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Variability in commercial and institutional food waste generation and implications for sustainable management systems

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ABSTRACT

Disposing food waste in landfills leads to significant greenhouse gas emissions and lost economic and environmental resources, motivating the need for alternative treatment processes to convert waste to energy and value-added products. Developing the networks and infrastructure required to make these processes economically viable depends on high quality information about the volume and characteristics of food waste requiring treatment. Traditionally, food waste generation estimates have come from limited empirical studies and theoretical tools that predict the volume of food waste that will result from different types and intensities of economic activity. Resulting estimations are quick and don't require extensive investment to collect, but only provide single, static snapshots of expected waste generation. In reality, however, food waste would vary depending on the season, geography, and type and magnitude of the waste generating activity. This study provides an analysis of this potential variability using empirical data from commercial and institutional food waste generators in New York State and a publicly available database of food waste estimates. Results show that 57 % of food waste generated within the region comes from only 4 % of commercial facilities. Moreover, statewide generation varies monthly by approximately 37 % and significantly across different regions due to concentrations of facility locations. Study findings underscore how policy or facility siting decisions based on a single, static food waste estimation may not capture the full complexity of food waste management. Future work can improve common estimation approaches and methods for collecting empirical data to support robust policy.

1. Introduction

The production and disposal of food waste (FW) along the food supply chain is a growing global concern. In the United States alone, food wasted in the past decade has been estimated between 49–89 million metric tons per year (Buzby et al., 2014; Conrad et al., 2018; ReFED, 2017). Most FW in the U.S. is disposed in landfills resulting in an estimated 115–160 MMT 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 (Vandermeersch et al., 2014; Zhang et al., 2014), but shifting to a new waste management approach will require new technology development, deployment, and adoption by FW generators.

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 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). Many empirical studies and policy analyses on FW management take a similar approach of estimating the theoretical amount of FW generation rather than collecting empirical data from FW generating facilities (Cascadia Consulting Group, 2015; Draper/Lennon Inc., 2002, 2001; Okazaki et al., 2008; Seven Generations Ahead, 2015). This estimation method is generally summarized as follows:

*Theoretical Generation = Generation Activity*Generation Factor*

The estimation takes into account specific activities within a company or organization that lead to food being wasted ("generation activity") and the relative amount of food wasted from each activity ("generation factor") (Draper/Lennon Inc., 2001). These parameters are specific to the type of FW generator. For instance, at a university, students enrolled (and likely consuming food on campus) are considered the generation activity and an empirically-derived mass of FW generated per student is considered the generation factor.

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The user-friendly nature of this estimation methodology is attractive because of its accessible formulation and data inputs; however, its broader use in FW policy or system design is limited due to lack of consideration for variability and system dynamism. FW generation is not static or homogenous. FW from supermarkets, for example, will differ based on infrastructure, supply chain decisions, and culturally mediated food preferences (Fernie, 1995). These differences will not be reflected by a single FW generation factor for all supermarkets. In addition, 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). Further, the variability in spatial concentration of FW has direct implication to the costs of collecting and transporting FW, which in turn can influence the adoption of the overall FW management system (Gold and Seuring, 2011). Generation from commercial sources such as supermarkets has been shown to vary seasonally in European case studies (Eriksson, 2012; Lebersorger and Schneider, 2014). FW generation from municipal sources has been shown to vary geographically at smaller regional scales (Breunig et al., 2017) and between 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 waste management operations literature has emphasized the importance of anticipating waste variation and uncertainty for system development such as siting of disposal and 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.

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 heterogeneity. Understanding the number and type of facilities within a state that contribute the most towards FW generation will help inform policy targets for diversion. Assessing how FW generation varies month to month can help haulers and recycling operators to anticipate changes in FW availability for collection and treatment systems. Finally, pinpointing where FW originates can also help centralize diversion operations and reduce management inefficiencies. While the case study presented here focuses on a single region (New York State), the modeling framework is suitably flexible due to its integration of empirical and publicly accessible data, enabling future studies 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.

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 94 t 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 (USEPA, 2018), which accounts for underlying activities that lead to wasted food using the method introduced in Section 1, formalized as Eq. (1) below.

$$\textit{Theoretical Generation}_i^c = \textit{Generation Activity}_i^c * \textit{Generation Factor}^c \quad (1)$$

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 1360 kg/yr/employee would be estimated to generate 68 t 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 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

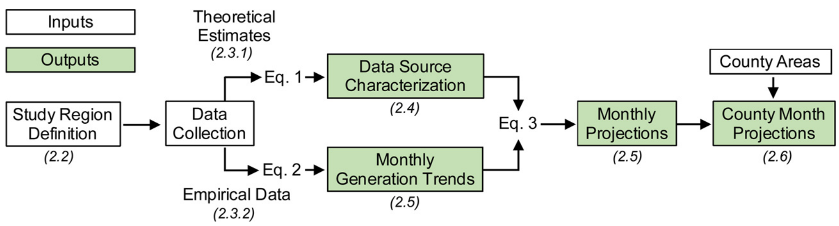

Fig. 1. Graphical representation of the variation analysis framework used in this study. Clear boxes represent information inputs and shaded boxes represent results. Black arrows indicate the study steps. Numbers in parentheses and italics relate to relevant sections where the methods are described further.

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.

2.4. Variability in FW generators

FW generation is expected to vary when looking across generators that have fundamentally different attributes, such as size, 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 94 t 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 94 t, 47 t, and 24 t 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.

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

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.

Table 1
FW generation at commercial and institutional facilities in NYS. The range in monthly FW generation, data years, and regional locations are presented. Data are generalized to ensure confidentiality of sources.

Facility type	Facility size	Diversion range (t/year)	Diversion range (t/month)	Data years	Location
Supermarkets					
Supermarket 1	450–750 employees	570–617	29.9–69.7	2015–2018	Western NY
Supermarket 2		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	840–880 students	9.0	0–1.5	2018	Western NY
School 2		4.8	0–0.8	2018	Western NY
Universities					
University 1	2,200–16,500 students	82–85	1.6–13.5	2014–2017	Western NY
University 2		136–146	2.3–20.9	2015–2018	Western NY
University 3		173–175	2.1–23.8	2015–2018	Central NY

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 (Eq. (3)). These projections account for the anomaly in FW trends according to generator category (c), month (m), and specific facility (i).

$$Monthly\ Projection_i^{c,m} = Anomaly^{c,m} \times (Activity_i^c \times Factor^c)/12\,, \forall i \in I,\ c \in C,\ m \in M \quad (3)$$

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 1000 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. Eqs. (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 also 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 or institutional sector, 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 (Fig. 2).

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 94 t/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

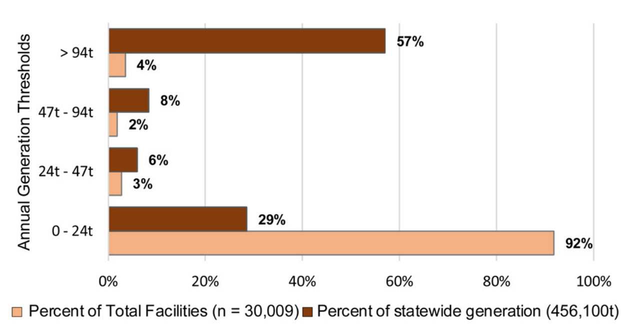

Fig. 2. Commercial and institutional FW generators in New York State, grouped by annual anticipated FW generation threshold (y-axis). Generation thresholds correspond to the amount of FW a commercial generator must produce to be covered under regulations in NYS and nearby states. The proportional amount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

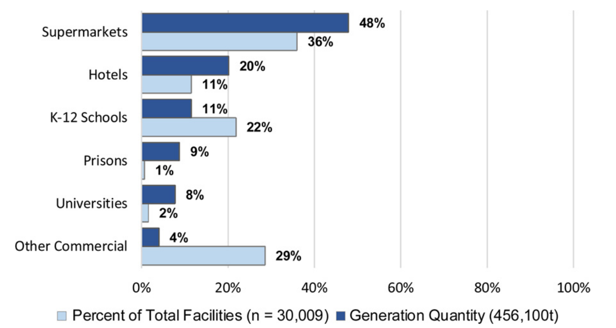

Fig. 3. Commercial and institutional generators in New York State, grouped by generator type (y-axis). The proportional amount of facilities of each type are compared to their mass contribution to total state-wide FW generation.

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.

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 94 t threshold but exempts hospitals and K-12 schools. Applying these legislative standards to the data predicts that 4 % (1070) of total facilities will be affected, which are responsible for 57 % (260,000 t) 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).

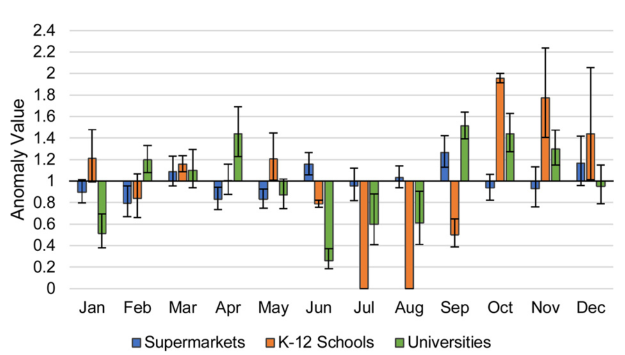

Fig. 4. Monthly variability in FW generation relative to the average generation. Monthly anomaly values are the geometric mean of monthly deviations calculated for each year. An anomaly value = 1 indicates that actual recorded FW generation in that month is equal to the estimated average generation per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

Supermarket FW trends are relatively consistent throughout the year, except for noticeably higher generation values during June, September, and December. The observed increases are likely due to a number of interacting factors, including buyer behavior, supply chain inefficiencies, 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 (Marsh and McLennan Companies, 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). 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 3.5). 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 completely 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.

The temporal variability results for the eight NYS generators for which real data were available (Fig. 4) were then combined with statewide 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.

Variability from educational institutions is expected to have the greatest impact on statewide generation estimates (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 %. On the other hand, supermarkets show more consistent month-to-month

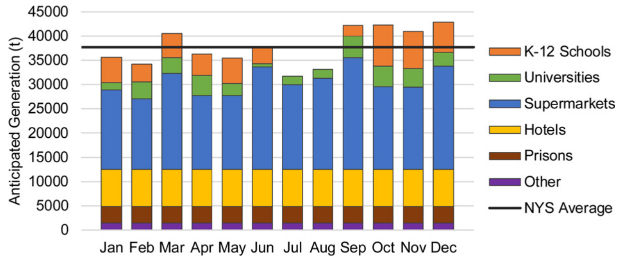

Fig. 5. Anticipated monthly estimates of NYS FW generation. Estimates combined empirically determined monthly variations for schools, universities, and supermarkets with facility type and size data from the EPA database. Monthly variation for hotels, prisons, and other commercial generators were not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

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 (32,000 t). But additive effects are seen in later months of the year, with the highest generation rate observed in December (43,000 t), 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.

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 in 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 are 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 efforts in nearby populous counties to reduce initial investments in transportation and hauling infrastructure, which may in turn translate into better overall economic performance of the waste management 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, Western NY contains two counties with approximately 10 times more total FW generation than counties immediately adjacent (Fig. 6). A diversion system designed for that region may not work effectively for the northern-most counties of the state where generation rates are anticipated to be lower and more uniform. By contrast, the southeastern area that includes New York City will require its own solutions to accommodate FW generation from the

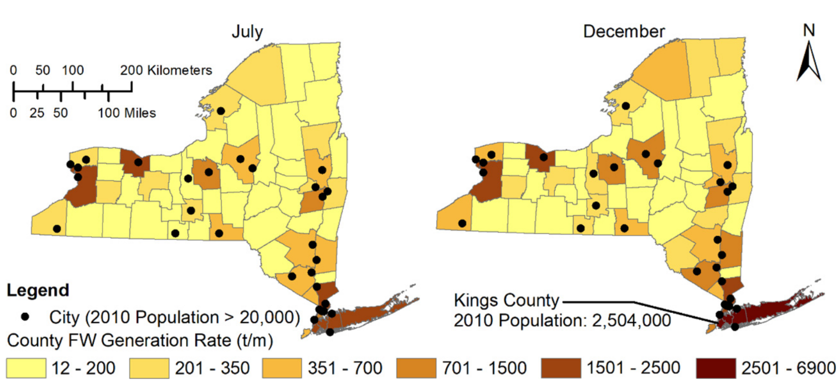

Fig. 6. Anticipated monthly FW generation from commercial and institutional facilities within each county were summed to show geospatial variation in tons per month (t/m). Darker colors correspond to higher FW generation intensity within a county. The maps also designate cities containing populations over 20,000 people and the most populous county in the state (Kings County).

city as well as the geographically constrained Long Island region. 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 FW amounts relative to the underlying generation activities in each area. For example, Monroe and Westchester Counties are both projected to generate about 22,000–23,000 t of FW annually (S.I. Table 2), but this total generation is spread across 70 % more facilities in Westchester county (S.I. Table 3). Similarly, a breakdown of generation by facility type shows that supermarkets are responsible for almost 60 % of FW in both counties. However, in Monroe County, this contribution is associated with only 220 supermarket facilities, whereas in Westchester country, the same amount is spread across 609 different facilities. Thus, the collection and diversion systems likely to be effective in each of these counties may be fundamentally different, to account for the relative differences in FW generation in more centralized or decentralized cases.

Spatial trends also show different patterns when normalized to population in each of the counties mapped (S.I. Fig. 3 and S.I. Table 4). 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 population-normalized values may add useful insight, such as determining how to distribute diversion costs across residents in a region or identifying successful model solutions coming from counties with similar demographics but lower per capita generation rates.

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

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.

3.5. 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 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 were only available for the whole U.S. (Statista, 2019) and New York City (NYS and Company, 2019) and the average occupancy rates per month from these data are shown in the supplemental information file (Fig. S2). Although slight trends towards increased occupancy during summer 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 that may be perceived negatively by customers.

4. Conclusions

This study shows that FW generation from commercial and institutional sources in New York State cannot be fully represented with a

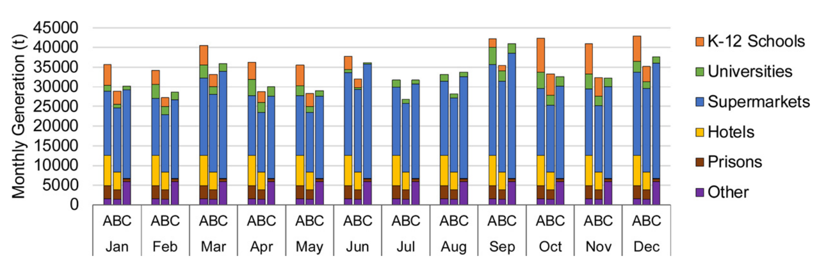

Fig. 7. Comparison of monthly generation projections from different data sources. (A): Baseline analysis using the EPA database. (B): Analysis using lower estimates in EPA database. (C): NYSP2I ORL. The ORL does not include K-12 schools in its database, therefore no projections were shown for that category.

single annual value. Capturing the endogenous spatial and temporal variability in this system is necessary for developing sustainable policy solutions and then deploying 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 currently covered under a regulation threshold of 94 t/year (2 U.S. tons/week). Of this total, supermarkets represent the greatest contribution (48 %) of facility types considered here. The seasonal variability in FW amount and spatial variability based on regional population density will greatly influence planning and site selection of treatment plants. Thus, large supermarkets will likely be the critical backbone for developing regional FW management systems, which in turn must be responsive to the expected variation in timing and amount of FW to be collected and treated from these stores. Moving forward towards more comprehensive diversion targets, these findings support extending diversion mandates to generators of at least 24 t/year to divert additional FW with only small disruption to the population of generators. Further, anticipating variability from other generators as they are included in policy mandates will be important to balance the network's resource flows and maintain a robust, sustainable management system.

Urban centers were demonstrated to be hotspots of commercial FW, from the perspective of having a high and relatively consistent degree of FW generation over time. Systems-level sources of variability point to potential challenges and opportunities for optimizing future siting of FW management infrastructure. For instance, incentivizing the development of treatment facilities near urban centers will reduce collection costs due to the concentration and proximity of FW resources to treatment centers. However, locating treatment facilities near population centers could make it less likely that rural generators will participate in collection programs due to prohibitive collection and hauling costs and policy exemptions for generators located farther than 25 miles from a recycling facility. Decentralizing treatment facility development could reach scattered FW sources, but inevitably smaller facilities may not benefit from the economies of scale associated with larger, centralized treatment sites. Alternatively, building transfer or drop-off stations in less populated areas can serve to concentrate FW in the local area for less expensive transport to main treatment locations. Such a strategy would benefit from extending policy to include such stations within distance-based compliance requirements. Furthermore, co-locating pre-treatment and storage with transfer stations to reduce FW degradation along the supply chain could help buffer against month-to-month FW variability and increase network-wide resilience. Regardless of management system design, future policy iterations should focus on incentivizing build-out and continuous improvement of treatment plants as the diversion network matures. These improvements would help to increase benefits and reduce costs, attracting more participants in FW diversion beyond those required by legislative mandate.

Future policy enhancements may also offer a pathway to solving FW data gaps discussed here. A requirement for companies and institutions 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 with an aim to improve network efficiency. 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.

CRediT authorship contribution statement

William R. Armington: Conceptualization, Methodology, Formal analysis, Writing - original draft. **Callie W. Babbitt:** Conceptualization, Writing - review & editing, Project administration, Funding acquisition. **Roger B. Chen:** Methodology, Writing - review & editing, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.resconrec.2019.104622.

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