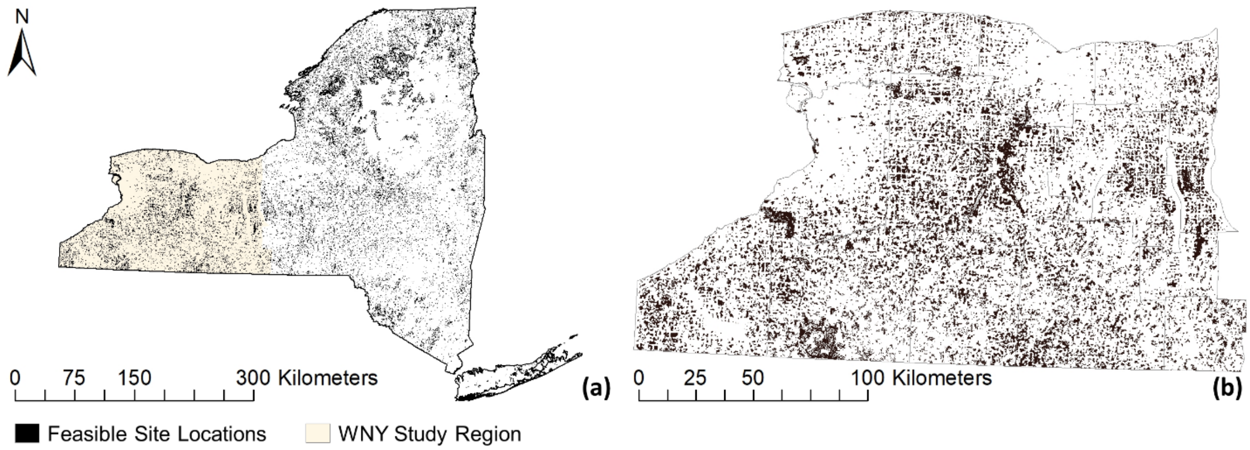

Figure 5-2: Feasible locations resulting from the land exclusion assessment criteria for NYS (a) and the study region (b). The five counties comprising New York City are omitted from the map and assumed that no AD facility can be built there.

After land exclusion criteria were applied to NYS and controlled for the minimum size, it was found that 11.1% of the state contained feasible locations for potential AD facilities (Figure 2). Feasible locations are most prevalent around the center of the state, away from major cities and populated areas. The large area of infeasible locations in the north-center of the state is a state park protected by the NYSDEC. Areas around NYC and on Long Island show notably lower concentrations of feasible locations.

In the study region (Figure 2b), feasible locations are available in the rural areas outside of major cities Buffalo (northwest) and Rochester (north-central), and total 12.1% of land area. Three discernable issues were noted in the results of the exclusion assessment. The cluster of feasibility on the western edge of the study area is land owned by Native Americans whose land was not included the original land exclusion assessment criteria. On the eastern side of the study area, the two dense clusters of feasible areas are a military base (north) and the Finger Lakes National Forest (south). Military bases were not included in the assessment criteria, and the national forest is not maintained by the DEC and was thus not included in the protected lands data file used for exclusion.

When compared to current location of AD facilities, the assessment was able to show feasibility in the general area of facilities, but only showed feasibility on current AD facilities on a few occasions. Resulting images from the assessment are not carried through the analysis visually, but potential sites should be chosen with this exclusion assessment in mind.

3.2 Manure and Food Waste

3.2.1 Quantity and Phosphorus Availability

Results from the quantification of FW and manure and subsequent phosphorus availability from digesting these materials are illustrated in Figure 3.

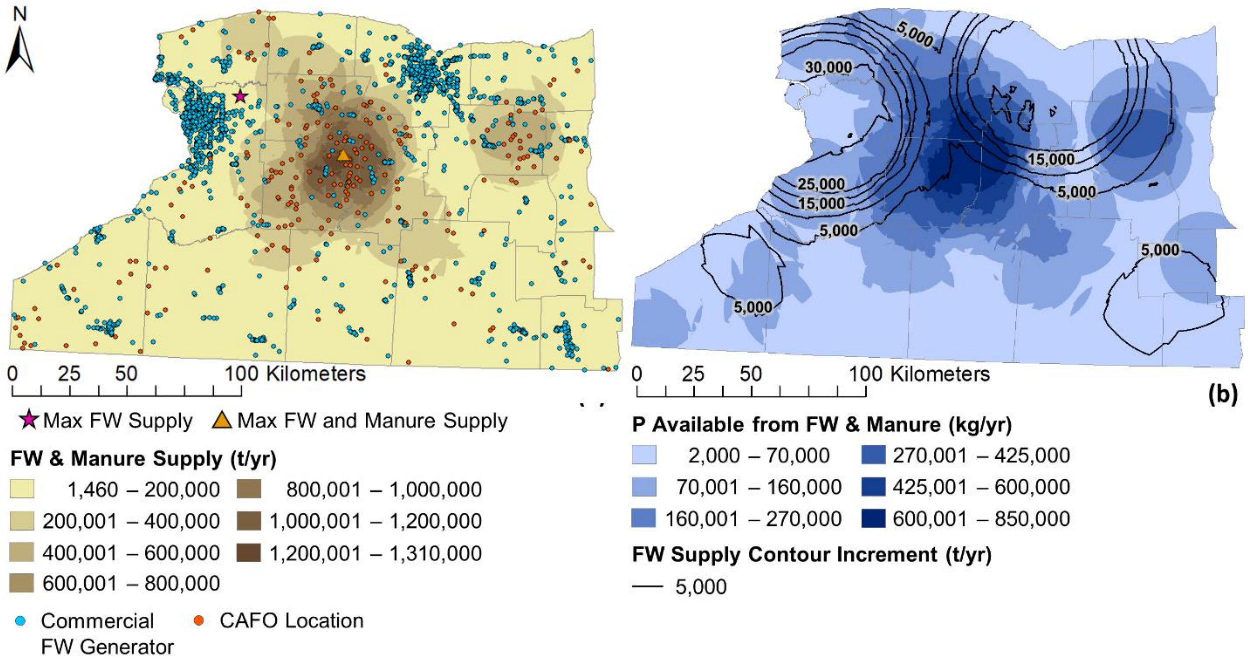

Figure 5-3: Annual manure and FW supply from commercial generators and CAFOs (a) and the quantity converted to kg phosphorus/yr (b). Supply contours for FW remain on the combined phosphorus availability map to maintain the sourcing focus on FW.

Based on material inputs alone, siting a new facility in center of the region would be able to take advantage of the large quantity of source material (orange triangle). However, it is unlikely a single facility could be constructed to utilize all 1.3 million annual tons of manure considering that the largest AD facility in the word only processes 335,000 tons of material annually (Silva, 2018). Furthermore, commercial FW only constitutes 0.4% of the total material at the highest concentrated location. As potential sites closer to city centers are evaluated, the ratio of FW to manure reaches its peak at the pink star location, where the total material is comprised of 19.8% commercial FW.

Phosphorous follows a similar trend in concentration (Figure 1b) but the higher phosphorus content in FW translates to higher contributions to overall phosphorus levels: 0.8% and 35.5% at the space two locations. While the total quantity of FW plus manure may be useful for deriving energy products, owners and operators will have to find suitable land for digestate application to mitigate the eutrophication risks of phosphorus overapplication. Figure 4 identifies the farmland available for digestate application and resulting phosphorus capacities.

3.2.2 Phosphorus Acceptance Capacity of Farmland

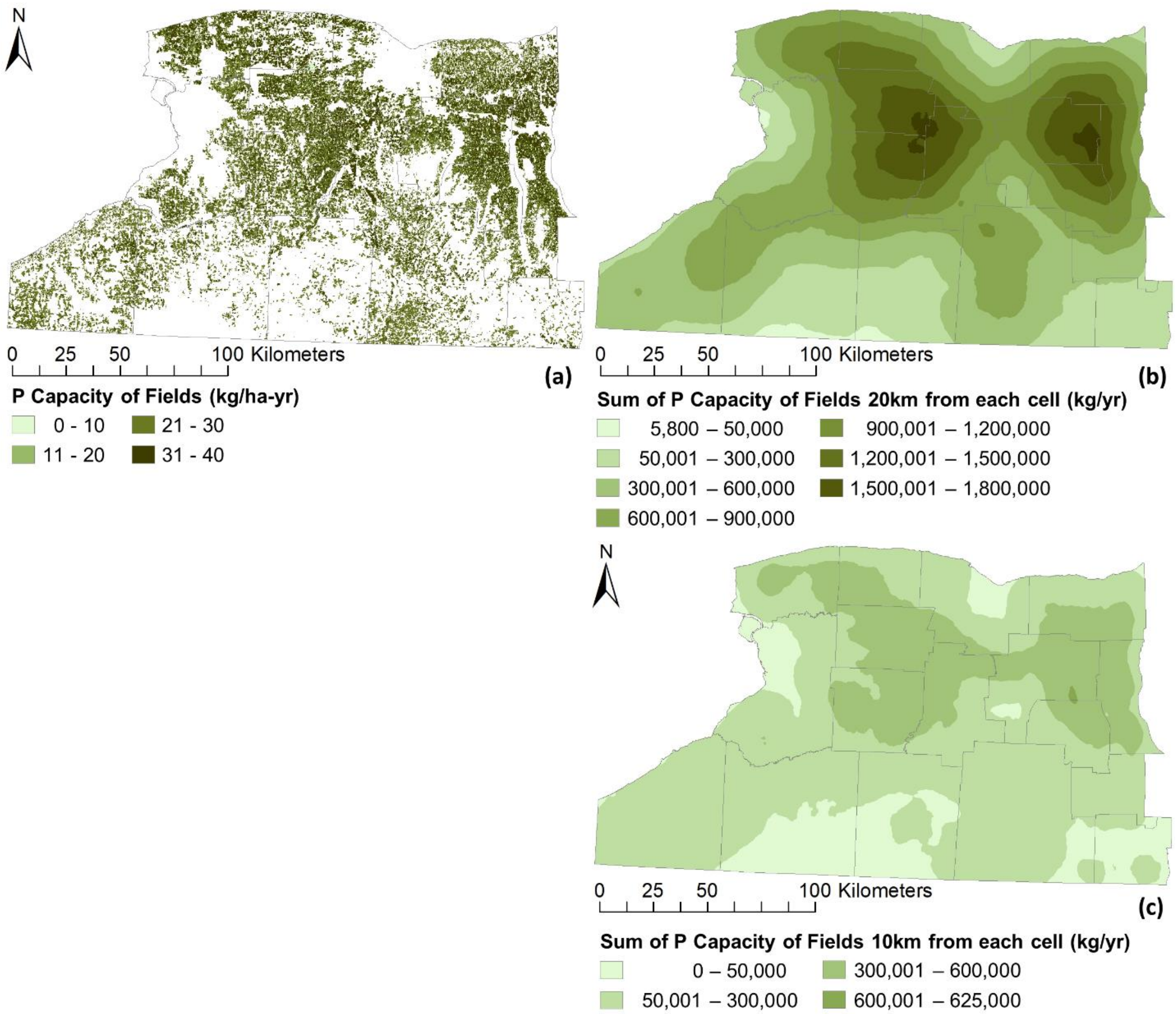

Figure 5-4: Crop fields identified from satellite imagery that are assumed to need applications of phosphorus to grow (a). Manure from CAFOs was assumed to be held for transportation rather than field applied, increasing the available fields for digestate application. The sum of digestate application capacities of fields within 20km from each cell are calculated for potential digesters (b). Incorporating the uncertainty of digestate transport distance, the sum of digestate application capacities of fields within 10km from each cell are calculated (c).

The majority of crops identified in the region consist of corn, grass, hay, soybeans, winter wheat, and dry beans, constituting approximately 98% of total cropland and each growing more than 10,000ha. Of those crops, corn and hay (60% of total crops) are expected to uptake more than 30kg/ha of phosphorus during their growing cycle, the highest of all crops considered. These high uptake rates and spatial distribution of those crops in the center and eastern portions of the region (Figure B1) contribute to the higher concentrations of dark green observed in Figure 3a. Other regions that grow these types of crops may also make good candidates for digestate application.

When digestate transportation distance is assumed to be 10km (Figure 3c), the location with highest phosphorus application capacity is calculated at approximately 625,000kg/yr. When digestate transportation distance is increased to 20km, phosphorus application capacity triples in many areas. A doubling of feasible transportation (Figure 3b) quadruples the total area that can be considered for digestate application and the high concentration of farm fields means that much of the new area is available for digestate application.

This intermediate result indicates the importance for considering digestate transportation distance. Although the concentration of farmland in this region translates to a large increase in capacity for digestate application. Other regions looking to develop AD facilities might want to emphasize the ability to transport digestate as far as possible.

3.2.3 Comparison of Digestate Phosphorus Availability and Farmland Capacity

The phosphorus availability of digestate resulting from source material is compared to the application capacity of farmland from each cell using phosphorus balances.

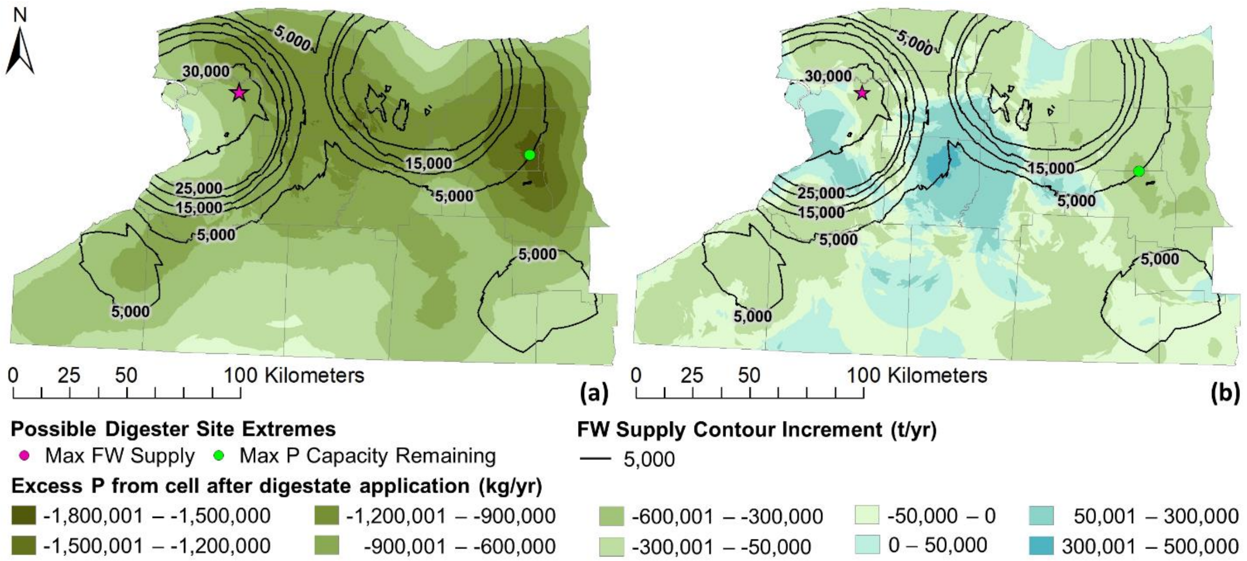

Figure 5-5: Balance of phosphorus for digestate derived from manure and FW is compared to field capacities within 20km (a) and 10km (b) of potential digester locations. Positive values indicate excess phosphorus availability while negative values indicate excess remaining capacity. Contours indicate commercial FW supply from Figure 3a. The site with maximum potential to source FW (star) and maximum remaining capacity after digestate produced from sourced inputs is applied to fields in the transport radius (circle) are shown to illustrate two siting extremes.

Comparing phosphorus availability from digestate to application capacity of farm fields reveals a range of results. When a 10km digestate transportation distance is assumed, there are many locations that show an oversupply of phosphorus (Figure 4b). Many potential sites would not be able to source all of the FW and manure within the specified sourcing distances without excess buildup of digestate. While many of the locations are technically available for siting from the exclusion analysis, some of the digestate produced would have to be transported further than 10km to ensure that phosphorus is not overapplied to farm fields.

Doubling digestate transportation distance (Figure 4a) appears to not only fix the phosphorus oversupply issue for many locations but appears to create excess digestate application capacity for nearly all locations. The only location that is still observed to have excess phosphorus is in the City of Buffalo on the western side of the region. However, consulting the available site locations (Figure 2) shows that there are very few potential sites for new AD facilities within urban areas. The major takeaway from this result is that increasing digestate transportation distance just by 10km has a considerable positive impact on the ability to manage digestate without overloading soil phosphorus. Developers, planners, and policy makers should consider digestate transportation distance as a key factor to their siting criteria.

Introducing siting preferences based both on source material and digestate disposal capacity creates a multi-criteria problem for identifying preferred site locations. Performing a spatially explicit analysis allows identification of those locations that might accomplish specific objectives set forth by a new AD developer such as maximizing FW supply, maximizing digestate disposal capacity, or finding a site that strikes a balance. For example, Figure 4 illustrates sites with maximum FW supply and digestate capacity. Layering both input and capacity information allows for comparison. For instance, the site with maximum FW supply still has farm fields with unmet digestate application capacity after the initial digestate is applied to farm fields within both transportation distances.

3.3 Food Waste Only Digestion

3.3.1 Food Waste Supply and Phosphorus Availability

Figure 6 illustrates the supply of mixed commercial FW when separated from manure and subsequent phosphorus availability of digestate based on methods.

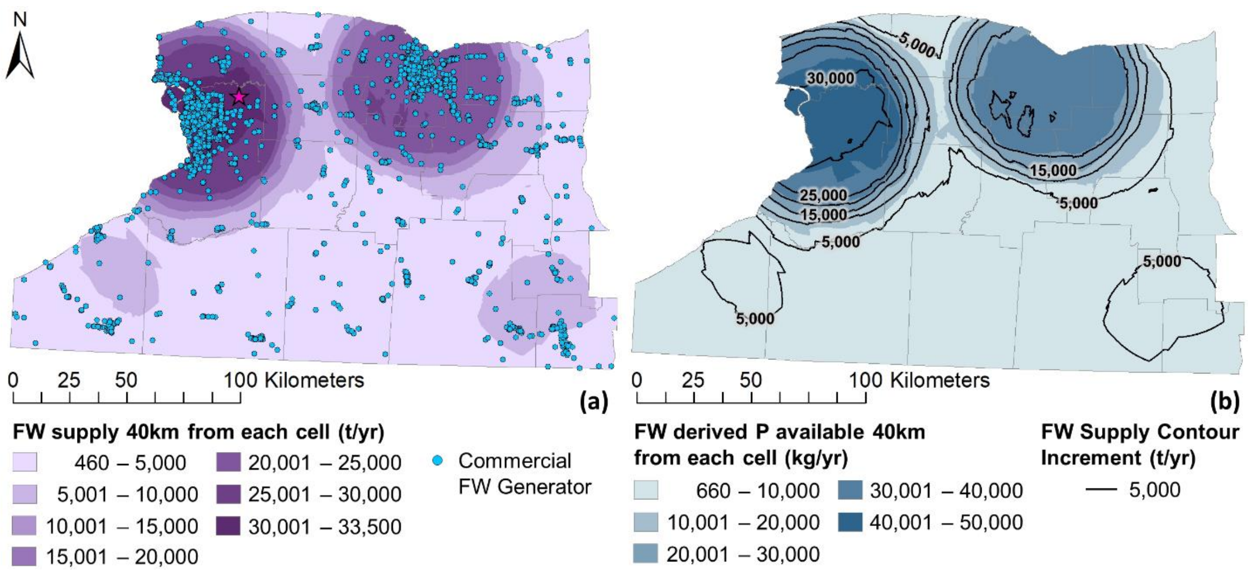

Figure 5-6: Annual supply of FW from commercial generators within 40km of each cell (a). Darker coloring indicates higher concentration of supply. Annual supply is converted to availability of phosphorus (P) in kg and shown via color (b). Contours lines of FW supply are overlaid on the phosphorus availability.

When commercial FW is considered alone, the landscape of material supply changes drastically compared to inclusion of manure. Locations with the most FW supply are those near commercial generators located in and around urban centers. Due to the spatial distribution of generators, the single location with the most supply of FW (pink star) is outside of a major urban center (Buffalo) rather than in the middle of generators. Although not the highest, this trend appears similar for Rochester, where the highest concentration of FW supply is just south of the city. This trend likely occurs since both cities border major water bodies. Other cities located on the edges of defined geographic boarders might see similar trends.

Like in the FW and manure scenario, phosphorus supply from digesting FW follows the trend of the material.

3.3.2 Phosphorus Acceptance Capacity of Farmland

The capacity of farmland to accept phosphorus from digestate was calculated in the same way as for the previous scenario. However, manure is no longer considered for digestion because technology improvements have allowed FW to be digested alone. Manure is instead assumed to be applied, either directly or through an existing digestion process, to available farmland around each CAFO (Figure 7).

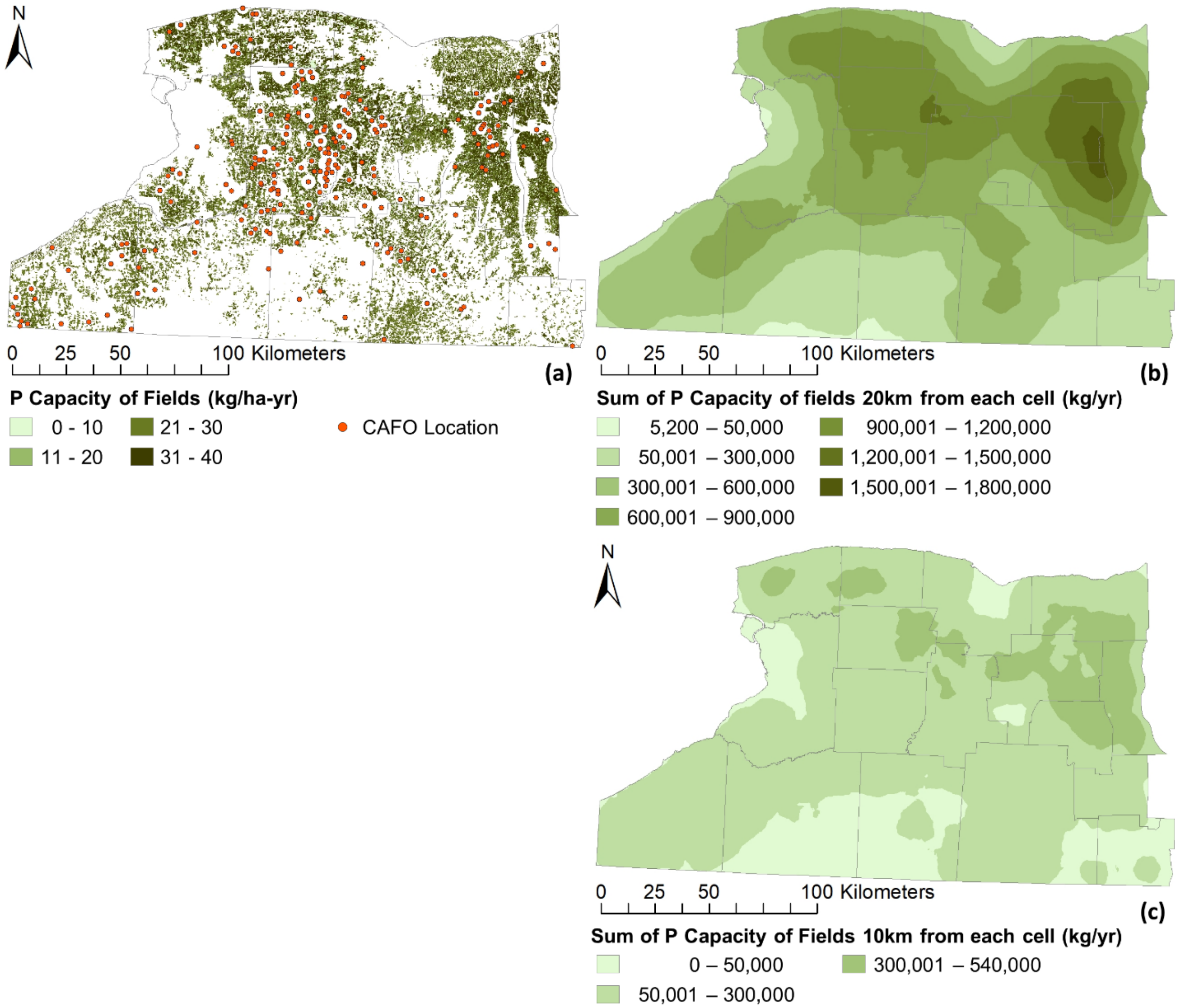

Figure 5-7: Crop fields identified from satellite imagery that are assumed to need applications of phosphorus to grow (a). Fields surrounding CAFOs where application of manure assumed to meet field capacity are removed for FW digestate application. The sum of digestate application capacities of fields within 20km from each cell are calculated for potential digesters (b). Incorporating the uncertainty of digestate transport distance, the sum of digestate application capacities of fields within 10km from each cell are calculated (c).

The resulting capacity available for digestate application from FW only is noticeably diminished due to direct manure application on farm land. Both the 10km and 20km transport distance scenarios show reduced capacity in the center of the region. The eastern portion of the region appears only to be slightly affected, likely due to the lower concentration of manure produced by CAFOs in the area.

3.3.3 Comparison of Digestate Phosphorus Availability and Farmland Capacity

Figure 8 shows the expected balance of phosphorus when field application capacity is subtracted from phosphorus availability from FW only digestate.

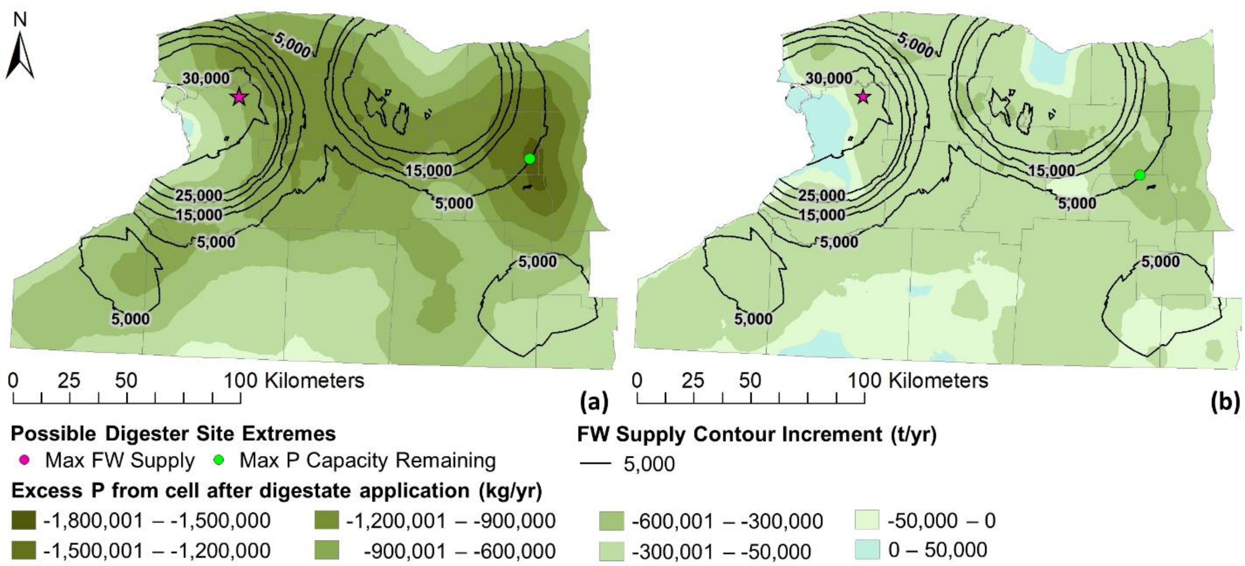

Figure 5-8: Balance of phosphorus (P) for digestate derived from FW is compared to field capacities within 20km (a) and 10km (b) of potential digester locations. Positive values indicate excess phosphorus availability while negative values indicate excess remaining capacity. Contours indicate commercial FW supply from Figure 3a. The site with maximum potential to source FW (star) and maximum remaining capacity after digestate produced from sourced inputs is applied to fields in the transport radius (circle) are shown to illustrate two siting extremes.

Eliminating manure from the sourced material considerably decreases the quantity of phosphorus in digestate that must be managed, resulting in more remaining capacity of farm fields after the initial digestate is applied within 10km of a potential AD site (Figure 7b). Moreover, there are now additional sites that show extra digestate application capacity. Increasing the digestate transportation distance to 20km results in a similar increase in extra capacity as the FW and manure scenario. In fact, direct comparison of the two scenarios with 20km digestate transport reveals the spatial distribution of excess capacity to be approximately the same. This occurs due to the manure transport assumption of 20km in the first scenario.

If technology develops such that commercial FW can be digested without the need for manure as a stabilizing material, this analysis indicates that the results are tangible for digestate management. There is considerably less phosphorus in digestate to manage, thus allowing more flexibility in digestate application. Reduction in eutrophication risks could occur by applying lesser amounts of digestate over fields or selecting specific fields with lower runoff potential for land application. For the latter to be true, additional environmental analysis is necessary to identify site specific risk of surface water runoff.

Furthermore, less input material could mean construction of smaller facilities. Manure only and co-digesters that currently exist in the region are often millions of dollars due to size. If less, high quality material like commercial FW can be sourced instead of lower quality material like manure, digesters can be built smaller and cost less. Energy product generation will be more efficient due to higher biomethane content (Alexander, 2012; Ebner et al., 2016), and nutrient content of digestate may be higher, making it a more valuable fertilizer substitute (Nkoa, 2014). The excess digestate application capacity could also be viewed as opportunities to expand operations to source other, high quality materials such as industrial FW, agricultural waste, or even serve as a treatment site for residential FW.

3.4 Summary and Limitations

Consideration of digestate management when identify potential AD sites has shown two important conclusions. First, Transportation distance for digestate application has considerable impact on the capacity to manage phosphorus content of digestate. Doubling the transportation distance in this study translated to a considerable increase in capacity for digestate application on farmland. While other regions may not see increases to the degree of this study due to the quantity of farmland in the region, the trend is expected to be similar. This part of the FW management network could be a key target for policy incentives or process improvements.

Second, technology that could potentially process FW without the need for manure could decrease the cost of infrastructure buildout to meet FW diversion goals. Additionally, the increased flexibility in digestate management could provide an opportunity to divert other FW material to increase total FW diversion.

Since this is the first study known to the authors that considers the downstream digestate management challenge when siting potential AD facilities, there are many simplifications that should be noted.

There exist additional environmental factors that could impede digestate application on cropland. Eutrophication impacts of fertilizer runoff are a prolific issue in the U.S. (Danz et al., 2007), and digestate may cause similar issues if used in the same manner. More detailed environmental risk analysis considering watershed properties and nutrient loading is critical to identifying fields where digestate application is least risky.

Application of digestate on crop fields has not been extensively studied in literature from an economic risk perspective. Assumptions in this study are preliminary and should be further explored and supported. While this study identified the phosphorus demand associated with crop yields, the previously mentioned industry reports suggest that applying digestate is less economically efficient than raw manure due to its higher moisture content (Delzeit and Kellner, 2013). The economic ability to apply digestate likely depends on the willingness of a farmer to work more even if the AD facility provides compensation for accepting the digestate. Application costs could be alleviated by adopting an integrated biogas-digestate optimization approach for AD operations could increase the value of digestate (Chen et al., 2012; Linville et al., 2015). Alternatively, technologies that remove moisture and concentrate digestate nutrients can be utilized to reduce transport and application costs (Fuchs and Drosg, 2013). Ultimately, a thorough techno-economic analysis should capture the economic feasibility of various solutions.

This chapter used a simplistic assumption of FW collection and transportation to determine the distance for sourcing. The transportation distance set forth by NYS legislation is intended to identify generators that will be required to manage their FW, not to define collection distances.

CHAPTER 6
CONCLUSION, LIMITATION, AND FUTURE RESEARCH

As the U.S. moves toward more sustainable practices, diversion of food waste from landfills has emerged as a key activity for reducing environmental impacts associated with landfill disposal. The U.S. is estimated to have produced at least 63 million tons of food waste in 2015 from the agriculture, industrial, commercial, and residential sectors (ReFED, 2017). Many state and local governments are emphasizing landfill alternatives for food waste management either by enacting legislation or supporting collection efforts. Additionally, there are emerging food waste management technologies that show promise in recovering energy and resources from food waste in addition to reducing the overall contribution to greenhouse gas emissions (Levis and Barlaz, 2011). However, as management networks emerge, logistics challenges will inevitably arise due to the different considerations needed for food waste management that are not encountered in conventional municipal solid waste and recycling systems. Therefore, the goal of this dissertation was to characterize these unique characteristics to anticipate logistical challenges that might arise as food waste management becomes more common.

The first step of this research was to characterize variability in food waste generation and resulting estimates (Chapter 2). Empirically collected data was used to better inform spatial and temporal variability in food waste generation from many types of commercial generators. Empirical data was combined with prevailing estimation methods to characterize the magnitude of food waste variation at a regional scale.

New collection and hauling services that will be required to transfer food waste from where it is generated to the new treatment locations. Chapter 3 considered how spatial variability of food waste generation can affect collection feasibility. This concept is tested using residential neighborhoods to separate spatial density from differences in variability. Additionally, it contributes to insights for collection of food waste from residential neighborhoods, estimated significantly contribute to overall food waste generation. Chapter 4 introduces a new ecologically inspired vehicle routing model to understand how variability in food waste generation rates at the commercial level will affect collection feasibility. Furthermore, this chapter shows how food waste specific assumptions support best practices for waste collection modeling to generate results meaningful to stakeholders. The ecological perspective of this research allows stakeholders to quantify characteristics of emerging collection networks to inform effective food waste collection services.

Managing the source separated food waste from generators may require construction of new treatment facilities. While most facility siting research focuses on locating facilities such as anaerobic digesters close to food waste sources, appropriate management of low-quality material outputs such as digestate is not considered. Chapter 5 is the first known study to consider siting of anaerobic digesters that includes the spatially explicit capacity to manage digestate outputs via nutrient balance. The phosphorus content of digestate and capacity of agricultural crops to use phosphorus were quantified and compared to identify locations suitable for digestion facilities. This research shows that including the system perspective when considering the use of new technologies is critical to understanding the range of potential challenges that could be encountered.

Key Takeaways

Development and application of these models and tools advances the understanding of logistics challenges that will be encountered as food waste management expands. Major findings are summarized below.

- Variability in food waste generation will impact FW management policy and network development. Anticipating this variability will help local governments coordinate management efforts, sourcing FW to maintain more consistent monthly supply and consolidating infrastructure development to take advantage of concentrations of FW sources.

- New waste-to-energy facilities operate differently than conventional waste management infrastructure. It is important to consider the whole system of inputs and outputs when identifying new locations for these facilities. Siting anaerobic digestion facilities without initial regard for digestate management may cause problems for operation in the future.

- Higher participation density in food waste management is critical to reducing the cost of emerging collection services for future participants. Identifying critical points in participation density that meet customer expectations will be important for the sustainable growth of collection services

- Heterogeneity in food waste generation rates are critical for initially providing less costly commercial collection services. Exploiting large generators for initial food waste collection is key for the early stages of service development. Assuming that generation rates are homogeneous for ease of analysis may delay entry of food waste collection into new regions due to inaccurate conclusions of economic feasibility.

Research Implications and Recommendations to Stakeholders

Food waste management in the U.S. is still in its early stages. There are many logistics challenges that will be encountered as networks develop nationally. While development has so far paralleled conventional waste management practices, there are characteristics unique to food waste management that will need to be identified and addresses at the operational and research levels, such as concentration and variability FW generation, willingness-to-pay for a new service, and post-treatment product application. Generators, transportation companies, and treatment facility operators should not be afraid to collaborate with researchers and policy makers to provide data and perspectives from the industry.

Variability in food waste has implications for management strategies. Month-to-month variability in different FW sources can cause peaks and valleys in regional generation that could overwhelm collection services or cause a lack of FW resources. Concentrations of FW generation geographically are important to consider for building out management networks efficiently. Communication between stakeholders invested in the system is key so that variability does not impact management networks in unexpected ways. Developing flexible systems that incorporate information flows may help to accommodate spatial and generation variability in new management networks to maintain consistent effectiveness. Anticipating variability through well-constructed communication systems able to plan for and reduce the potential impacts.

Information on the food waste system is scarce, affecting analyses, projections, and ultimately decisions. More information is needed on food waste generation at finer resolutions. For instance, how stakeholders make decisions and sentiments placed on food waste management from all stakeholders. More information will allow for more informed research and decision making so that policies and solutions are more relevant and effective. Additional information should be collected on food waste generation rates over long durations to understand temporal variation in generation and for treatment facilities to anticipate large, short-term influxes or plan for a dearth in material supply.

Collection and transportation within the food waste network will incur high costs as the systems are implemented and grow initially. There is often a mismatch between cost of transportation and the budgets, or willingness-to-pay, of stakeholders throughout the transport chain. This research shows that these costs are highly related to the concentration of FW generation geographically. This research shows that an important way to reduce these costs is to increase the quantity of participation in collection service areas. Additionally, targeting larger generators of FW are important for the initial service offerings to keep collection costs down so that "undue hardships" are not a reason for obtaining diversion waivers. As services expand, policy incentives could bridge the initial gap to assist in the buildout of services in order to maximize food waste diversion. As collection and transport become less expensive over time, incentives can be phased out as service and product markets are established. However, it is important that food waste management practices do not become reliant on incentives for operation so that progress is not lost as the system matures.

This research shows that it is important to consider post-treatment use of FW products when considering potential treatment sites. Combing FW with manure for wet anaerobic digestion, based on this research, could lead to overabundance of phosphorus rich digestate compared to available farmland, presenting potential difficulty in siting new treatment facilities in locations advantageous to both FW supply and digestate disposal capacity. If technology and processes specifically designed for food waste management are the focus of research and policy, less post-treatment products would need to be managed and siting might be easier. However, the reality is that there are many organic substrates that also benefit from treatment, such as manure, agricultural waste, and yard vegetation. Technologies and processes currently used to accommodate food waste have been adapted from existing methods used for these other substrates. While these methods have initially worked for food waste management, economic barriers due to logistics are being encountered as operational networks grow. Products and their management remain the same despite the variety of nutrients FW can provide. Focusing on developing food waste specific technologies and processes to develop more valuable products will help to overcome logistics challenges and provide more economically feasible management solutions.

Limitations and Extensions

This research was limited by the quality and quantity of data available, especially in food waste generation. Although conclusions and recommendations derived from this research strive to be based data and system relationships, the lack of information at many points could alter these conclusions. Much of this research can be revisited in the future to solidify and validate conclusions when more information is available. The genesis of many methods presented originate from considering food waste management from new perspectives. Therefore, these methods should be treated as preliminary methods used to identify basic relationships. Improving these methods in future research will help to capture more realistic representations of food waste management.

Implications of this research can be extended to disaster management and planning. Rather than planning for long term trends, short-term influxes of material could spike dramatically due to impacts from natural hazards. Often when natural hazards occur, electricity can be knocked out due to intense environmental conditions or, more recently, intentionally shut off to reduce disaster risk. A recent example of disaster risk management is the shut-off of electrical systems in

California to reduce forest fire risk (Fuller, 2019). These types of risk management strategies may become more frequent due to uncertainties in variable weather conditions due to climate change (Aldunce et al., 2015; Birkmann and von Teichman, 2010). Loss of electricity presents an issue for FW infrastructure because large quantities of food will spoil in a short amount of time from residential, commercial, and industrial sources and will need managing. Developing an infrastructure network to be able to adapt to massive influxes of FW in addition to normal annual variability could be important for reducing human health risks associated with decomposing and putrescible waste (Luther, 2008; Rouse and Reed, 2013). Locating residential clusters and larger facilities that may generate large quantities of FW during disasters could be helpful for developing management plans. Additionally, anticipating these potential flows of FW may be important to development and operation of FW diversion infrastructure. Regional networks could be mandated to be able to absorb spikes in FW generation or reduce operating volumes ahead of anticipated disaster impacts. The research from this study could help anticipate and plan for influxes of FW from disaster related electrical outages rather than reacting after the disaster occurs.

This research focuses on NYS as a case study for these concepts; however, findings and conclusions are intended to be generally applicable outside of the NYS geography. At least in the U.S., publicly available databases of FW related information are becoming more available both at the national and state levels. These databases generally contain details on potential generators and rough approximations of FW generation, but provide a consistent starting point for evaluating FW management potential. The methods outlined in this dissertation have utilized these databases as foundational components to remain initially applicable to other regions. For instance, Colorado could begin to consider FW management statewide. It could apply the methods and findings from this research to develop an initial idea of variability in generation, transportation challenges, and potential for treatment technologies using basic and publicly available information. After initial evaluation of priorities and focus areas, more regionally specific data from additional studies could be included in the methods to enhanced outcomes and findings relevant to the state. These methods are also applicable outside of the U.S., as long as there is comparable data or estimates that can be obtained. However, data used should be as regionally specific as possible to produce relevant outcomes for developing networks for FW management.

While the focus of this research has been on a popular type of anaerobic digestion technology in western NY, this siting method could be applied beyond the technology and regional boundaries in this study. While wet anaerobic digestion produces a liquid slurry, processes such as dry anaerobic digestion and composting produce drier, soil like products. Instead of availability of farm fields as limiting, accessibility of compost markets, for instance, may be a more limiting factor. Different treatment technologies may be more useful in different regions and provide different material outputs that need to be managed. Eastern NY, for instance, contains fewer AD systems due to fewer dairy farms, thus composting FW may become more prolific. Another state or region may want to deploy different treatment technologies depending on their sources of FW and additional organic substrates available. Multiple technology types can integrate into these methods as long as FW inputs and subsequent outputs to/from these technologies are documented. Identifying these markets will take on a different approach than characterizing farm fields but considering the use of FW post-treatment in facility siting should still be included.

This research considered waste generation, transportation, and treatment, focusing on specific components from those research areas. Future research should strive to consider these components working together to present a more holistic interpretation of food waste management. The larger system perspective will allow for other work to explicitly characterize the social, economic, and environmental tradeoffs of the system. Chapter 5 outlined how useful insights from models using ecological inspiration could be gained. This can certainly be extended to identify how transportation systems might react to the food waste variability identified in Chapter 2 and how the process adjusts. Moreover, viewing the food waste system management from an ecological lens could provide additional insights for infrastructure buildout that accounts for food waste management in the context of learning agents and evolving food waste sources.

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APPENDIX A

Sample Calculations:
Equation 1

$$Theoretical\ Generation_i^c = Generation\ Activity_i^c * Generation\ Factor^c \quad (1)$$

Supermarket i Generation Activity: 120 employees
Supermarket Generation Factor: 1,360 kg/employee-year

$$\text{Theoretical Generation} = 120\ \text{Emp.} * 1{,}360\ {}^{\text{kg}}\!/\!{}_{\text{Emp.}\cdot\ \text{yr}} = 163{,}200\ {}^{\text{kg}}\!/\!{}_{\text{yr}}$$

Equation 2

$$Deviation_{iy}^m = \frac{Recorded\ Quantity_{iy}^m}{Average\ per\ Month_{iy}}\ i \in I, y \in Y, m \in M \quad (2)$$

Supermarket i Average Generation per Month (2015): 10,000 kg
Recorded Quantity in February (2015): 7,000kg
Recorded Quantity in September (2015): 14,000kg

$$\text{Deviation in February} = \frac{7{,}000\ \text{kg}}{10{,}000\ \text{kg}} = 0.7$$

$$\text{Deviation in September} = \frac{14{,}000\ \text{kg}}{10{,}000\ \text{kg}} = 1.4$$

Equation 3

$$Monthly\ Projection_i^{cm} = Anomaly^{cm}\frac{(Theoretical\ Generation_i^c)}{12}\ i \in I, c \in C, m \in M \quad (3)$$

Anomaly of Supermarket i for February = 0.78 (Geometric Mean of Deviations across years)
Theoretical Generation from Eq. 1 = 163.2 t/yr

$$\text{February Projection} = 0.78 * \frac{163.2\ {}^{\text{t}}\!/\!{}_{\text{yr}}}{12} = 10.6\ t$$

Table A1: Monthly food waste generation projections (metrics tons) for counties in New York State using the methodology in Section 2.6.

County	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Albany	941	981	1106	1043	968	986	907	940	1205	1142	1108	1134
Allegany	67	81	93	91	76	67	62	65	107	104	98	94
Bronx	1597	1473	1797	1590	1590	1618	1225	1285	1755	2005	1919	1943
Broome	384	391	461	421	392	411	359	377	504	478	462	481
Cattaraugus	140	129	166	139	136	159	127	135	179	166	161	178
Cayuga	176	170	196	177	174	189	165	171	205	198	194	205
Chautauqua	286	277	334	295	284	314	266	280	360	339	329	353
Chemung	217	207	236	215	214	228	200	206	241	241	236	247
Chenango	66	57	73	61	63	73	56	59	75	75	73	80
Clinton	210	216	230	226	216	208	196	199	237	244	238	234
Columbia	128	116	147	122	123	147	121	128	158	142	139	157
Cortland	107	112	133	122	111	115	102	108	150	138	133	138
Delaware	59	61	72	66	61	62	52	55	77	77	74	75
Dutchess	628	625	720	663	635	656	573	595	758	753	730	750
Erie	2049	1962	2357	2077	2027	2235	1889	1981	2506	2392	2327	2489
Essex	170	166	178	169	168	175	164	167	182	179	177	182
Franklin	197	192	208	197	196	203	188	191	212	211	208	214
Fulton	97	87	109	91	93	110	88	93	114	108	106	118
Genesee	128	125	147	132	128	137	118	123	156	151	147	154
Greene	195	188	203	191	192	203	188	191	206	203	201	209
Hamilton	13	12	13	12	12	13	12	12	14	13	13	14
Herkimer	82	77	96	82	81	89	71	75	101	100	96	103
Jefferson	297	280	321	290	292	315	274	283	328	326	320	337
Kings	2708	2437	3059	2640	2669	2785	2036	2152	2980	3402	3254	3338
Lewis	30	26	34	28	29	33	24	25	33	35	34	37
Livingston	150	154	172	163	154	154	141	145	183	180	175	177
Madison	126	134	159	146	131	134	118	125	179	167	160	165
Monroe	1751	1687	2051	1794	1734	1938	1637	1725	2217	2064	2006	2167
Montgomery	70	65	84	70	69	80	62	67	90	85	82	91
Nassau	2048	1891	2379	2031	2010	2234	1753	1860	2480	2479	2392	2562
New York	6043	6192	6610	6425	6159	6119	5818	5924	6891	6836	6697	6715
Niagara	324	303	372	323	319	353	287	302	389	383	371	397
Oneida	582	558	669	588	574	643	550	577	718	667	652	705
Onondaga	1049	1012	1244	1081	1040	1167	977	1033	1353	1254	1216	1317

Table A1 cont.

County	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Ontario	247	236	292	251	243	279	234	247	318	289	281	309
Orange	720	666	820	712	709	768	607	640	839	866	836	881
Orleans	134	126	142	129	131	142	127	130	144	141	140	147
Oswego	139	141	169	155	144	141	114	120	178	188	179	179
Otsego	147	155	179	167	152	157	143	150	199	184	178	184
Putnam	112	96	128	102	106	127	93	100	131	131	127	142
Queens	2457	2249	2784	2415	2420	2581	1987	2094	2792	3000	2887	3008
Rensselaer	258	261	320	285	264	280	233	248	352	336	322	338
Richmond	594	541	676	579	581	635	490	518	685	716	691	730
Rockland	504	467	572	500	497	531	417	439	579	611	589	614
Saratoga	451	426	518	451	443	496	414	436	550	522	509	549
Schenectady	287	267	340	286	280	326	263	280	368	340	330	365
Schoharie	58	59	71	64	59	62	54	57	78	73	70	74
Schuyler	53	50	56	52	52	56	51	52	57	56	55	58
Seneca	104	102	109	104	104	107	99	100	110	112	110	112
St Lawrence	291	304	351	326	300	309	279	291	387	362	350	361
Steuben	109	102	121	109	108	110	88	91	120	133	128	130
Suffolk	2310	2121	2657	2267	2258	2523	1991	2108	2760	2752	2662	2860
Sullivan	199	192	212	197	197	206	185	189	214	217	213	220
Tioga	62	53	70	57	59	70	52	56	72	71	69	77
Tompkins	260	308	342	339	287	264	258	270	397	367	350	343
Ulster	523	510	576	529	520	555	498	514	603	581	570	598
Warren	219	211	247	220	216	241	212	221	264	243	239	258
Washington	148	137	159	141	144	160	138	143	164	159	156	168
Wayne	107	94	119	100	103	116	89	94	118	124	120	129
Westchester	1772	1647	2018	1751	1740	1917	1549	1630	2091	2089	2025	2158
Wyoming	224	216	233	219	220	234	219	222	238	230	229	239
Yates	21	23	26	26	23	20	16	17	28	31	29	28

Table A2: Annual generation rate (metric tons) of facilities in each county extracted from the EPA Excess Food Opportunities Map

County	Correctional	Elementary schools	Hotels and Motels	Colleges, Universities	Supermarkets and Other Grocery	Other Commercial
Albany	2,652	715	1,992	1,823	5,017	314
Allegany	0	109	33	364	500	8
Bronx	3,553	4,242	200	1,484	9,315	1,130
Broome	7	438	1,162	754	2,694	107
Cattaraugus	0	207	135	119	1,331	41
Cayuga	779	166	192	109	953	33
Chautauqua	350	328	499	330	2,150	87
Chemung	1,011	226	331	93	996	57
Chenango	96	122	52	1	528	16
Clinton	1,456	178	237	277	464	52
Columbia	262	124	38	36	1,187	47
Cortland	35	110	189	282	849	17
Delaware	0	99	132	138	399	30
Dutchess	2,124	775	727	861	3,356	251
Erie	1,871	2,439	5,151	1,903	14,408	701
Essex	775	79	742	40	426	13
Franklin	1,465	125	190	59	564	28
Fulton	198	131	69	0	793	30
Genesee	214	150	287	143	806	58
Greene	1,150	98	581	0	537	11
Hamilton	0	7	96	0	49	2
Herkimer	0	148	121	86	673	27
Jefferson	983	304	844	69	1,390	90
Kings	1,145	7,715	1,731	2,066	18,108	3,001
Lewis	0	73	52	0	242	5
Livingston	817	143	67	250	670	14
Madison	87	153	98	373	1,012	36
Monroe	550	1,953	4,407	1,933	13,689	409
Montgomery	0	119	38	63	688	14
Nassau	134	3,902	2,587	1,797	16,656	1,286
New York	3,042	3,522	43,671	6,823	15,779	3,818
Niagara	0	504	842	255	2,380	171
Oneida	1,354	560	713	481	4,197	229
Onondaga	88	1,244	2,179	1,304	8,777	263

Table A2 cont.

County	Correctional	Elementary schools	Hotels and Motels	Colleges, Universities	Supermarkets and Other Grocery	Other Commercial
Ontario	44	258	525	246	2,130	49
Orange	1,047	1,405	827	560	5,063	229
Orleans	997	96	6	0	524	16
Oswego	0	315	222	349	949	30
Otsego	0	116	517	341	990	53
Putnam	0	244	20		1,095	49
Queens	1,573	5,621	3,393	1,856	16,739	1,751
Rensselaer	0	402	263	587	2,224	53
Richmond	358	1,269	809	394	4,396	303
Rockland	6	1,049	1,207	412	3,360	331
Saratoga	524	551	897	354	3,346	134
Schenectady	142	396	189	254	2,694	87
Schoharie	0	68	110	126	454	25
Schuyler	320	34	78	0	199	20
Seneca	787	71	143	25	240	8
St Lawrence	955	258	184	641	1,877	25
Steuben	0	243	436	102	582	26
Suffolk	0	4,156	3,974	1,643	18,258	1,436
Sullivan	809	176	715	60	730	26
Tioga	0	125	79	0	558	11
Tompkins	79	182	748	1,178	1,612	24
Ulster	1,359	395	1,935	335	2,451	132
Warren	0	146	1,116	138	1,354	53
Washington	897	133	5	0	781	22
Wayne	219	220	39	5	782	57
Westchester	1,769	2,939	3,067	1,242	12,656	883
Wyoming	2,011	80	5	0	614	18
Yates	0	60	31	77	111	13

Table A3: Number of commercial and institutional facilities in each county extracted from the EPA Excess Food Opportunities Map

County	Correctional	Elementary schools	Hotels and Motels	Colleges, Universities	Supermarkets and Other Grocery	Other Commercial
Albany	13	109	86	22	143	133
Allegany	0	25	7	3	19	10
Bronx	12	501	43	12	1140	513
Broome	1	58	44	6	64	73
Cattaraugus	1	52	13	4	21	31
Cayuga	3	34	15	3	21	23
Chautauqua	2	69	41	3	45	54
Chemung	3	33	16	3	23	35
Chenango	1	24	7	1	14	12
Clinton	2	34	26	4	25	30
Columbia	2	23	18	1	34	30
Cortland	1	22	13	1	13	20
Delaware	0	26	25	1	16	19
Dutchess	9	115	55	8	123	103
Erie	7	300	177	24	338	387
Essex	3	25	56	1	18	15
Franklin	7	25	28	1	24	16
Fulton	2	21	11	0	21	21
Genesee	1	28	21	3	18	20
Greene	3	18	56	0	17	13
Hamilton	0	6	22	0	6	1
Herkimer	0	27	19	2	25	19
Jefferson	4	44	57	2	39	27
Kings	11	890	139	51	2200	1312
Lewis	0	19	9	0	11	7
Livingston	2	25	12	1	15	20
Madison	1	29	8	3	15	20
Monroe	4	252	116	22	220	279
Montgomery	0	24	7	2	21	14
Nassau	4	441	129	29	648	730
New York	17	508	731	97	1173	939
Niagara	1	66	70	6	50	105
Oneida	5	82	55	9	84	90
Onondaga	4	152	95	16	198	187

Table A3 cont.

County	Correctional	Elementary schools	Hotels and Motels	Colleges, Universities	Supermarkets and Other Grocery	Other Commercial
Ontario	1	36	35	4	20	40
Orange	6	119	69	6	166	137
Orleans	3	15	3	0	11	17
Oswego	0	47	36	2	28	42
Otsego	0	28	43	3	20	16
Putnam	0	30	5	0	39	37
Queens	10	528	157	28	1463	933
Rensselaer	0	59	23	5	62	60
Richmond	4	116	22	5	246	233
Rockland	1	128	33	14	138	141
Saratoga	2	66	67	4	69	75
Schenectady	1	55	18	5	78	51
Schoharie	0	13	10	1	8	10
Schuyler	1	9	18	0	3	9
Seneca	2	21	12	1	7	12
St Lawrence	6	56	20	4	45	30
Steuben	0	47	36	3	34	35
Suffolk	4	419	208	14	646	716
Sullivan	3	28	35	3	45	14
Tioga	0	24	7	0	11	12
Tompkins	1	39	46	4	21	25
Ulster	5	65	66	3	79	82
Warren	0	22	123	3	28	23
Washington	5	27	4	0	26	15
Wayne	1	40	9	1	16	30
Westchester	7	356	92	25	609	432
Wyoming	4	17	4	0	15	14
Yates	0	27	9	1	13	18

Table A4: Normalized monthly food waste generation projections (metrics tons) per 1,000 people for counties in New York State using the methodology in Section 2.6 based on 2010 population.

County	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Albany	3.09	3.22	3.63	3.43	3.18	3.24	2.98	3.09	3.96	3.75	3.64	3.73
Allegany	1.38	1.65	1.89	1.86	1.54	1.36	1.26	1.33	2.18	2.12	2.00	1.92
Bronx	1.15	1.06	1.30	1.15	1.15	1.17	0.88	0.93	1.27	1.45	1.39	1.40
Broome	1.92	1.95	2.30	2.10	1.95	2.05	1.79	1.88	2.51	2.38	2.30	2.40
Cattaraugus	1.75	1.61	2.07	1.73	1.70	1.98	1.58	1.69	2.23	2.07	2.01	2.22
Cayuga	2.20	2.12	2.45	2.21	2.18	2.36	2.06	2.14	2.56	2.48	2.42	2.56
Chautauqua	2.12	2.05	2.48	2.18	2.11	2.33	1.97	2.08	2.67	2.51	2.44	2.61
Chemung	2.44	2.33	2.65	2.42	2.41	2.57	2.25	2.32	2.72	2.71	2.66	2.78
Chenango	1.30	1.14	1.45	1.20	1.24	1.44	1.11	1.17	1.48	1.48	1.44	1.58
Clinton	2.56	2.63	2.80	2.75	2.62	2.53	2.39	2.43	2.88	2.97	2.89	2.85
Columbia	2.02	1.85	2.32	1.94	1.94	2.33	1.92	2.03	2.51	2.25	2.20	2.49
Cortland	2.17	2.28	2.70	2.48	2.24	2.34	2.07	2.18	3.04	2.80	2.69	2.80
Delaware	1.24	1.27	1.50	1.38	1.28	1.28	1.09	1.14	1.61	1.61	1.54	1.57
Dutchess	2.11	2.10	2.42	2.23	2.13	2.20	1.93	2.00	2.55	2.53	2.45	2.52
Erie	2.23	2.13	2.56	2.26	2.21	2.43	2.06	2.16	2.73	2.60	2.53	2.71
Essex	4.31	4.21	4.52	4.29	4.28	4.45	4.17	4.24	4.61	4.54	4.50	4.63
Franklin	3.82	3.72	4.03	3.81	3.79	3.94	3.64	3.71	4.10	4.09	4.04	4.15
Fulton	1.75	1.56	1.97	1.64	1.67	1.98	1.59	1.68	2.05	1.94	1.90	2.12
Genesee	2.13	2.08	2.45	2.20	2.13	2.29	1.97	2.05	2.60	2.51	2.44	2.57
Greene	3.97	3.81	4.13	3.87	3.91	4.13	3.82	3.89	4.18	4.12	4.09	4.25
Hamilton	2.59	2.46	2.74	2.51	2.53	2.76	2.50	2.56	2.82	2.71	2.68	2.84
Herkimer	1.27	1.19	1.49	1.28	1.25	1.39	1.10	1.17	1.57	1.55	1.49	1.60
Jefferson	2.56	2.41	2.76	2.50	2.51	2.71	2.36	2.43	2.82	2.80	2.75	2.90
Kings	1.08	0.97	1.22	1.05	1.07	1.11	0.81	0.86	1.19	1.36	1.30	1.33
Lewis	1.11	0.95	1.24	1.02	1.06	1.21	0.88	0.94	1.23	1.31	1.26	1.36
Livingston	2.29	2.36	2.63	2.50	2.35	2.36	2.15	2.22	2.80	2.75	2.67	2.70
Madison	1.71	1.82	2.17	1.99	1.79	1.83	1.61	1.70	2.43	2.28	2.18	2.25
Monroe	2.35	2.27	2.76	2.41	2.33	2.60	2.20	2.32	2.98	2.77	2.70	2.91
Montgomery	1.40	1.29	1.67	1.39	1.37	1.59	1.24	1.33	1.79	1.69	1.63	1.80
Nassau	1.53	1.41	1.78	1.52	1.50	1.67	1.31	1.39	1.85	1.85	1.79	1.91
New York	3.81	3.90	4.17	4.05	3.88	3.86	3.67	3.74	4.35	4.31	4.22	4.23
Niagara	1.50	1.40	1.72	1.49	1.47	1.63	1.33	1.40	1.80	1.77	1.71	1.83
Oneida	2.48	2.37	2.85	2.50	2.44	2.74	2.34	2.46	3.06	2.84	2.77	3.00
Onondaga	2.25	2.17	2.66	2.32	2.23	2.50	2.09	2.21	2.90	2.68	2.60	2.82

Table A4 cont.

County	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Ontario	2.29	2.18	2.70	2.32	2.25	2.59	2.17	2.29	2.95	2.68	2.61	2.86
Orange	1.93	1.79	2.20	1.91	1.90	2.06	1.63	1.72	2.25	2.32	2.24	2.36
Orleans	3.12	2.95	3.30	3.02	3.05	3.31	2.96	3.03	3.36	3.30	3.26	3.44
Oswego	1.14	1.15	1.39	1.27	1.18	1.15	0.93	0.99	1.46	1.54	1.47	1.46
Otsego	2.37	2.49	2.88	2.67	2.45	2.53	2.30	2.40	3.20	2.96	2.86	2.96
Putnam	1.13	0.96	1.29	1.03	1.07	1.28	0.93	1.00	1.32	1.31	1.27	1.42
Queens	1.10	1.01	1.25	1.08	1.08	1.16	0.89	0.94	1.25	1.34	1.29	1.35
Rensselaer	1.62	1.64	2.01	1.79	1.65	1.76	1.46	1.55	2.21	2.10	2.02	2.12
Richmond	1.27	1.15	1.44	1.24	1.24	1.35	1.05	1.11	1.46	1.53	1.47	1.56
Rockland	1.62	1.50	1.83	1.60	1.60	1.70	1.34	1.41	1.86	1.96	1.89	1.97
Saratoga	2.05	1.94	2.36	2.05	2.02	2.26	1.89	1.98	2.51	2.38	2.32	2.50
Schenectady	1.86	1.73	2.20	1.85	1.81	2.11	1.70	1.81	2.38	2.20	2.13	2.36
Schoharie	1.76	1.80	2.15	1.94	1.80	1.90	1.65	1.74	2.38	2.23	2.14	2.25
Schuyler	2.90	2.75	3.06	2.81	2.84	3.07	2.76	2.83	3.12	3.05	3.02	3.18
Seneca	2.96	2.88	3.09	2.95	2.95	3.02	2.80	2.84	3.11	3.16	3.12	3.18
St Lawrence	2.60	2.71	3.13	2.91	2.68	2.76	2.49	2.60	3.45	3.24	3.13	3.23
Steuben	1.10	1.03	1.23	1.10	1.09	1.12	0.89	0.92	1.22	1.34	1.29	1.31
Suffolk	1.55	1.42	1.78	1.52	1.51	1.69	1.33	1.41	1.85	1.84	1.78	1.92
Sullivan	2.57	2.47	2.73	2.54	2.54	2.66	2.39	2.44	2.76	2.79	2.75	2.83
Tioga	1.21	1.04	1.37	1.11	1.15	1.36	1.02	1.09	1.40	1.40	1.35	1.50
Tompkins	2.56	3.04	3.37	3.34	2.82	2.60	2.54	2.65	3.91	3.62	3.45	3.38
Ulster	2.87	2.79	3.16	2.90	2.85	3.04	2.73	2.82	3.30	3.18	3.12	3.28
Warren	3.34	3.22	3.75	3.35	3.29	3.66	3.23	3.36	4.01	3.70	3.64	3.92
Washington	2.34	2.17	2.52	2.24	2.27	2.53	2.19	2.26	2.59	2.51	2.47	2.65
Wayne	1.14	1.00	1.26	1.06	1.10	1.24	0.95	1.00	1.26	1.32	1.28	1.38
Westchester	1.87	1.74	2.13	1.84	1.83	2.02	1.63	1.72	2.20	2.20	2.13	2.27
Wyoming	5.30	5.12	5.52	5.19	5.22	5.55	5.18	5.28	5.64	5.47	5.43	5.67
Yates	0.84	0.90	1.04	1.01	0.90	0.79	0.65	0.68	1.09	1.23	1.16	1.09

Table A5: 2010 population of New York State counties

County	2010 Population	County	2010 Population
Albany	304,204	Ontario	107,931
Allegany	48,946	Orange	372,813
Bronx	1,385,108	Orleans	42,883
Broome	200,600	Oswego	122,109
Cattaraugus	80,317	Otsego	62,259
Cayuga	80,026	Putnam	99,710
Chautauqua	134,905	Queens	2,230,722
Chemung	88,830	Rensselaer	159,429
Chenango	50,477	Richmond	468,730
Clinton	82,128	Rockland	311,687
Columbia	63,096	Saratoga	219,607
Cortland	49,336	Schenectady	154,727
Delaware	47,980	Schoharie	32,749
Dutchess	297,488	Schuyler	18,343
Erie	919,040	Seneca	35,251
Essex	39,370	St Lawrence	111,944
Franklin	51,599	Steuben	98,990
Fulton	55,531	Suffolk	1,493,350
Genesee	60,079	Sullivan	77,547
Greene	49,221	Tioga	51,125
Hamilton	4,836	Tompkins	101,564
Herkimer	64,519	Ulster	182,493
Jefferson	116,229	Warren	65,707
Kings	2,504,700	Washington	63,216
Lewis	27,087	Wayne	93,772
Livingston	65,393	Westchester	949,113
Madison	73,442	Wyoming	42,155
Monroe	744,344	Yates	25,348
Montgomery	50,219		
Nassau	1,339,532		
New York	1,585,873		
Niagara	216,469		
Oneida	234,878		
Onondaga	467,026		

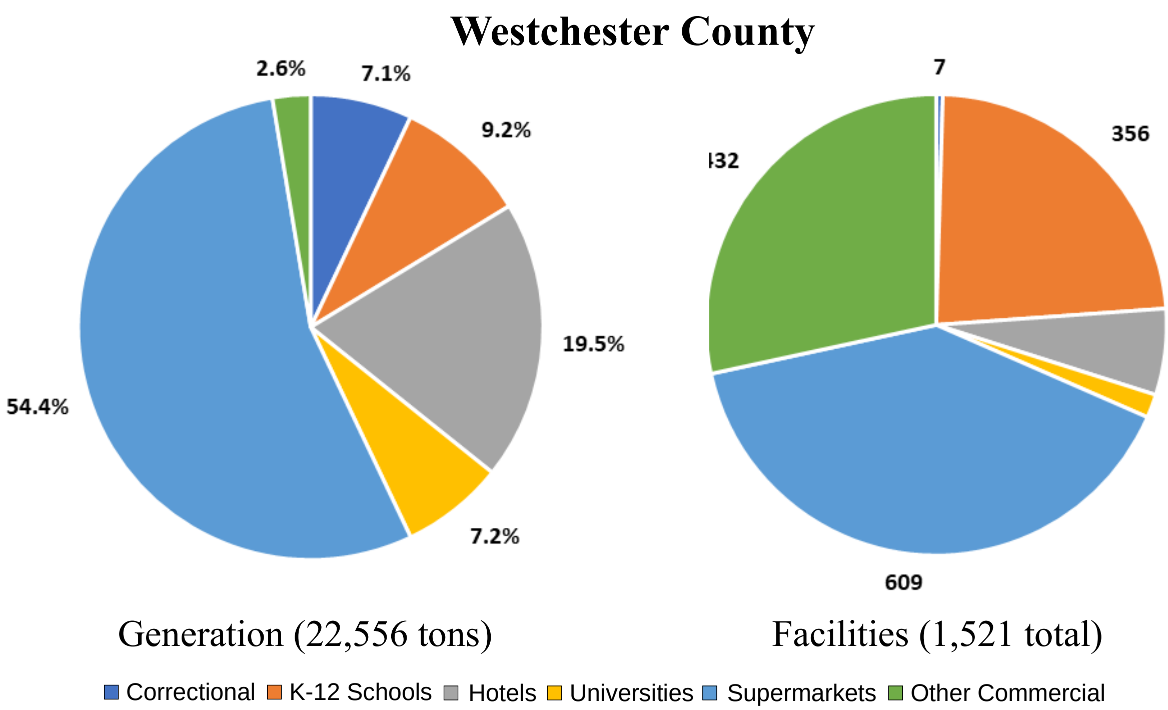

Figure A1: Annual FW generation rate and facility breakdown of Westchester County extracted from the EPA Excess Food Opportunities Map.

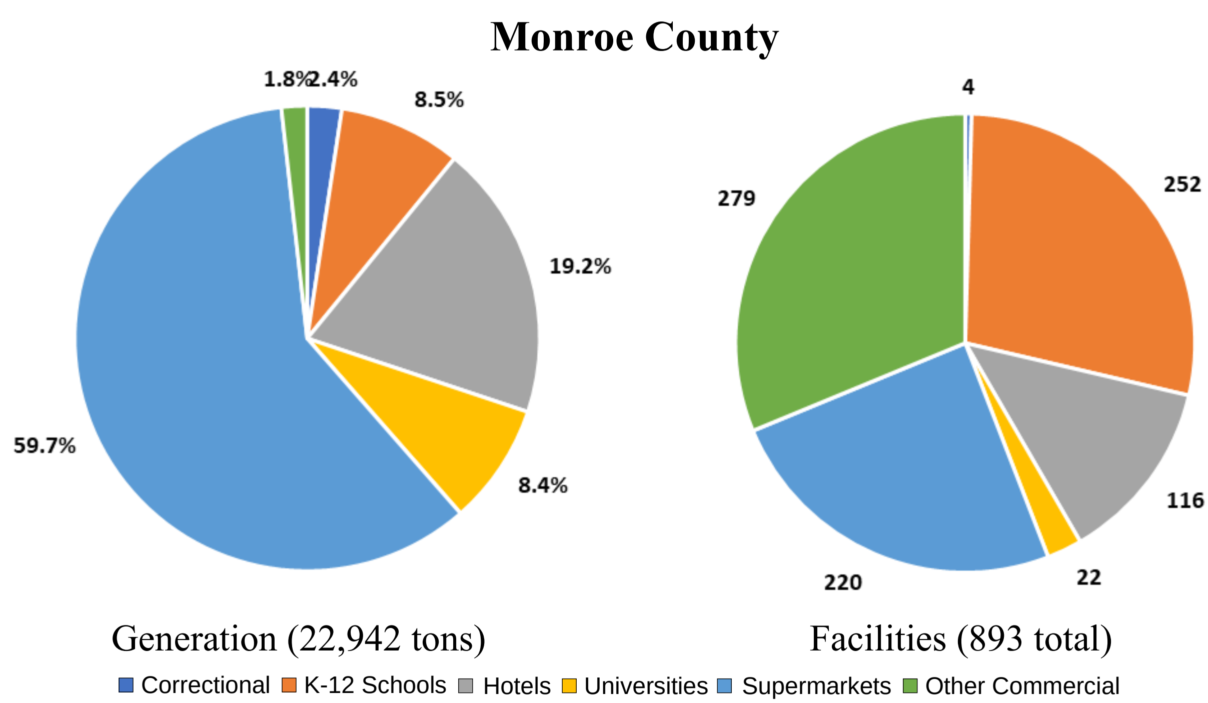

Figure A2: Annual FW generation rate and facility breakdown of Monroe County extracted from the EPA Excess Food Opportunities Map.

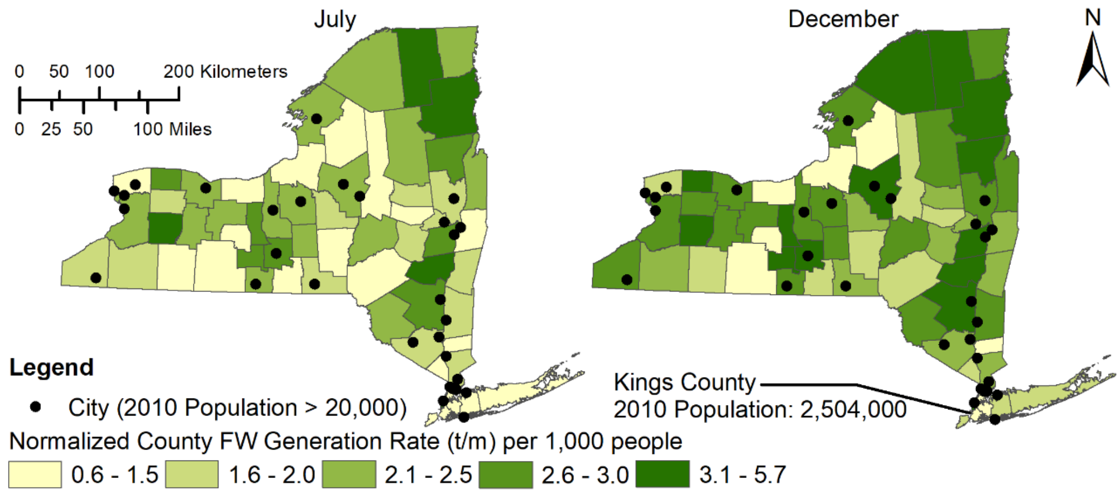

Figure A3: Monthly (m) anticipated FW generation of commercial facilities within each county (t) normalized per 1,000 people. Generation quantities were classified into five categories as described in Section 2.6. Cities containing populations over 20,000 people in 2010 are shown and Kings county, the most populous county, is identified.

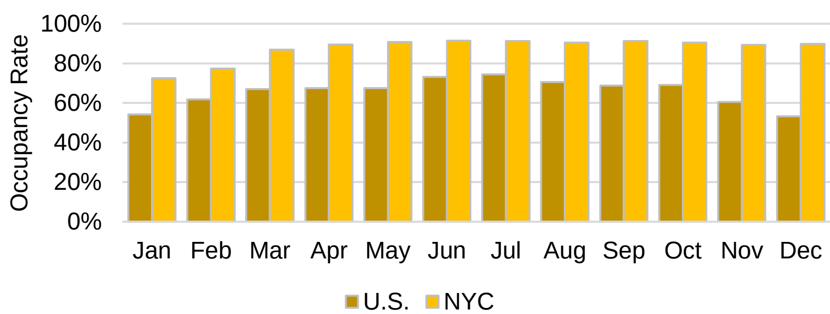

Figure A4: Average monthly hotel occupancy rates in the U.S. and New York City years 2015-2018.

APPENDIX B

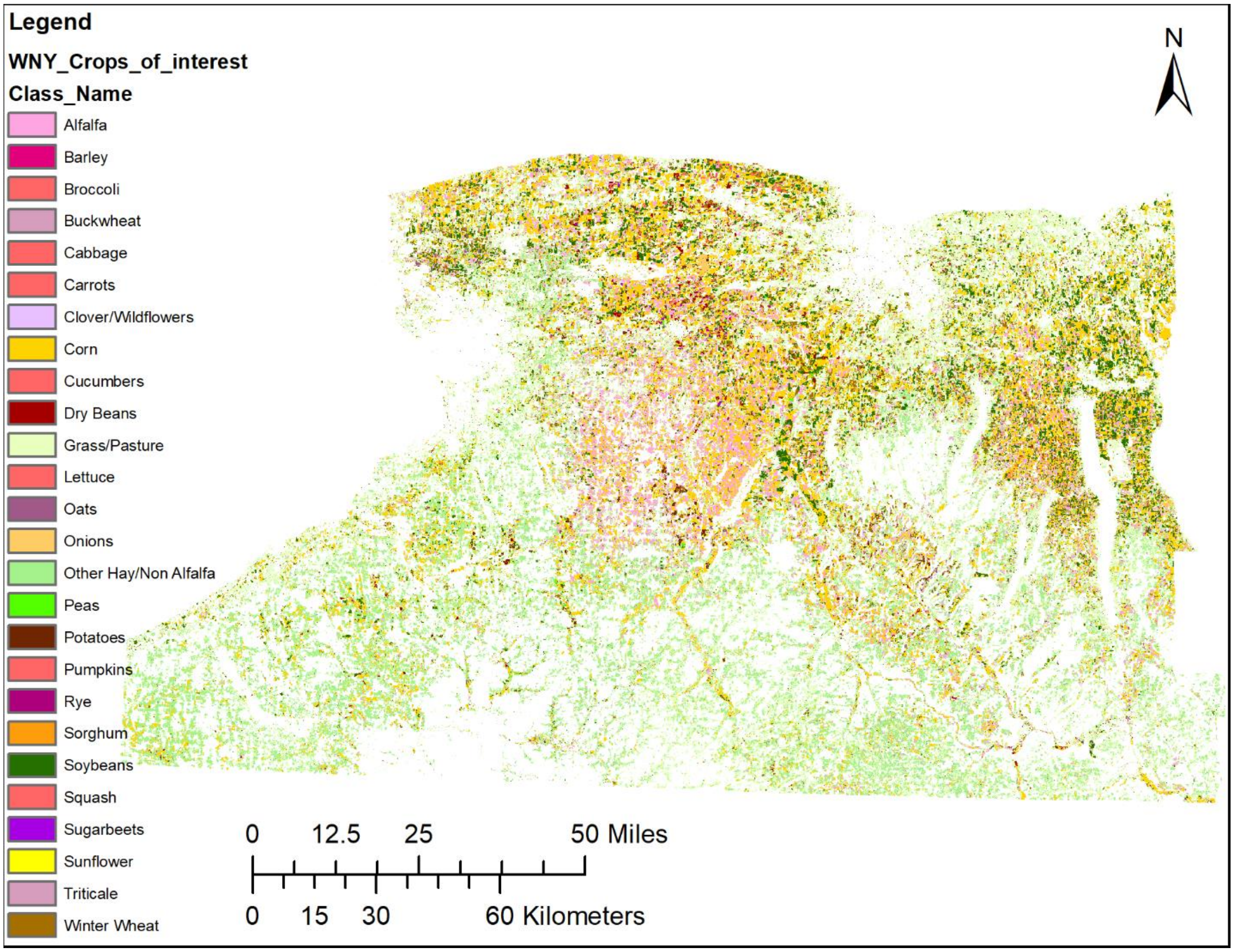

Figure B1: map of crop types in WNY

CLASS_NAME	Average yield range per acre	Unit (Imperial)	P2O5 Removal (lb/unit yield)	P Converted (kg/ha)	P Converted (kg/0.09ha)
Corn	180	bu	0.38	33.7	3.036
Grass/Pasture	2.75	ton	15	17.6	1.587
Other Hay/Non Alfalfa	4.25	ton	15	31.4	2.830
Alfalfa	6.05	ton	13	38.8	3.491
Soybeans	60	bu	0.8	23.7	2.131
Winter Wheat	70	bu	0.5	0.5	0.045
Dry Beans	25	cwt	1.2	14.8	1.332
Oats	75	bu	0.29	10.7	0.965
Potatoes	450	cwt	0.12	26.6	2.397
Clover/Wildflowers	3.75	ton	13	24.0	2.164
Cabbage	19	ton	1.6	15.0	1.349
Peas	3500	lb	0.0046	7.9	0.715
Onions	500	cwt	0.12	29.6	2.663
Triticale	3000	lb	0.011	16.3	1.465
Rye	42.5	bu	0.41	8.6	0.773
Sugarbeets	12.5	ton	1.3	8.0	0.721
Squash	14	ton	2.8	19.3	1.740
Cucumbers	7.5	ton	1.2	4.4	0.399
Carrots	25	ton	1.8	22.2	1.997
Barley	62.5	bu	0.4	12.3	1.110
Sorghum	75	bu	0.4	14.8	1.332
Buckwheat	1600	lb	0.013	10.3	0.923
Broccoli	5	ton	2	4.9	0.444
Lettuce	17.5	ton	2.3	19.9	1.787
Pumpkins	17.5	ton	2.9	25.0	2.253
Sunflower	2250	lb	0.012	13.3	1.198

Table B1: Crop phosphorus uptake rates

VALUE	CLASS_NAME	Count_30m	Area_ha
1	Corn	2913069	262176
176	Grass/Pasture	2762573	248632
37	Other Hay/Non Alfalfa	2328462	209562
36	Alfalfa	1578395	142056
5	Soybeans	1105179	99466
24	Winter Wheat	398249	35842
42	Dry Beans	125359	11282
28	Oats	60488	5444
43	Potatoes	41479	3733
58	Clover/Wildflowers	37363	3363
243	Cabbage	28719	2585
53	Peas	26368	2373
49	Onions	16513	1486
205	Triticale	11170	1005
27	Rye	10203	918
41	Sugarbeets	9656	869
222	Squash	8336	750
50	Cucumbers	8005	720
206	Carrots	3863	348
21	Barley	3216	289
4	Sorghum	3171	285
39	Buckwheat	3121	281
214	Broccoli	2609	235
227	Lettuce	1204	108
229	Pumpkins	946	85
6	Sunflower	935	84

Table B2: Crop types and quantities in WNY

Scenario	Dig Trans Distance (km)	Site (Extreme)	FW Supply (t/yr)	Manure Supply (t/yr)	P Avail (kg/yr)	P Capacity (kg/yr)	P Excess (kg/yr)
FW only	20	Max FW	33,100	--	47,300	640,800	-593,500
	20	Max Dig. Cap.	5,200	--	7,400	1,583,000	-1,575,600
Manure + FW	20	Max FW	33,100	134,100	133,200	640,800	-507,600
	20	Max Dig. Cap.	5,100	376,200	248,100	1,583,000	-1,334,900
FW only	10	Max FW	33,100	--	47,300	217,100	-169,800
	10	Max Dig. Cap.	5,200	--	7,400	526,000	-518,600
Manure + FW	10	Max FW	33,100	134,100	133,200	217,100	-83,900
	10	Max Dig. Cap.	5,100	328,900	217,800	526,000	-308,200

Table B3: Numeric comparison of extreme sites under considering uncertainty scenarios. FW = Food Waste, Dig = Digestate, Trans = Transportation, P = Phosphorus, Avail = Availability