Food Waste Geographies:
A GIS-based Spatial Analysis of Food Waste in Los Angeles County

By

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Abstract

In 2016, California passed Senate Bill (SB) 1383 which requires a 75% reduction in organic waste disposed of in landfills by 2025 as part of a larger mandate to reduce greenhouse gas (GHG) emissions in the state. These targets will be achieved primarily through diversion to compost and anaerobic digestion (AD), however significant infrastructural investments are needed to capture and treat this waste stream. Food waste (FW) is the largest portion of the municipal organics waste stream and is an ideal target for diversion to AD, which can be built as self-contained, scalable units deployed throughout urban areas. Using spatial models, an optimal network of ADs can be developed that not only reduces GHG emissions associated with FW disposal, but also reduces those associated with the collection and transportation stages of the waste system. Within this context, this research presents a novel method of estimating commercial FW generation in Los Angeles County, California that can be used to model a network of containerized ADs for FW.

Following a review of three classes of spatial models and their practical use in waste management modelling, a simulated "FW Geography" (FWG) dataset is developed that consists of 273,023 points representing FW generators from 16 industry groups that in total generate 1,046,713 tons FW/year. This dataset was developed using non-spatial waste generation data from California Department of Resources and Recovery (CalRecycle) in the form of Tons Per Employee Per Year (TPEPY) values as well as spatial, Census-tract level employment and business data from ESRI Business Analyst (BA) and parcel-scale land use data from the Southern California Association of Governments (SCAG). Significant preprocessing of the datasets was needed to match the production-oriented industry groups of the ESRI BA and SCAG data to the waste-oriented industry groups of the CalRecycle TPEPY values. The FWG is less spatially aggregated than the municipal level waste generation estimates released by CalRecycle and can be used as an input to spatial models to develop a network of ADs.

Using the FWG to develop a network of ADs requires careful consideration of the strengths and weaknesses of the spatial models, balancing model runtime with solution quality in real world instances.

The time it takes to run a model is dependent on the number of points in the input dataset; with over 200,000 points in the FWG, these models will take an unreasonable time to solve. This problem is addressed in the discussion, which outlines methods of data aggregation that not only reduces the size of the FWG, but also increases its accuracy. These methods make use of a Tons Per Business Per Year (TPBPY) value developed for this study which captures the competing modelling goals of maximizing FW treatment while minimizing collection points and the Vehicle Miles Travelled (VMT) between them. The fine spatial scale of the SCAG zoning dataset can also be leveraged to reduce the size of the FWG; by aggregating FW generator points in close proximity to one another, modelling shared collection bins among FW producers, the spatial accuracy of the FWG can be increased. The resulting FWG can be used to develop a network of containerized ADs for FW that reduces overall GHG emissions of the waste management system and creates a circular economy of food.

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Introduction

In 2016, California enacted Senate Bill (SB) 1383, one of the most comprehensive climate pollutant mitigation policies to date which established emissions reduction targets for methane and other short lived climate pollutants. One of the largest contributors of statewide greenhouse gas (GHG) emissions is the waste management sector, with emissions from the decomposition of organic matter in landfills alone accounting for 20.2% of total methane (CH_4) emissions (148.0 MMT CO_2-eq.) in 2014 (EPA 2016). Seeking to reduce these emissions through aggressive waste management policy, SB1383 mandates a 50% reduction from 2014 levels in organic waste in landfills by 2020 and a 75% reduction of disposed organic waste by 2025. These disposal reduction targets will be achieved primarily through diverting waste to compost or anaerobic digestion (AD) facilities; however, SB1383 also mandates a 20% increase in donations of edible food which would otherwise be thrown away to address larger concerns of rising food insecurity and economic inequality in the state. This method of food waste (FW) reduction and prevention of FW generation at the source also reduces GHG emissions associated with upstream processes such as food production, processing, and transportation (Papargyropoulou et al. 2014). However, due to the materiality of food (i.e., short temporality and inedible materials), as well as cultural factors influencing edibility and food safety requirements, a large amount of food ultimately ends up disposed as municipal solid waste (MSW), with nonmeat-not donatable FW, the single most prevalent material class in California's MSW stream, making up 9.5% of the waste disposed of in California's landfills alone (CalRecycle 2020).

Diverting this waste stream from landfills at scale under SB1383 is expected to significantly reduce GHG emissions; however, California's current organic waste treatment infrastructure is limited in capacity to treat the diverted material. California currently has an estimated organics treatment capacity of 4 million tons, far less than the 12 to 14 million tons to be diverted under SB1383 (CalRecycle 2019). While compost facilities are the primary method of organic waste management, AD is increasingly being used as an alternative treatment option. However, local capacity for FW treatment through AD is insufficient in 60% of counties in at least part of the year (Breunig et al. 2017). The lack of local capacity for organic waste treatment leaves municipalities who must comply with SB1383 to bear the economic burden of transporting this waste elsewhere or building new facilities. Limited statewide capacity will likely increase market pressure for organic waste treatment, potentially increasing per ton disposal fees at existing facilities. Meanwhile, transportation to out of state facilities is subject to high transportation costs and increases GHG emissions associated with the organic waste system. SB1383, therefore, requires the construction of new organic waste infrastructure to increase local capacity for waste treatment. By designing this system explicitly to minimize hauling burdens, this system can simultaneously reduce the environmental impact (i.e., fossil fuel use and GHG emissions) as well as the potential health impacts (i.e., air pollution) associated with transportation of FW for treatment.

Increased local capacity for organic waste treatment is likely to come in the form of composting or AD facilities, both of which have specific strengths and weaknesses that must be considered before adoption. Inedible FW, the largest category of FW quantified by CalRecycle (CalRecycle 2020), is well suited for use as an input for AD given its high moisture content and readily available sugars which are broken down using microorganisms that convert FW into biogas and a nutrient-rich digestate (Pace et al. 2018). This biogas can be cleaned and used onsite as a renewable source of electricity and heat or compressed into fuel for natural gas vehicles. The nutrient-rich digestate produced by AD systems can be used as fertilizer and, like compost, can have other beneficial effects on soil quality (Garcia-Gil et al. 2004; Ryals et al. 2014; Fernández-Bayo et al. 2017, 2018). While both provide materials that can be used as soil amendments, the composting process requires constant aeration through mechanical turning or forced aeration, which uses energy and adds GHG emissions to those emitted from the decomposition of the FW itself (Pace et al. 2018). AD, however, captures this biogas to produce enough energy to heat and power itself as well as export energy. AD, therefore, represents an important potential investment into sustainable waste management infrastructure in response to SB1383, not only in producing renewable energy and reducing GHG emissions, but also advancing the principles of the circular economy by recycling digestate for use as fertilizer in the food supply chain (FSC).

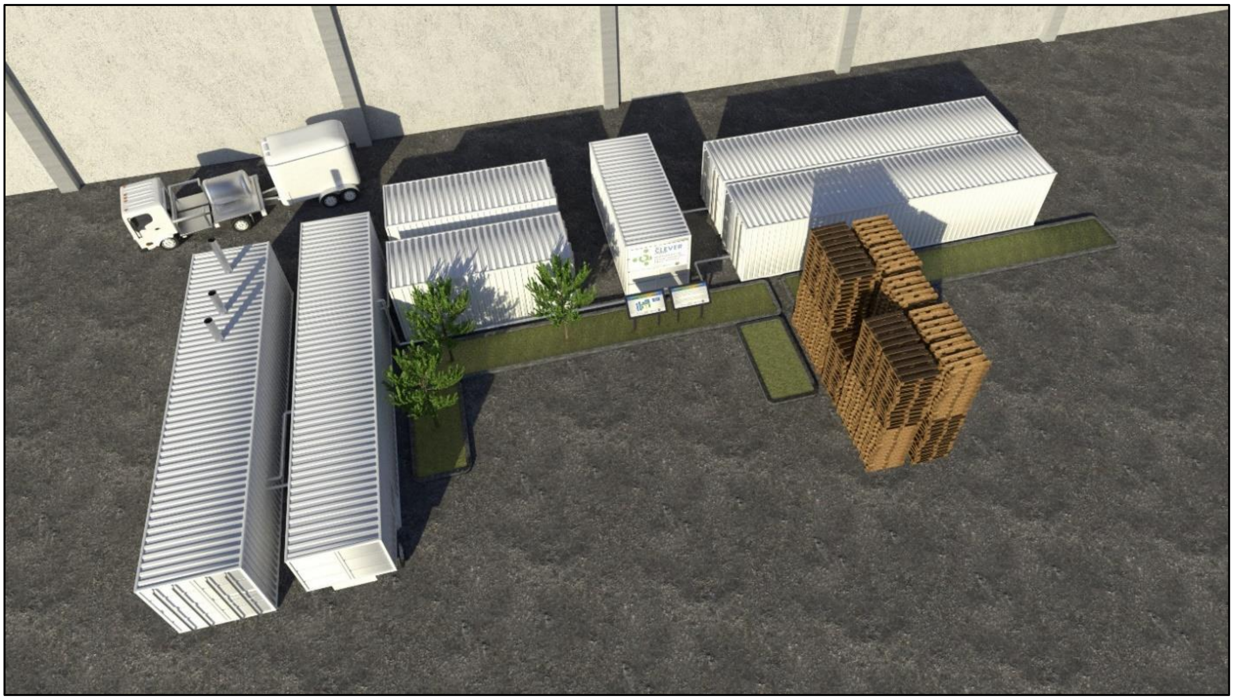

Figure 1. *Proposed layout of a small-scale, containerized anaerobic digestion facility. Rendering by Christopher W. Simmons. From Spang Lab (Spang Lab 2020)*

The question becomes what will this new system look like? The "blank-slate" landscape for developing waste infrastructure provided by SB1383 offers a rare opportunity to rethink typical waste infrastructure and challenge the idea that waste must be hidden away or otherwise dealt with far from the public. Unlike compost systems, which are generally large and often located away from urban areas, ADs can be built and efficiently operated at a range of scales including closed, containerized systems that can be placed within urban areas **(Figure 1)**. As both large- and small-scale AD systems achieve similar GHG reductions from landfill diversion of FW, the question of appropriate scale and location therefore comes down to GHG emissions associated with the collection and transportation of FW from the point of generation to the AD facility **(Figure 2)**. Large, centralized facilities can treat FW from more FW generators at once; however, due to limited space within urban areas they may need to be sited further from the point of FW generation, potentially increasing costs of transportation. The flexibility of ADs in size/scale enables the option to deploy a decentralized network of small-scale ADs throughout urban areas to minimize the distance required to transport this waste to larger, centralized facilities. Life Cycle

Analysis (LCA) in conjunction with a Geographic Information System (GIS) can be used to model both systems and determine the economic and environmental trade-offs between costs of facility construction, GHG emissions from collection and hauling, and GHG reductions between the two systems to assist with planning waste infrastructure.

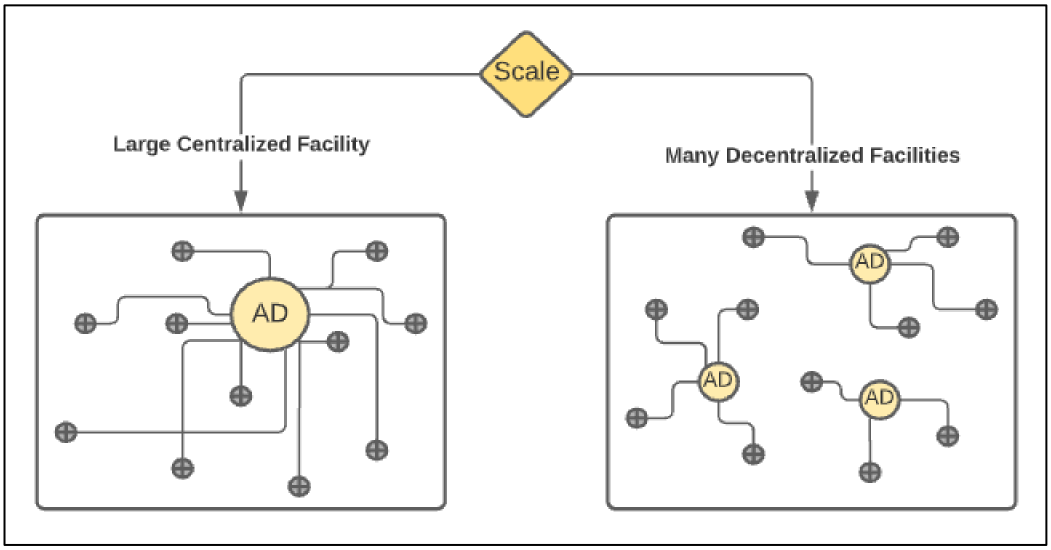

Figure 2. *Centralized vs Decentralized anaerobic digestion facilities. Assuming both systems divert equal volume of food waste from landfills, the majority of the remaining GHG emissions are from the collection and transportation phases of the waste system.*

In order to place these small-scale ADs near the point of FW generation, analyses need prior knowledge of where FW is produced. Contrary to the linear production-consumption-disposal model of the economy commonly found in the literature, FW is produced at all points within the FSC, which can stretch across large distances and consists of production, transportation, processing, retail, and final consumption phases. As part of this capital-intensive industrial FSC, FW can be considered a modern waste and can therefore be identified by its tonnage, toxicity, heterogeneity, and externalization (MacBride 2011; Liboiron 2013). The dichotomy of edible and inedible food, often used to characterize FW (Spang et al. 2019) can be categorized along the toxicity and heterogeneity dimensions of modern waste. The short-lived materiality of food means it can easily spoil and become FW unsafe for consumption (i.e., toxic), while some parts such as shells, peels, and bones were never edible in the first place (i.e., heterogenous). FW is also often characterized by its final disposal destination or by the stage of the FSC it drops out of, with distinctions made between food *loss* during production, harvest, and processing stages and food *waste* at the retail and consumer sectors of the FSC (Papargyropoulou et al. 2014; Spang et al. 2019) These distinctions are both ways that FW is externalized, either by externalizing to actors further down the FSC or through physical externalization by sending the FW elsewhere for disposal or treatment. The externalization dimension is the most important aspect of this study, as the primary data source is CalRecycle's Generator-Based Waste Characterization Study, which estimates and classifies FW from commercial businesses in the FSC and makes FW visible at the point of disposal. In order to address the issue of FW tonnage as mandated by SB1383, this externalization of FW must be understood as a spatial phenomenon where food becomes waste at discrete point sources (commercial businesses engaged in the FSC), which must be collected, transported, and treated as part of the waste management chain.

The purpose of this study is to develop an understanding of the spatial arrangement of FW generating nodes within the FSC. The chosen study area is Los Angeles County, the largest FW generating county in the state, representing 28.1% of the total statewide FW (CalRecycle 2020). Data from the 2014 CalRecycle Generator-Based Waste Characterization (WCS) study can be used for this; however, the purpose of the WCS is simply to measure and categorize waste within these municipalities without regard to the location of FW generation within the municipality itself (CalRecycle 2015). Therefore, after a brief review of models that can be used to plan waste infrastructure, this study outlines a novel method of combining CalRecycle WCS data with tract-level employment/industry datasets to develop a simulated "FW geography" (FWG). This dataset consists of clustered points representing FW generators which can be used to model an AD waste management network for FW. The results section compares this new FWG to waste generation data released by CalRecycle and highlights specific industries that are well suited to target for FW capture and treatment. Finally, considerations for modifying the FWG for use with spatial models to plan the AD network are discussed before concluding with considerations for implementing this network of ADs in the real world.

Literature Review: Fundamental Basic Models

The ultimate goal of SB1383 is to reduce greenhouse gas (GHG) emissions in the state; a large portion of these reductions will be accomplished through diversion of organic waste from landfills. This study specifically focuses on FW, the largest fraction of the municipal organics waste stream, from non-residential sources. The FW supply chain is composed of four general system components: (i) waste generation at food related businesses which is consolidated into single specified collection points, (ii) collection and transportation of waste in collection trucks, (iii) pretreatment and/or storage of the waste, and (iv) final disposal/treatment (Iakovou et al. 2010). This waste supply chain can be represented as points or nodes along a road network that is represented by connecting arcs. The collection and transportation stages can make up 60-80% of the costs of the FW supply chain as a whole (Karadimas et al. 2008), but there may be opportunities to reshape collection and transportation networks of the FW supply chain by optimizing the scale and location of treatment sites. Designing the system to lower the Vehicle Miles Travelled (VMT) of the waste system, which encompasses the total distance traveled by all trucks in a fleet for the collection and transportation of waste from the point of generation (discard) to the point of final disposal during a given time period, can result in environmentally and economically favorable outcomes.

The proposed infrastructure in this study is AD, which not only reduces GHGs through landfill diversion, but also produces biogas in self-supporting quantities, minimizing the need for external energy inputs. Containerized ADs are self-contained systems that can be built at a range of scales depending on local FW treatment needs. A decentralized network of ADs may be deployed within urban areas, potentially reducing overall VMT by locating them as close to the point of FW generation as possible. The VMT, and associated GHG emissions, of the waste management system for a municipality is dependent on the specific set of locations of waste generation, the AD locations that receives the waste, and the routes that collection trucks travel on the road network between the two. These factors can be optimized using GIS, such as the ESRI ArcMap Network Analyst, to help determine the optimal size/scale of the new FW recycling infrastructure required to implement SB1383.

The spatial models utilized by the waste sector generally fall under one of three fundamental classes of models: routing, location allocation, and clustering models. These spatial models can be formulated as either node-based (Hamiltonian) or arc-based (Eulerian) problems and can be differentiated by which aspects of the waste chain they hold fixed, and which they attempt to manipulate/optimize for. Developing a system of ADs for FW requires the relative strengths and weaknesses of each class of models to be considered in their ability to reduce VMT. The general goals of each type of model as well as their strengths and weaknesses are shown in **Table 1**. This literature review will survey the three general classes of models, briefly detailing their goals and function as well as their practical application to different parts of the FW supply chain. Representative examples of basic models in each class are given and general methods for solving the models are summarized at the end of this literature review.

Table 1. *General classes of spatial models to optimize waste systems.*

<table>
<tr><th>Model Class</th><th>Waste Chain Component</th><th>Strengths/Weaknesses</th><th>Use in Waste Modeling</th></tr>
<tr><td rowspan="2">Routing
• Shortest Route
• Travelling Salesman
• Postman
• Vehicle Routing</td><td rowspan="2">Collection Route</td><td>Strengths: Easily manipulatable WSC component; Truck operating costs and labor large part of budget</td><td rowspan="2">Manipulate collection and transportation stages to reduce VMT. Reduces GHGs, labor costs</td></tr>
<tr><td>Weaknesses: Limits to possible VMT reductions (cannot change road network for more direct routes)</td></tr>
<tr><td rowspan="2">Location-Allocation
• P-median
• Location Set
• Maximum Covering
• Capacitated Covering</td><td rowspan="2">Facility Location</td><td>Strengths: Locates new facilities to reach capacity necessary for SB1383</td><td rowspan="2">Find optimal locations for new facilities considering location of current facilities and demand points which reduces VMT</td></tr>
<tr><td>Weaknesses: Limitations to site availability & demand coverage</td></tr>
<tr><td rowspan="2">Clustering
• K-means
• Hierarchical</td><td rowspan="2">Waste Generation</td><td>Strengths: Unsupervised method requires little knowledge of data beforehand</td><td rowspan="2">Determine "natural clusters" of FW generators
Can be used to inform potential site selection</td></tr>
<tr><td>Weaknesses: Potential facility sites may not be available near identified clusters</td></tr>
</table>

Routing Models

In the waste management system, waste collection is contracted to different companies who must compete with one another to offer collection services at the lowest price. The significant portion of these costs are labor costs and vehicle operating costs that increase on a per mile basis; therefore, companies are incentivized to reduce non-productive travel time between collection points to minimize VMT (and associated GHG emissions). Given that the locations of waste facilities are generally fixed due to high capital costs of construction and land use limitations, the remaining factor that can be manipulated to reduce VMT is the collection route. Routing models manipulate the specific combination of arcs between the nodes of a network that forms a circuit (i.e., the collection route) and can be formulated as both Eulerian and Hamiltonian problems. As shown in **Figure 3,** these models can be applied to develop waste collection routes depending on the specific transportation needs of the three major waste sectors. This section will outline the basic mathematical problems underlying many commercial vehicle routing problems, starting with the shortest path problem, then the related postman's and travelling salesman's problems, before focusing on vehicle routing models specific to waste transportation.

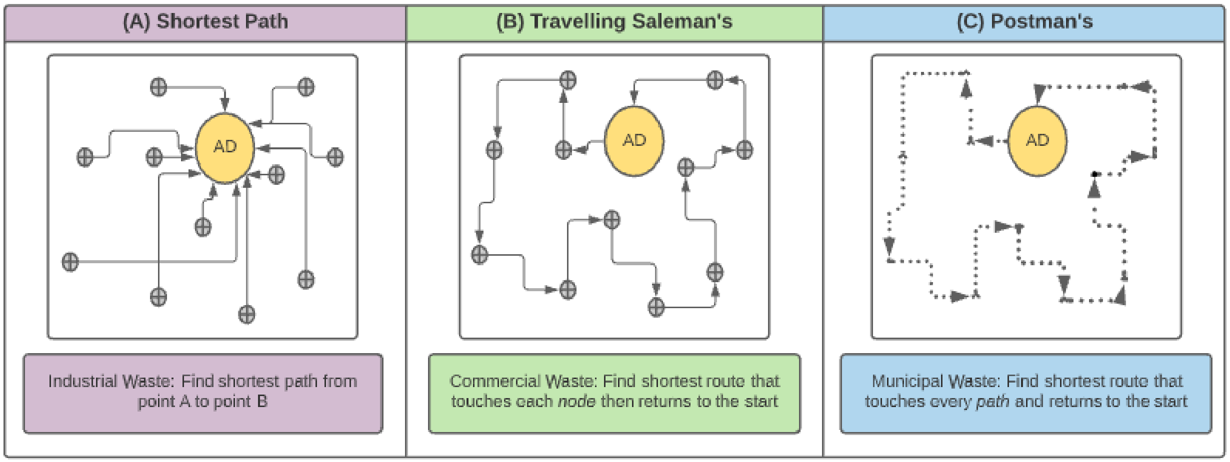

Figure 3. *Routing models for waste collection and transportation.* ***(A)*** *shortest path problem for industrial waste,* ***(B)*** *travelling salesman's problem for commercial waste, and* ***(C)*** *postman's problems for municipal waste.*

Shortest Path Problem

Fundamental to the development of complex path algorithms is the shortest path problem, shown in **Figure 3(A)**, which is used to determine the shortest path along a network from point A to point B. On a simple graph, this problem is found by devising the route with the fewest arcs; however, it becomes more complex in real problem instances where the network must be weighted to account for transportation distances and travel costs. The origins of the shortest path problem are unknown; however, it was first formulated as an optimization model by separately by Orden (Orden 1956) and Dantzig (Dantzig 1957) using linear programming. The shortest path problem is most applicable to industrial waste management, where large quantities of wastes are transported directly from the site of production to the disposal facility. Industrial waste is produced in quantities too large to be picked up in a collection route with multiple stops; therefore, each node of production must have a path directly to the disposal facility. Finding the shortest direct route between each site of production and each disposal facility creates an Origin-Destination (OD) cost matrix which can be used in decision-making to reduce overall costs and

GHG emissions of the system as a whole. The shortest path problem is fundamental to other path-based models, as many solutions to these problems use the OD cost matrix as an input to the model (Cook et al. 1998).

Travelling Salesman's Problem

Expanding on the single path node-to-node trip is the Hamiltonian path which, as shown in **Figure 3(B)**, connects all nodes in a network and returns to the starting node in the shortest, or least cost, possible path (Cook et al. 1998). This basic rule is commonly known as the Travelling Salesman's Problem (TSP), based on a scenario in which a travelling salesman must find the shortest route from his home city to each of a given group of cities, and then return home to the original starting point. The linear programming solution to the TSP was first described by Dantzig, Fulkerson, and Johnson in 1954 and many other optimization problems can be formulated as a TSP problem, making it useful for a variety of industries (Dantzig, Fulkerson, and Johnson 1954). Commercial waste management involves collecting waste from strip malls, restaurants, and other small buildings. Routes consist of 60-400 customers who dispose of their waste in large, shared bins that are periodically picked up by trucks with several trips to the dump site each day (Han and Cueto 2015). This arrangement suits itself to node-based modelling and TSP is commonly used to model commercial waste collection, modelling a collection truck leaving the dump, visiting every business to collect its waste, then returning to the dump. Further refinements to the problem have expanded the original problem statement, incorporating additional rules for other situations such as limited truck/labor capacity, time window constraints, and optimizing pickup scheduling.

Postman's Problem

The Eulerian, or arc-based, version of the TSP is often called the postman's problem, where a postman must devise a route to deliver mail to every house on all streets then return home. While mail must be delivered to each house, which could be considered a node, since the postman must travel every street regardless of the actual distribution of houses along the street, this situation can be considered an arc-routing problem for efficient computation. As shown in **Figure 3(C)**, the goal of the postman's problem is to find the shortest (least-cost) route that touches all arcs in a network, then returns home. This was first formulated as a linear programming model by Mei-Ko Kwan in 1960 and translated to English in 1962 (Han and Cueto 2015). The postman's problem is most often used to model municipal solid waste (MSW) collection as municipal routes generally service much larger numbers of customers, routes vary from 150 to 1,300 homes (Han and Cueto 2015). While each home could be considered a specific node, this situation is more suited to arc-based models because, the collection truck must traverse the entire street regardless of the specific position of the collection bins along it. Modelling residential MSW collection as an arc-based problem also greatly reduces computation time when compared to a node-based solution as it eliminates the need to model collection for each customer by grouping them into a whole street or block. As with the TSP, the Postman's problem can be modified to include capacity constraints, time windows for collection, and varying population densities.

Vehicle Routing Problem

An integrated waste collection system, which utilizes multiple trucks in a fleet, various dump sites located throughout the municipality, and differing transportation requirements for differing types of waste requires a more complex problem formulation called the Vehicle Routing Problem (VRP). As a widely used problem in transportation studies and waste management, the goal of the VRP is to determine the optimal routes used by a given fleet of vehicles initially located at a waste facility that will collect waste from a specified set of customers and return to the facility. First proposed by Dantzig and Ramserl (Dantzig and Ramser 1959) as a Hamiltonian/node-based problem, the VRP can also be formulated as a Eulerian problem for MSW collection. The VRP is widely used in supply chain management, and a number of models have been developed specifically for waste management. One such model is WasteRoute, designed for Waste Management Inc (WM) in 2002 after a series of business acquisitions left the company with many overlapping and inefficient waste collection routes. Utilizing the VRP in a web-based GIS, WasteRoute helped redesign the decentralized collection routes into regional, centralized collection sectors by eliminating 984 inefficient collection routes. With operating costs as high as $120,000 per vehicle per year, mostly due to labor and vehicle expenses, the reduction in routes saved

WM $44 million dollars after WasteRoute's deployment in 2003 (Sahoo et al. 2005). Utilizing the VRP when designing a decentralized network of ADs from the start may allow for the introduction of small-scale waste infrastructure without the inefficiencies experienced by WM prior to the introduction of WasteRoute.

Location Allocation Models

Capacity constraints of the current organics waste system require the buildout of new waste facilities to achieve the statewide diversion goals of SB1383, so the location of the waste facilities themselves can be manipulated to achieve a reduced VMT of FW collection. Location-allocation models are often used in GIS to determine the optimal set of facilities to place in which the sum of all distances from the facility to the allocated demand points is minimized; in the case of waste management, the demand points are FW generators. Location-allocation models are formulated to locate facilities to serve an objective based on the concept of "coverage", a service standard that reflects facility access based on a quality such as distance or time (Toregas and ReVelle 1972). In addition to this user-defined service standard, location-allocation models also require a predetermined set of potential facility locations as an input. These potential facility locations are often identified through a site selection process that takes operational factors into account such as the availability and cost of land. As shown in **Figure 4**, location-allocation models can be differentiated by the number of facilities they place and the amount of demand that the solution must cover. This section will outline three common location allocation problems, the p-median, maximum coverage, and capacitated maximum coverage location problems, that can be used to model a decentralized system of ADs for FW management.

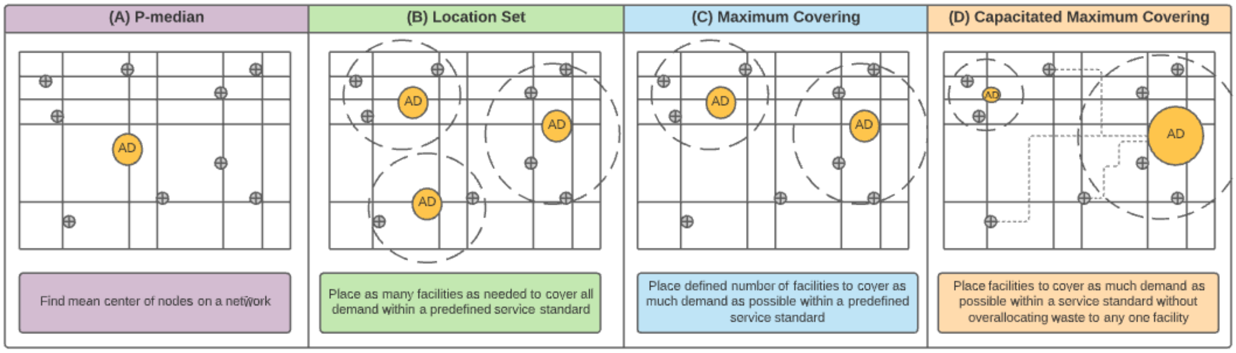

Figure 4. *Location allocation models for waste facility placement.* ***(A)*** *p-median,* ***(B)*** *location set,* ***(C)*** *maximum covering, and* ***(D)*** *capacitated maximum covering location problems*

P-median Problem

The p-median problem is one of the simplest location models; it is essentially the network version of the Fermat problem, finding the mean center of points on a network. First formulated by Hakimi (Hakimi 1964, 1965) to find the optimum location of a switching center in a communication network, the p-median problem places a facility at the mean center of a series of nodes on a network. The p-median problem may be most useful in waste management to locate large, centralized facilities that can meet the capacity of the system. By locating a new facility in the mean center of the network, the overall distance between nodes is minimized (**Figure 4(A)**). While the p-median problem is limited to placing a single facility, many other location problems can be formulated and solved as a p-median problem (Church and ReVelle 1974). Thus, it can be adapted to address more complex problems requiring the placement of multiple facilities, such as the development of FW recycling infrastructure proposed in this paper. Using a network-based model for waste collection places these facilities in locations accessible by a road network which optimizes the location of the systems nodes for a reduced VMT. Further modifications to the objective can be made to the model, such as a minimum required distance away from residential areas to reduce nuisance of the new facility (Flahaut, Laurent, and Thomas 2002).

Location Set and Maximum Covering Location Problems

Following the concept of network coverage in the p-median problem came the Location Set Covering Problem (LSCP) which locates multiple facilities to provide a service to all demand points within a specified standard (Toregas and ReVelle 1972). The LSCP was extremely influential and helped over 100 cities design fire stations, hospitals, and other municipal/emergency services in the 1970s (Church and Murray 2018). Despite its influence, it is limited in practice due to its goal of 100% service coverage where in many cases that may not be practical. The LSCP was extended by Church and ReVelle in 1974 with the development of the Maximum Covering Location Problem (MCLP), which aims to balance demand coverage and costs of facility deployment. By identifying a specified number of facilities from a set of potential sites that maximizes total demand covered within a defined service standard, the location of ADs can be optimized for reduced VMT (Church and ReVelle 1974). The LSCP and MCLP can be seen in **Figures 4(B)** and **4(C)**, respectively.

The MCLP differs from the LSCP in that a predefined number of facilities are found and total coverage may not be achieved with the MCLP. In the case of waste management, the MCLP is useful as both an exploratory and deterministic model. In exploratory contexts, the most cost-effective number of facilities to site can be determined by running the model at varying numbers of facilities and measuring the amount of demand satisfied. This creates a trade-off curve which often shows that close to maximum coverage can be achieved with relatively few facility points, increasing the efficiency of the overall system. The MCLP is also used in situations where the number of waste facilities to build has been predetermined by the municipality, usually based on factors such as the amount of waste to be treated, land availability, and construction costs. The MCLP has been used in conjunction with GIS and multi-criteria analysis to locate waste facilities in many cities such as Churiana de la Vega, a small village in Spain (Zamorano et al. 2009) or Coimbatore City in India (Nithya, Velumani, and Senthil Kumar 2012).

Capacitated Maximum Covering Location Problem

A major limitation of the MCLP is the assumption that the located facilities will be sized appropriately to cover demand. However, this is often not the case as there are often capacity constraints to the daily tonnage a disposal facility can treat, including the size of the AD. In this situation, the model objective must be modified to allow for capture of as much of the waste as possible while simultaneously ensuring no single facility is allocated demand over its capacity. Early efforts to introduce capacity into the equation are seen in Chung et. al (Chung, Schilling, and Carbone 1983) and Current and Storbeck (Current and Storbeck 1988) and the CMCLP has since been applied to waste management to place landfills and transfer stations in Alberta, Canada, for example (Eiselt 2006). In contrast to the MCLP, where FW is simply sent to its closest AD without consideration of the size of the AD, the CMCLP must consider the allocation of FW to each AD in its computations to ensure that none are overfilled, which would reduce the efficiency of the AD. This is done using allocation schemes, which are differentiated into user-optimal and system-optimal schemes. While user-optimal algorithms are the simplest, FW is allocated to the closest AD, a system-optimal scheme can allow FW to go to ADs that are further from the point of generation than others if it increases the overall amount of demand captured.

As shown in **Figure 4(D)**, the goal of the CMCLP is to cover as much demand as possible within a desired service standard, usually a value derived from distance such as travel time, without over allocating demand to any one facility. An important aspect of the CMCLP is that, unlike the MCLP, sufficient capacity for waste treatment must be built into the model to cover global demand as all waste is allocated to a facility even if it is not covered within the defined service standard. In a commercial or municipal waste management system where the allocation of demand to facilities is determined by the waste company a system-optimal design is desirable. In this case, the model objective may be modified to not only reduce VMT (and associated GHGs) through optimal network design, but also reduce GHG from the disposal of waste itself by allocating each demand point to a facility that can most easily treat its waste.

Clustering Models

The two types of models discussed above, routing and location allocation models, are widely used in waste management contexts as they both optimize a part of the waste management chain that is directly manipulatable by waste haulers, facility managers, city planners, and/or other decision makers. The part of the FW supply chain that is not changeable by these actors is the location of FW generation at commercial businesses. This portion of the FW supply chain is the subject of a third group of spatial models called unsupervised clustering models. Unsupervised models are useful when the user wishes to discover some unknown property of the data; in the case of FW management, this unknown property is the spatial layout of FW generation. In general, clustering models find homogenous subgroups of the input data and rely on a specified dissimilarity measure, such as distance between the points, to classify the input points into groups so that the distance between points of the same group is minimized. Since FW is generated at businesses that can be represented as points on a network, spatial clustering models can be used to identify natural clusters of FW generators to inform siting of ADs. The clusters can also be utilized in multicriteria analysis approaches for the identification of potential facility sites that are inputs of other models such as location-allocation models. As shown in **Figure 5**, clustering methods can be classified by algorithm type and in this review, we will focus on two different combinatorial algorithms that can perform unsupervised clustering, k-means and hierarchical clustering.

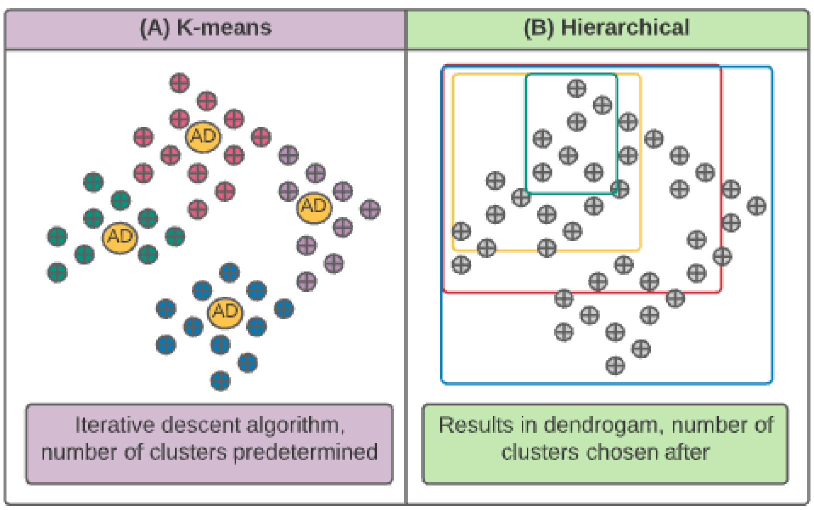

Figure 5. *Clustering models for the identification of natural clusters of FW generation.* ***(A)*** *k-means and* ***(B)*** *hierarchical clustering*

K-means Clustering

K-means clustering is a commonly used unsupervised clustering algorithm, as it is easy to use and generally creates visually attractive clusters. There are multiple k-means clustering algorithms, the most common being the Forgy/Lloyd algorithm (Forgy 1965; Lloyd 1982). K-means enables the partition of the FW generators into a user-specified number of clusters in such a way that within each cluster the squared distance between the observations in the cluster is minimized (Hastie, Tibshirani, and Friedman 2008). As an iterative descent clustering method, k-means clustering begins with a random assignment of FW generators into clusters, then iteratively modifies these assignments to improve the clusters, stopping modification when the algorithm is unable to further minimize the objective; this process is shown in **Figure 6.** While not the fastest algorithm to solve the k-means problem, the Forgy/Lloyd algorithm tends to create discreet, non-overlapping clusters with similar numbers of FW generators in each cluster. These qualities ensure that the collection routes of different clusters are compact and visually attractive, a generally desirable trait (Sahoo et al. 2005), but they cannot ensure that FW is equally distributed among the clusters. The k-means algorithm aims to balance the number of FW generators in the clusters without reference to the amount of FW the businesses themselves produce; the advantage of the proposed containerized ADs is that they can be built to match the scale of the clusters identified by the k-means model.

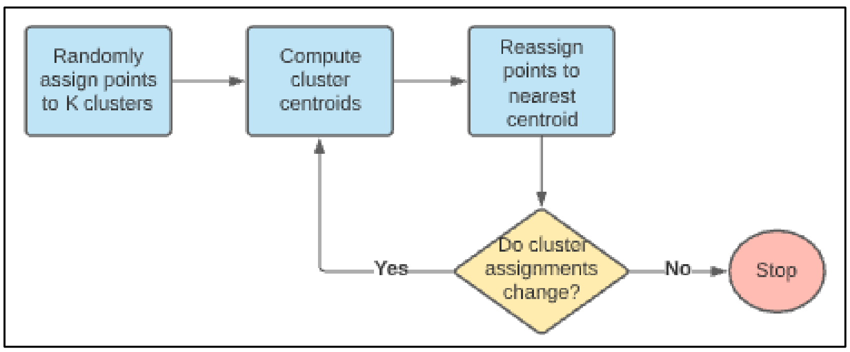

Figure 6. *The basic k-means clustering algorithm*

Another trade-off to using k-means clustering is the need for a user-specified number of clusters (K) as an input, as the number of "natural clusters" of waste generation may not be known beforehand. The elbow method is commonly used to determine optimal K to choose, in which the user runs the model at a range of K values and calculating the total within sum of squares (WSS) of the result in clusters; plotting these values results in an elbow shaped curve which shows diminishing returns of cluster quality as K increases. As with the MCLP, where nearly full coverage can be achieved with relatively few facilities, nearly optimal total WSS can be achieved with relatively few clusters, and it is generally accepted to choose the K value where the plot elbows (Tibshirani, Walther, and Hastie 2001). Since no FW-specific treatment network exists in California, the exploratory nature of k-means clustering makes it a very powerful tool to develop a decentralized system of containerized ADs that is optimized specifically to reduced VMT/GHGs in a given municipality.

Hierarchical Clustering

The second class of clustering models, hierarchical clustering models, are more flexible models that have some advantage over k-means in exploratory situations due to its non-parametric approach. Hierarchical models can be classified by their partitioning algorithm as either agglomerative (bottom-up) or divisive (top-down) algorithms. Agglomerative schemes begin with each point partitioned into its own cluster, then the algorithm iteratively merges the current closest pair of clusters together until there is one final cluster left that encompasses the entire dataset; this process can be seen in **Figure 7.** Divisive models work in the reverse, starting with the whole dataset and partitioning it into multiple clusters iteratively until all clusters are in their own cluster of a single point. This simple algorithm allows the results to be displayed as a dendrogram, where the height of each node in the tree is proportional to the value of the dissimilarity (distance) between the two daughter branches (Hastie, Tibshirani, and Friedman 2008). Opposite of k-means clustering, the number of clusters to create (the selected K value) is decided after the fact by the user by drawing a horizontal line across this dendrogram; the height of the cut can be decided by the user or using statistical methods such as the gap statistic (Tibshirani, Walther, and Hastie 2001).

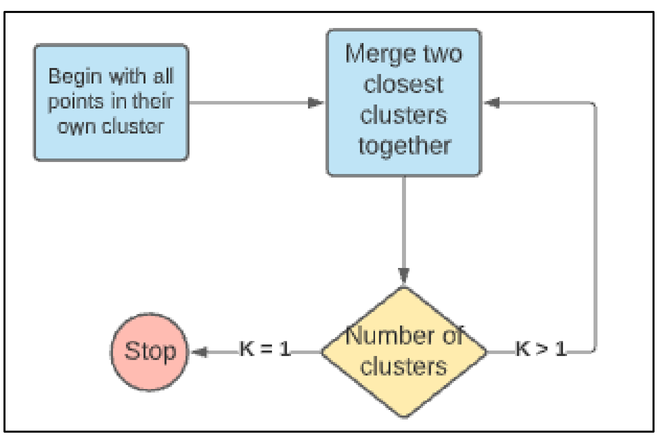

Figure 7. *Basic agglomerative hierarchical clustering algorithm*

An important consideration for using hierarchical clustering is the assumption of a hierarchical structure of the data; the term “hierarchical” refers to the fact that clusters obtained by cutting the dendrogram at a given height are contained within the larger clusters obtained by cutting the dendrogram at a greater height (James et al. 2017). Hierarchical clustering is commonly used in non-spatial aspects of waste management such as generating customer waste profiles (Oribe-Garcia et al. 2015) and, like k-means clustering, may be used to assist spatial models discussed previously. However, the assumption for a hierarchical structure of the data may not be true for the spatial patterns of FW generation, potentially resulting in worse clusters than those created from k-means clustering. Further research on the spatial arrangement of FW generation and business locations is needed to determine the usefulness of spatial hierarchical clustering as a planning tool for waste management infrastructure.

Solving the Models

The models discussed above fall into a larger class of models in the field of mathematics called combinatorial analysis, which is the study of the arrangement, grouping, or selection of a finite number of discrete objects. Heavily used in operations research, supply chain management, transportation studies, and GIS, combinatorial analysis has since evolved into the field of computational optimization. The challenge of computational optimization is to develop algorithms for solving complex combinatorial problems in which the number of elementary computational steps to solve the problem is as small as possible (Hastie, Tibshirani, and Friedman 2008). The usage of the term “elementary steps” allows for a machine-independent theory of computational optimization which helps to standardize discussions of calculation time across different computers. The time it takes to solve the model by a solution algorithm can therefore be expressed as a function of the size of the particular problem instance to be studied. In the case of commercial FW, the size of the problem would be determined by the number of FW generator points and the number of facilities to be placed. Defining the difficulty of a problem is one of the basic tasks of computational optimization.

The standard of polynomial boundedness states that an algorithm is considered "good" if the number of steps it takes to solve the problem is bounded by a polynomial in the size of the specific problem instance (Lawler 1976). If no such solution has been proven to exist, the problem is considered NP-hard and requires the development of algorithms, known as heuristics, to find an approximate solution in a shorter amount of time. Even when a problem can be solved in polynomial time, in some cases the polynomial is too large to solve real-world instances in a reasonable time, further necessitating the development of heuristics. While heuristics can quickly find an approximate solution to the problem, the solution they find is without proof of optimality. Balancing the needs of optimality and solution time is an important consideration when using heuristics to solve real world problems (Mladenović et al. 2007). All of the models discussed above are graph-based, NP-hard problems, and therefore can be solved using heuristics that operate under similar principles. Two of the most used algorithm classes used to solve the models are greedy heuristics and local search algorithms which can be adapted to fit the goals of routing, location-allocation, and clustering models. An example of these solution heuristics using the travelling salesman's problem is shown in **Figure 8**.

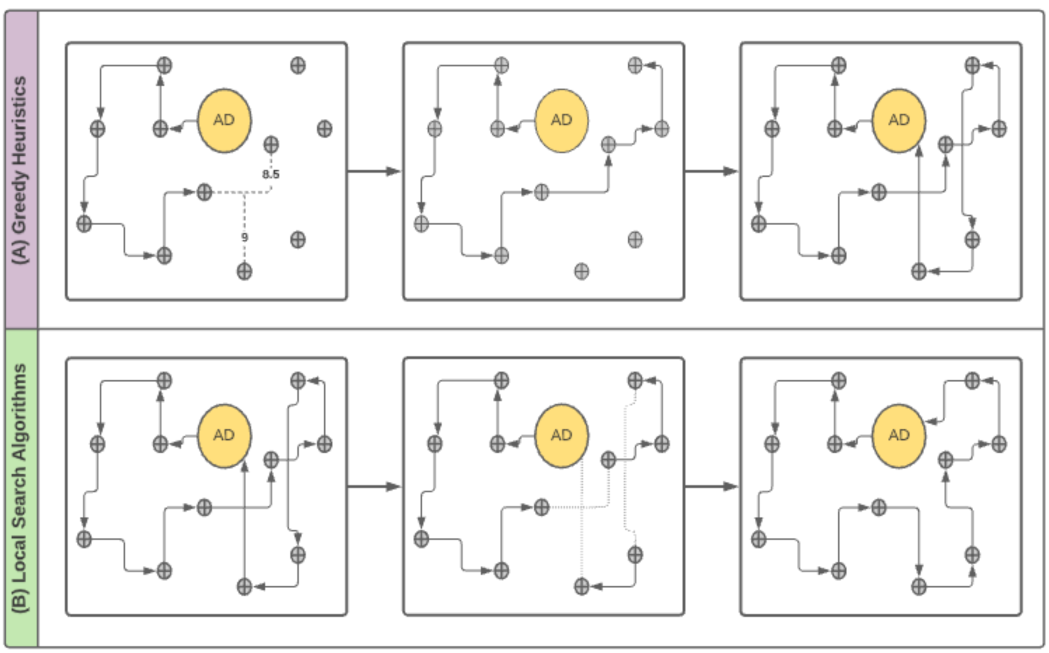

Figure 8. *Solution heuristics for the Travelling Salesman's Problem. Construction of a sub-optimal tour using the nearest neighbor greedy algorithm* ***(A)*** *and improvement of the tour using a 3-opt local search algorithm* ***(B)***

Greedy Heuristics

Greedy heuristics are algorithms that make the most optimal decision at each iterative step of the algorithm and, like the name implies, do not reverse the decisions. They are simple and intuitive algorithms that make the best decision based on local conditions without looking forward at the overall structure of the data. While this does not ensure a globally optimal solution, greedy heuristics are often the first step to solving combinatorial problems as they can quickly find an initial solution that can be improved upon in subsequent steps. A simple example of a greedy algorithm is the nearest neighbor algorithm used for routing problems to construct a tour from scratch (**Figure 8(A)**). To implement the nearest neighbor search on the travelling salesman's problem, for example, one starts at an initial node and adds successive nodes by visiting the nearest (or least-cost) unvisited neighbor, once all points have been visited the tour returns to the starting node. In the case of the p-median problem, as an example of a location-allocation problem, greedy heuristics work very similar. The greedy algorithm developed by Keuhn and Hamburger (1963) works very similar to the nearest neighbor tour construction technique by adding the least-costly single potential facility at each iterative step. The reverse of the algorithm, known as the greedy drop algorithm, begins with all potential facility locations and iteratively removes the most-costly location from the network until p-locations are found.

The main problem with greedy algorithms is that once a path or location is selected, it remains in the solution even if successive moves make the location less than optimal. While greedy-type algorithms can solve combinatorial problems relatively quickly, they are often suboptimal solutions, usually within 10-15% of optimal (Johnson and McGeoch 1997). One can see how this lack of a global scope can produce inefficient solutions, where the algorithm makes a locally-optimal decision that results in a longer overall route; this is shown in **Figure 8(A)**. While this may in fact be the most optimal solution to the problem, heuristically derived solutions are without proof of optimality (Mladenović et al. 2007). Further improvement of the solution can be done using simple local search algorithms to correct the initial solution found using greedy solutions.

Local Search Algorithms

Local search algorithms improve upon initial solutions by using simple modifications and have been shown to increase optimality to 1-2% of the most optimal solution (Johnson and McGeoch 1997). The simple modifications used by local search algorithms are different based on the model to be modified, but in general they consist of switching nodes or arcs in and out of the solution until a more optimal solution is found. An example of a simple switching algorithm is the 2-opt refinement algorithm for the travelling salesman's problem. This refinement repeatedly breaks the path into two by deleting the two longest edges then reconnects the two paths in such a way that the overall length of the path is reduced. This process continues until these operations can no longer create a shorter tour, i.e., the local optimum has been reached. The 2-opt local search algorithm works the same for location-allocation problems, but instead, candidate nodes are switched in and out of the solution space until an optimum is reached. The 2-opt algorithms can be expanded into 3-opt, 4-opt, K-opt methods which delete 3, 4, K edges or nodes at once; an example of 3-opt refinement for the travelling salesman's solution found by nearest neighbors' tour constructor is shown in **Figure 8(B)**. Local search algorithms can vastly improve the quality of the solution; they are sensitive to the initial solution chosen, making the choice of tour construction heuristic non-trivial. While the increased optimality is desirable, the dependence on an initial solution is a major drawback as this increases the overall time required to solve the problem.

Clustering models are mathematically similar to other combinatorial optimization problems; they can be formulated as a TSP problem (Hastie, Tibshirani, and Friedman 2008), and therefore have well-defined heuristic algorithms. Clustering algorithms, such as the previously discussed Forgy/Lloyd algorithm for k-means clustering work similarly to local search algorithms, iteratively switch the classification of individual nodes from one cluster to another until a solution is found. Like all local search algorithms, the solution quality is sensitive to the initial solution used as an input to the model. Given that unsupervised clustering is most often done in situations where little is known about the input data, the initial solution for k-means clustering is frequently chosen at random. Finding an optimal solution for a given problem instance using unsupervised clustering often requires the use of Monte Carlo

Simulation. While repeatedly running the code obviously increases overall runtime, Monte Carlo Simulation is well suited for parallel computing, mitigating this concern.

Other Heuristics

Greedy and local search heuristics are part of a larger group of heuristics called classical heuristics, which are some of the earliest algorithms developed to solve computational problems. More recently, another class of heuristics, called metaheuristics, has been developed that take advantage of the memory and processing capabilities of modern computers to achieve more accurate results. Notable examples of these metaheuristics that have significantly advanced the field of computational optimization are ant colony optimization, variable search, simulated annealing, and neural networks (Mladenović et al. 2007). Many of these metaheuristics have been used to solve problems related to waste collection, such as Karidima et al's use of ant colony optimization to solve waste collection vehicle routing problems (Karadimas et al. 2008) or the modified simulated annealing metaheuristic deployed in WM proprietary WasteRoute program (Sahoo et al. 2005). While metaheuristics can improve the quality of solutions in large problem sets, they are not as easily implemented in GIS as the classical heuristics. For example, while tabu search, ant colony optimization, and simulated annealing can all be found implemented in R packages, they are generalized packages that can solve any combinatorial optimization problem and are not specifically designed for spatial models. In contrast, greedy and local search heuristics can be found in R packages that directly implement the models above such as the TSP package for the traveling salesman's problem, the tbart package for the p-median problem, and the kmeans function found in the stats package. Furthermore, the greedy-add with 2-opt refinement algorithm is the heuristic solution method used by ESRI ArcGIS Network Analyst, a widely used GUI-based GIS that can solve location-allocation, routing, and clustering problems. Determining which heuristic to use for a given problem is a difficult decision as one must balance the needs of solution optimality, solve time, and ease of use.

Literature Review Summary

The models discussed above can all be used to optimize waste management systems through the manipulation of one of the four essential components of the waste supply chain: waste generation, collection and transportation, storage, and final disposal. The choice of model, as well as the selection of a solution heuristic, is non-trivial and is dependent on the general goals of the modelling process as well as the on-the-ground realities of the system under study. In an established waste system, routing models are frequently used to optimize the collection and transportation stages of the system to lower VMT (and the associated GHGs and costs) as the collection route is easily modifiable. Location-allocation models, which work to optimize the location of new storage and disposal facilities in relation to existing sites and the waste generators they serve, are also commonly used in waste planning as generally only a few additional locations need to be sited. The increased needs for organic waste management, especially FW management, because of SB1383 provide an opportunity to use unsupervised clustering models in planning as an entirely new set of waste facilities need to be sited. Focusing specifically on the waste generators, clustering models can help explore the potential for a network of containerized ADs by determining natural clusters of FW generation geographies sized to the capacity of the AD systems. Since GHGs are generated at each step of the FW supply chain, optimizing this new system for overall reductions in GHG emissions may require the development of a new model that combines the goals of all three classes of models. In order to develop such a model, the real-world characteristics of the FW system must be represented in such a way that it can be used as mathematical inputs to the models, i.e., as nodes and arcs of a graph. Since the needs of a new FW supply chain are dependent on the intensity and location of FW generation, accurately simulating this geography in GIS is an important first step to developing new environmentally and economically optimal waste infrastructure.

Methods

The buildout of new organic waste recycling facilities in response to SB1383 is an opportunity to rethink the size of waste infrastructure and to design a decentralized network of ADs within urban areas. This approach can include placing waste facilities closer to the points of FW generation, potentially minimizing costs and GHG emissions associated with collection and hauling of waste. Focusing specifically on non-residential FW produced in urban areas, which comes from discreet point sources such as restaurants, grocery stores, and food processing factories, allows for large volumes of FW to be captured from a relatively small area and diverted for treatment. All of the spatial models discussed in the Literature Review are graph-based models, meaning that FW generation must be input as a discreet set of points (nodes) on a network. FW generation and disposal data are available from the California Department of Resources and Recovery (CalRecycle) but require significant geoprocessing to transform them into a format that can be used as a model input. Following a brief description of the chosen study area, Los Angeles County, this section will then review the three sources of data before outlining the method used to combine these datasets to create a simulated "FW geography" (FWG) dataset composed of a series of points representing FW generators that can be used for modelling FW processing facilities.

Study Area

As the most populous county in California with over 10 million people (25.4% of the CA population), Los Angeles County is also the largest municipal solid waste generator in the state. In 2018, the county disposed of 10,098,794 tons of commercial waste, contributing to 28.1% of statewide tonnage (CalRecycle 2020). Statewide, 9.5% of the overall waste stream is classified as Not Donatable – Non-Meat, an ideal AD feedstock due to its high moisture content, meaning that Los Angeles County has a significant opportunity to reduce GHG emissions through FW diversion to AD. As shown in **Figure 9**, most of the population is in the southern half of the county with scattered pockets of smaller communities in the northern portion of the county. Generally, an increase in population corresponds with an increase in commercial activity, and therefore FW generation. Conversely, FW is unlikely to be generated in conservation areas such as the 650,000-acre (1,094 sq mi) Angeles National Forest, which divides the county into north and south as well as the Santa Monica Mountains in the south west. Los Angeles County also includes a number of coastal islands, the largest of which is Santa Catalina Island, which attracts over 1 million visitors per year (City of Avalon 2021). Despite this potential for FW generation and the need for diversion, all islands were excluded from the study to simplify transportation modelling. After removal of the Angeles National Forest and islands from the county, the total study area is reduced to 4,058 square miles. Considering the massive amounts of FW produced, the variety of population densities, and the variety of industries, Los Angeles County makes a good test subject for modeling an AD-based waste treatment system.

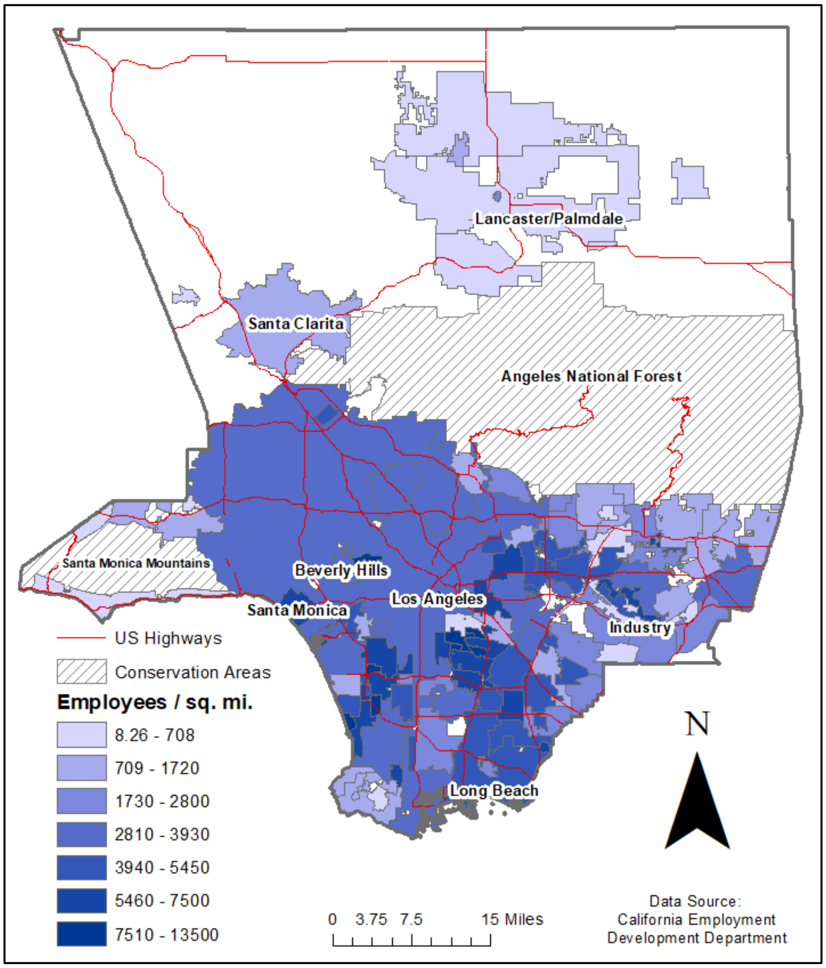

Figure 9. *The Los Angeles County study area and its municipal boundaries (Census Designated Cities), major US highways, and conservation areas. Cities are colored by employment density (number of employees/sq. mile).*

Primary Data

The three sources of data used in this study, CalRecycle, ESRI ArcGIS Business Analyst (BA), and the Southern California Association of Governments (SCAG), are shown in **Table 2**. Waste generation estimates for the state of California are available through the CalRecycle's 2014 Generator-Based Waste Characterization Study (WCS). This study sorted, categorized, and quantified waste materials at the point in which they are discarded by commercial businesses in landfill trash, curbside organics and recycling, and other disposal containers. Measuring waste generation at the point of discard allows the WCS to categorize waste by its destination for final disposal and by its location of generation within the FSC, both of which can be mapped as discreet point locations. Survey results are reported as Tons Per Employee Per Year (TPEPY) values to provide equal comparison of data across business size and industry types. CalRecycle developed 5,440 TPEPY values for Los Angeles County, one for each combination of the 62 reported material types, 5 diversion streams, and 16 industry groups. Industry groups were created using standardized three-digit North American Industry Classification System (NAICS) codes, a 5-digit hierarchical system which groups commercial businesses together according to the similarity of the goods and services they produce. It is important to note that the industry groups created by CalRecycle for the TPEPY values are waste-oriented, grouping businesses together according to their waste generation profiles with a specific focus on keeping industries that generate large amounts of food and organic waste together (CalRecycle 2015). The ESRI BA and SCAG zoning datasets are production-oriented and use the standard industry groups used by the NAICS system, so an industry group labeled "Manufacturing" in the ESRI BA data may contain different businesses than the same industry labeled "Manufacturing" in the CalRecycle TPEPY groups. Therefore, significant processing of the data is required to match the employment data to the TPEPY value's underlying NAICS codes which ensures that the TPEPY value is applied to the specific business type it was developed for when estimating industry FW generation.

__Table 2.__ The three sources of data used in this study

Data Source	Dataset	Industry Groups	Spatial Resolution
CalRecycle Waste Characterization Study (WCS)	Waste generation/ disposal data	16 waste-based industry groups using 3-digit NAICS codes	Aspatial Tons Per Employee Per Year (TPEPY) values
ESRI ArcGIS Business Analyst (BA)	Employee counts Number of businesses	18 production-based industry groups using 2-4 digit NAICS codes	Census tract (all industries) & individual business points (selected industries)
Southern California Association of Governments (SCAG)	Combined commercial zoning/land use GIS layer covering Los Angeles County	Production-oriented groups differentiated by hierarchical numeric codes	Very fine, parcel level

An industry's FW generation can be estimated by multiplying its employee count by the corresponding TPEPY value. Data on industry employment at the Census Tract level is available from the ESRI BA tool and is the primary source of employment data used in this study. As an ESRI product, this dataset comes in the form of a Census Tract shapefile and is readily usable within GIS. However, since FW generation must be represented as points to be used with spatial models, additional data on the number of businesses in each tract is also used. The processes used to manipulate these datasets are almost identical, as both use the same industry groups to disaggregate their data. While point data at the scale of the individual business are also available from ESRI BA, these data are costly and cannot be accurately geocoded. Therefore, these data are minimally used in this study and only when necessary to match industry groups to the TPEPY values.

Using Census Tract level data on the number of businesses helps ensure spatial accuracy; the estimated locations of businesses from each industry within each tract can be further constrained using zoning data from SCAG. This dataset is a combined dataset that includes all general plan land use, specific plan land use, and existing land uses from local municipalities within Los Angeles County to create one combined land use dataset covering the entirety of Los Angeles County. It consists of high spatial resolution polygons delineating individual parcels of land, each with a 2-4 digit zoning code, similar to NAICS codes, that designates which businesses/industries may be found within each zone.

Qualitative descriptions of these zone codes were used to match the zones to the TPEPY industry groups to ensure that the points created to represent FW generators within each industry are located in areas they are likely to be found.

Generating the FW Geography

Matching Industry Groups to CalRecycle

The first step in creating the comprehensive FWG map is establishing FW generation, number of businesses, and zoning layers for each CalRecycle TPEPY industry group. Additional processing is required for the ESRI BA industry groups, which can be differentiated into 3 types (*Type A*, *B*, or *C*) based on the amount of geoprocessing required. Industries classified as *Type A* have component NAICS codes that exactly match the codes used for the corresponding CalRecycle TPEPY industry and do not require additional processing. Five ESRI BA industry groups were classified as *Type B industries*; industry groups whose NAICs codes all belong to the same TPEPY group and can simply be added to other groups as a whole without additional processing. Five other ESRI BA industry groups were classified as *Type C industries*, which are grouped based on 2-digit NAICS codes and must be split into their component 3-digit codes before rearranging with other industries to match the TPEPY industry groups. The component 3-digit NAICS codes and matching TPEPY industry groups for ESRI BA industry groups classified as *Type B* and *Type C* are shown in **Table 3**. The rest of this section describes the process of generating the zoning, number of business, and FW generation layers for each industry.

Table 3. *ESRI BA Industry groups requiring further processing by splitting into component NAICS codes or removed by adding to another industry group. A full table of CalRecycle industry groups and their corresponding NAICS codes is in the appendix.*

ESRI Industry Group	Type	CR NAICS Codes	Matching CalRecycle Industry Group(s)
Agriculture, Forestry, Fishing, Hunting	B	111-115	Not Elsewhere Classified
Mining	B	211-213	Not Elsewhere Classified
Utilities	B	221	Not Elsewhere Classified
Management of Companies & Enterprises	B	551	Services - Management, Administrative, Support, & Social
Administrative Support of Waste Management & Remediation	B	561	Services - Management, Administrative, Support, & Social
Manufacturing	C	311-316, 321-325, 334, 335	Manufacturing - All Other Manufacturing – Electronic Manufacturing - Food & Nondurable Wholesale
Transportation & Warehousing	C	481, 484, 491-493	Durable, Wholesale & Trucking Not Elsewhere Classified
Wholesale & Trade	C	423-425	Durable, Wholesale & Trucking Manufacturing - Food & Nondurable Wholesale Services - Management, Administrative, Support, & Social
Health Care & Social Assistance	C	621-624	Medical & Health Services - Management, Administrative, Support, & Social
Other Services excluding Public Administration	C	811-813	Services - Management, Administrative, Support, & Social Services - Repair & Personal

FW Data

The process of matching ESRI BA industry groups to the CalRecycle TPEPY groups is shown in **Figure 10.** For most industries, *Type A* industries, tract-level FW generation can be simply estimated by multiplying the industries employee count by the corresponding TPEPY value (**Figure 10(A)**). Breaking apart *Type C* industries for recombination with each other or with *Type B* industries required additional point-level dataset from ESRI BA, where each point represents a commercial business and includes its three-digit NAICS code and its number of employees. The tract-level industry employment was split into employment for three-digit NAICS codes according to the proportion of the point dataset for that industry that was classified with that code (**Figure 10(B))**. Once the tract-level employment was determined for all of the three-digit NAICS codes, the data was recombined to match the NAICS codes in the CalRecycle industry group (**Figure 10(C)).** The respective industry TPEPY values were then multiplied by the corrected employee counts to estimate tract-level FW generation and disposal in tons per year (**Figure 10(D)).**

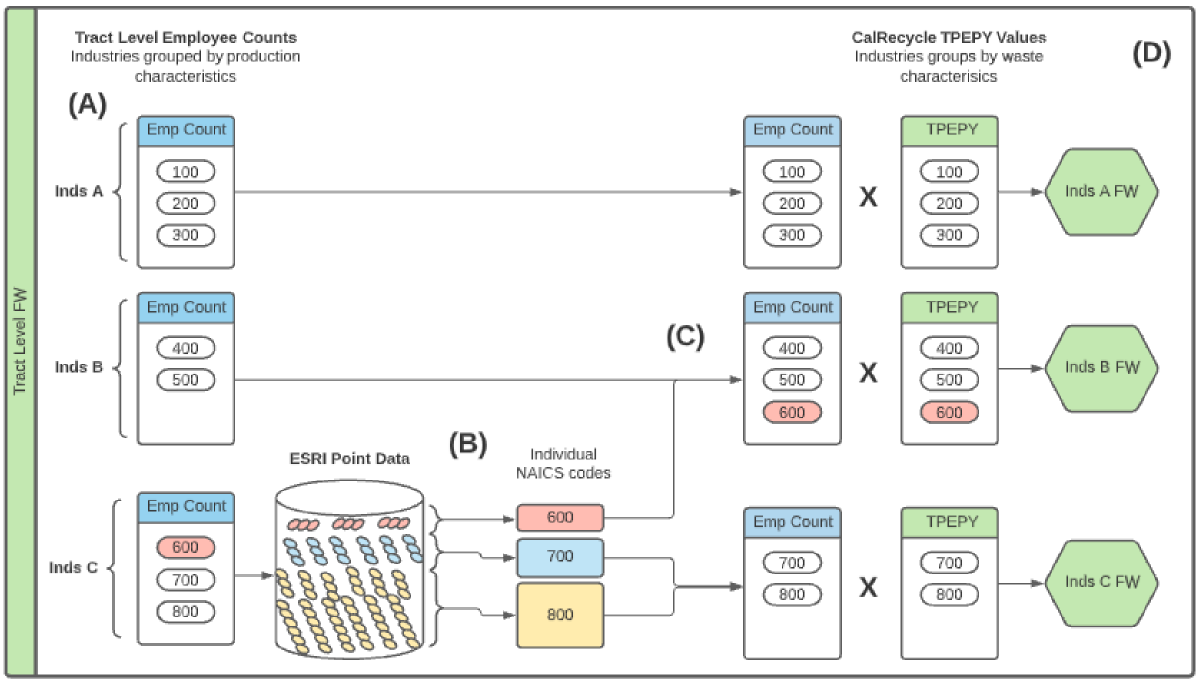

Figure 10. *Developing tract-level food waste generation values for each industry type. Type A industries do not require additional processing **(A)**. Type B industries can be combined with others without additional processing **(C)** and Type C industries must be broken down into 3-digit NAICS codes **(B)** to match the CalRecycle TPEPY Group. Estimations of food waste generation for each industry are made by multiplying the calculated employee count to its respective TPEPY value.*

Number of Businesses

Determining the number of businesses for each industry in each tract is necessary to generate the points/nodes of the FWG to use as an input to spatial models. Both the employment and number of business data have the same format as both are from ESRI BA. Therefore, the process used to match the production-oriented industry groups of the employment data to the waste-oriented TPEPY industry groups can be repeated for the number of business data. This process is identical to **Figure 10** with the exception of not multiplying the ESRI BA data to the TPEPY value.

Zoning Layers

Generating a zoning layer for each industry was done using the SCAG zone codes by qualitatively matching the description of businesses that may be found within a specific zone and the description of businesses contained by the CalRecycle TPEPY group. As shown in **Figure 11**, industry groups may be matched to multiple SCAG zones (*Industry C*), and SCAG zones can be assigned to multiple industry groups (*Zone Y*). The zones designated for the CalRecycle TPEPY industries are described in **Table A.1** and the size of each zoning layer can be found in **Table A.2 in the Appendix**. To ensure maximum spatial specificity with the hierarchical zoning codes, 3-digit SCAG zoning codes were used as much as possible. However, many parcels were given broader 2-digit codes and have a greater variability in the types of businesses that may be found within them. Parcels with 2-digit zone codes were therefore only included as a potential site for an industry when two or more 3-digit zone codes within the larger 2-digit code were included for that industry. An example of this can be seen in the Restaurant industry, which can be assigned to 2-digit parcels coded as 1200 (Commercial and Services) since the descriptions of 1220 (Retail Stores and Commercial Services) and 1230 (Other Commercial) codes within 1200 contain reference to restaurants. Given this study's focus on commercial food waste generation, residential zones were not included; however, mixed-use zones were included for applicable industries.

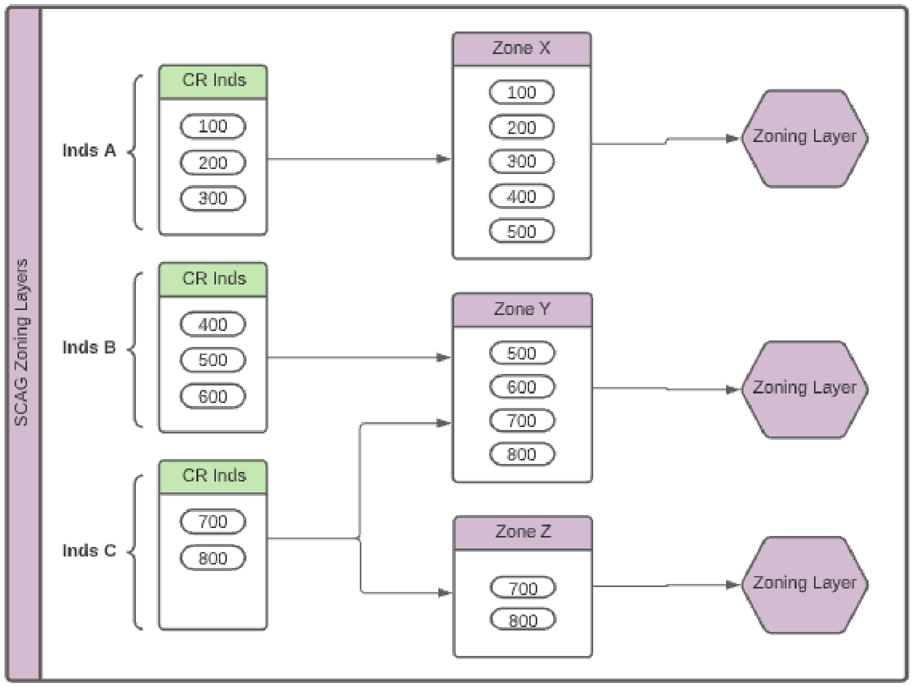

Figure 11. *Generating industry zoning layers from the SCAG dataset that match the descriptions of CalRecycle industry groups*

The models discussed in the literature review all require sets of points as the input variables, which can be randomly placed within each tract. The simplest way to aggregate tract-level business data into points is to randomly distribute points throughout each tract; however, doing so results in points being placed in areas where no commercial businesses are likely to be present, such as in the middle of the Angeles National Forest. Zoning and land use data from SCAG was therefore used to spatially constrain the business point locations to areas they are likely to be found. By constraining the random distribution of points to areas of Los Angeles County that are zoned for commercial businesses, the resulting FW geography more closely simulates the real-world spatial distribution of FW generation (**Figure 12**) and allows for more accurate modeling.

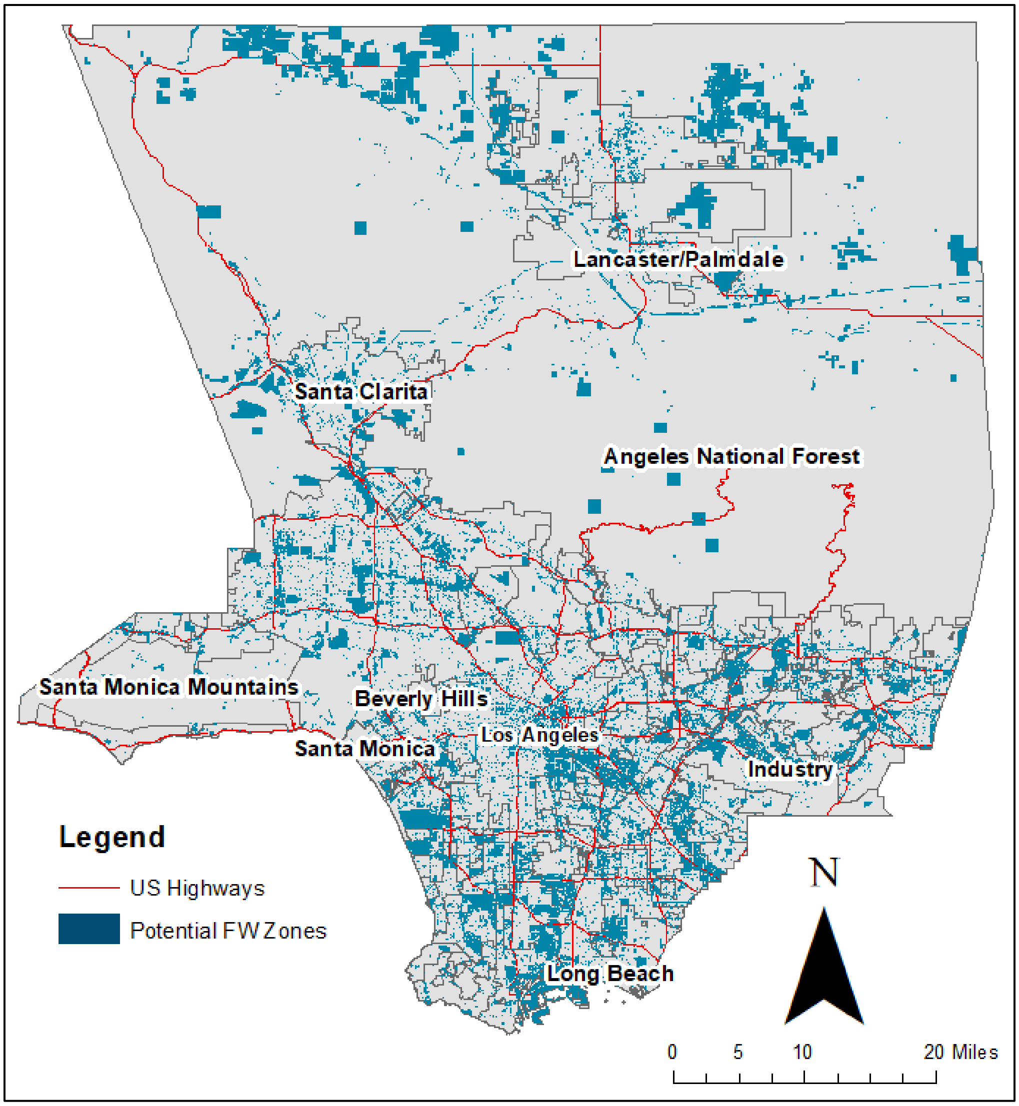

Figure 12. *Map of potential food waste generator zones for all industries. Food waste generator zones are clustered within high population and industrial areas near major US highways.*

Final FW Geography

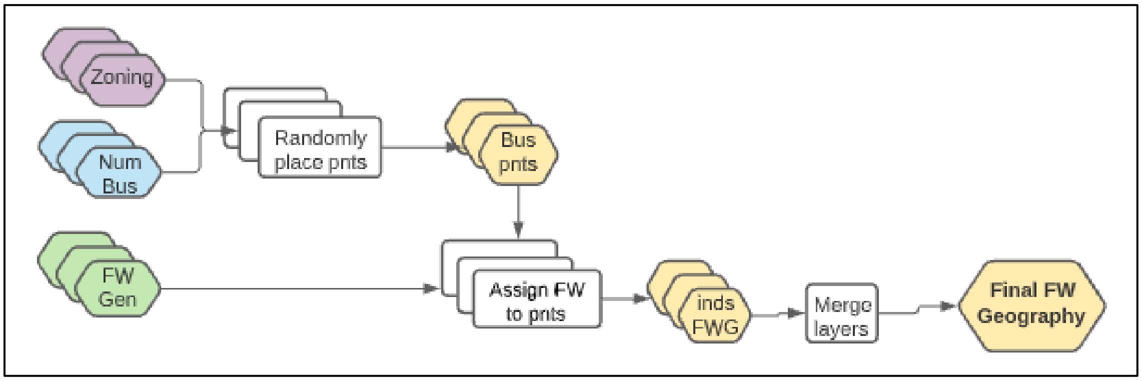

Figure 13. *The overall process of creating the Food Waste Geography (FWG) dataset. Points representing food waste generators are created for each industry, then combined to form the final FWG.*

Once the tract-level FW generation, number of businesses, and industry potential zones are determined for each industry, the final FWG can be created, as shown in **Figure 13.** Points representing FW generators for each industry within the tract were randomly distributed throughout the tract but also constrained to their specific zone. Industry FW was distributed equally among the points in each tract to generate a FWG dataset for each industry. These industry FWGs were then merged to form a comprehensive FWG, a set of points that represents FW generators of all sizes and from all industries within Los Angeles County (**Figure 14**) in which all FW generators, regardless of size, act as a point of discard within the food supply chain. While realistically, many FW generators will share a collection bin or be exempt from SB1383 altogether, this dataset serves as a starting point for modelling purposes. With the addition of a road network obtained from the US Census TIGER/line files, the FWG is represented as nodes on a network which can be used for routing, location-allocation, and clustering models to develop a network of containerized ADs at an appropriate scale.

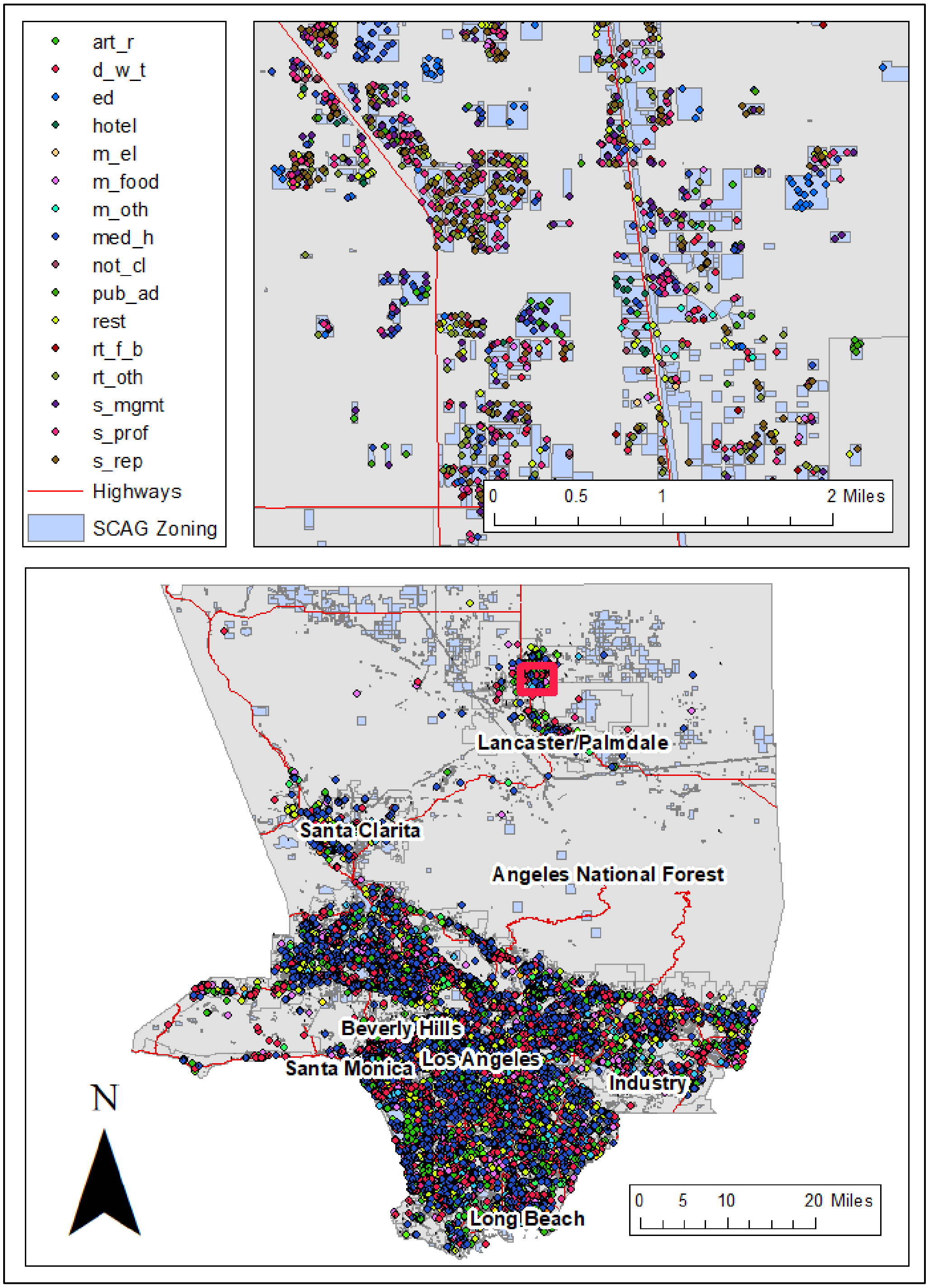

Figure 14. *The FWG, a point dataset consisting of 273,023 points representing food waste generators. Inset map (top) shows detail of points clustered within the SCAG zoning layer.*

Results

Estimated FW Generation

The final FWG map layer contains 273,023 points representing FW generators across 17 industries that in total generate 1,046,706 tons FW/year. The number of FW generators and FW generation across all industries at the census tract level is shown in **Figure 15**. FW generation was aggregated by tract for display purposes given the high number and density of individual generator points. Most of the FW generators are in the southern half of the county, with major clusters located near Los Angeles, Beverly Hills, and Santa Monica, as well as the cities of Industry and Long Beach. In the northern half of the county, smaller clusters of FW generators are located near Santa Clarita and the Lancaster/Palmdale urban area. Modelling the siting of a decentralized network of ADs for the treatment of FW will need to consider this varied density and spatial arrangement of FW across the county.

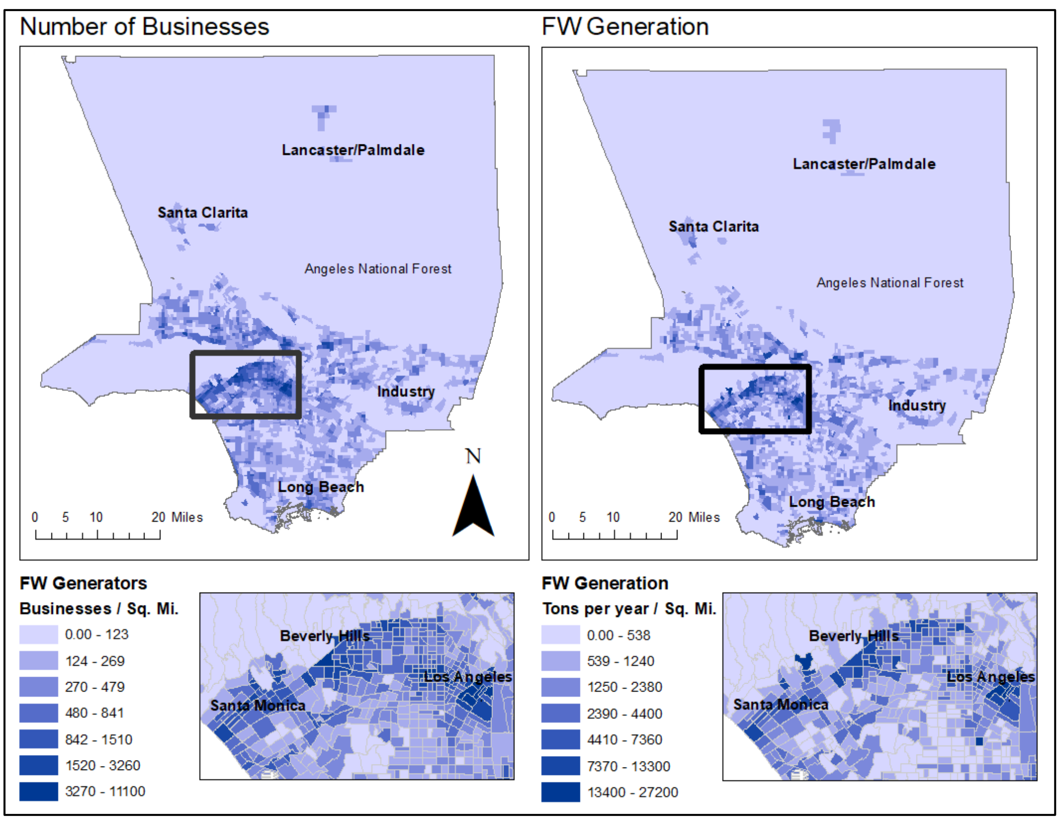

Figure 15: *Calculated Census Tract-level number of businesses (left) and total food waste generation (right) for all industries in Los Angeles County. Inset maps (bottom) show detail of tracts near Santa Monica, Beverly Hills, and Los Angeles.*

The overall FWG can be broken down into industry specific FWGs, as the quantity and spatial distribution of overall FW generation within Los Angeles County is fundamentally based on the relative distribution of employees and business points for each individual industry. **Table 4** shows employee counts, the CalRecycle TPEPY value, and FW generation by industry; industries were also given a short keyword used throughout this section, which is also indicated in **Table 4**. The top five FW producing industries are: Restaurants (rests) (285,575 tons/year), Retail Trade – Food & Beverage Stores (rt_f_b) (146,793 tons/year), Retail Trade – All Other (rt_oth) (123,423 tons/year), Manufacturing – Food & Nondurable Wholesale (m_food) (81,330 tons/year), and Arts, Entertainment & Recreation (art_r) (76,389 tons/year). These five industries together employ 29.7% of the people (1,009,465 employees) and produce 67.9% of the FW in the county (713,515 tons/year). Some of these industries, such as rt_f_b, rests, and m_food, are obvious targets for FW reduction policies, as they are directly part of the FSC and have documented higher food waste generation rates. Others, such as rt_oth and art_r, are less obvious inclusions to the top five FW generating industries as their business operations intuitively produce less FW than other industries that clearly prepare and serve food to the final consumer such as the education (ed), medical (med_h), and hospitality (hotel) sectors. The size of an industry as a whole, as measured by employee counts, is therefore an important guide of total industry FW generation.

Table 4. *Industry TPEPY values and calculated number of businesses, employees, and food waste (FW) generation in the Food Waste Geography (FWG) ordered by FW generation. Short industry keywords are also indicated.*

Keyword	CalRecycle Industry Group	TPEPY	Businesses (% of total)	Employees (% of total)	FW Gen. (tons/year) (% of total)
rests	Restaurants	0.9047	25253 (9.2)	315649 (9.3)	285576 (27.3)
rt_f_b	Retail Trade - Food & Beverage Stores	1.5491	7556 (2.8)	94763 (2.8)	146794 (14)
rt_oth	Retail Trade - All Other	0.3154	42252 (15.5)	391318 (11.5)	123424 (11.8)
m_food	Manufacturing - Food & Nondurable Wholesale	0.8155	7484 (2.7)	99732 (2.9)	81331 (7.8)
art_r	Arts, Entertainment, & Recreation	0.7073	7479 (2.7)	108003 (3.2)	76390 (7.3)
s_prof	Services - Professional, Technical, & Financial	0.1356	47537 (17.4)	490291 (14.4)	66471 (6.4)
med_h	Medical & Health	0.127	24780 (9.1)	422586 (12.4)	53662 (5.1)
ed	Education	0.1352	9740 (3.6)	370618 (10.9)	50098 (4.8)
s_mgmt	Services - Management, Administrative, Support, & Social	0.1517	30190 (11.1)	300087 (8.8)	45513 (4.3)
s_rep	Services - Repair & Personal	0.2647	34480 (12.6)	167088 (4.9)	44234 (4.2)
hotel	Hotels & Lodging	0.4894	1981 (0.7)	62987 (1.9)	30828 (2.9)
not_cl	Not Elsewhere Classified	0.2565	6352 (2.3)	63625 (1.9)	16322 (1.6)
pub_ad	Public Administration	0.0532	3989 (1.5)	215791 (6.3)	11488 (1.1)
d_w_t	Durable Wholesale & Trucking	0.0581	16513 (6.0)	173335 (5.1)	10067 (1.0)
m_el	Manufacturing -Electronic Equipment	0.0423	2355 (0.9)	56651 (1.7)	2395 (0.2)
m_oth	Manufacturing - All Other	0.0307	5082 (1.9)	69109 (2.0)	2120 (0.2)
all	All Industries	-	273023 (100)	3401633 (100)	1046713 (100)

FW generation is a function of TPEPY factor and number of employees in the industry; therefore, the ranking of industries by FW generation can be explained by the industry's values for either of these two factors. For example, rt_f_b has the highest TPEPY value (1.549) of all industries, yet it employs a relatively small number of employees, only 2.8% of the total employment, and is therefore the second highest FW generating industry behind rests, which makes up 9.3% of total employment. A seemingly counterintuitive result is rt_oth', a catchall industry group, which ranks ahead of businesses that predictably produce a significant amount of FW such as art_r, which includes food serving recreational centers such as amusement parks, arcades and casinos, as well as large sporting and entertainment venues, or m_food, which contains food manufacturing establishments, merchant wholesalers of food, and other nondurable goods. Despite the higher TPEPY values of art_r (0.707) and m_food (0.815) compared to rt_oth (0.315), rt_oth has significantly more employees, 11.5% of total employees in the county compared to 3.2% and 2.9% for art_r and m_food, and therefore has a higher overall industry FW generation. Furthermore, the Services – Professional, Technical, & Financial (s_prof) industry, the largest employer of the county (14% of total, 490,291 employees), ranks the sixth highest FW generating industry (66,471 tons/year), despite its relatively low TPEPY value of 0.136. The total FW generation by industry can be used to focus policy directives toward specific industries that produce significant amounts of FW; however, one must also investigate the spatial distribution of this waste when planning waste infrastructure, especially when the primary goal is a reduced VMT and associated GHG emissions.

The relative spatial distribution of FW generation across LA County is different between industries; **Figure 16** shows the Census tract-level FW generation for the rt_f_b, rests, and m_food industry groups. Unsurprisingly, the tract-level FW generation for rests, the highest FW producing industry, is spatially very similar to the overall FW generation, as over 27% of all FW generated within Los Angeles County comes from restaurants. Like the overall FW generation map, rests has the most densely packed tracts located near Beverly Hills, Santa Monica, and the City of Los Angeles, with tracts reaching up to 7,240 tons FW generated per year per sq. mile. The second highest FW generating industry, rt_f_b, produces 14% of overall FW generated (146,793 tons/year) and has a different distribution of FW generation across the county. Most of the FW generated in this industry, which comes from grocery stores, convenience stores, and meat, fish, & vegetable markets, is located near the cities of Commerce, Irwindale, and Industry, which are all major manufacturing cities in Los Angeles County. The FW geography of rt_f_b is similar to that of m_food, which is the fourth highest FW generating industry; however, FW generation for rt_f_b is present in more tracts than m_food. Since most businesses in the m_food industry group are not customer facing retail stores, it is not surprising that m_food is concentrated in industrial/manufacturing heavy areas of the county. In addition to the quantity of FW generated by each industry, the spatial distribution of this waste is an important factor for infrastructure planning. Understanding industry FW generation at the tract-level, as opposed to the municipality-level estimations released by CalRecycle, allows for a more accurate node-based FWG to be created, which than can be used for small-scale infrastructure planning.

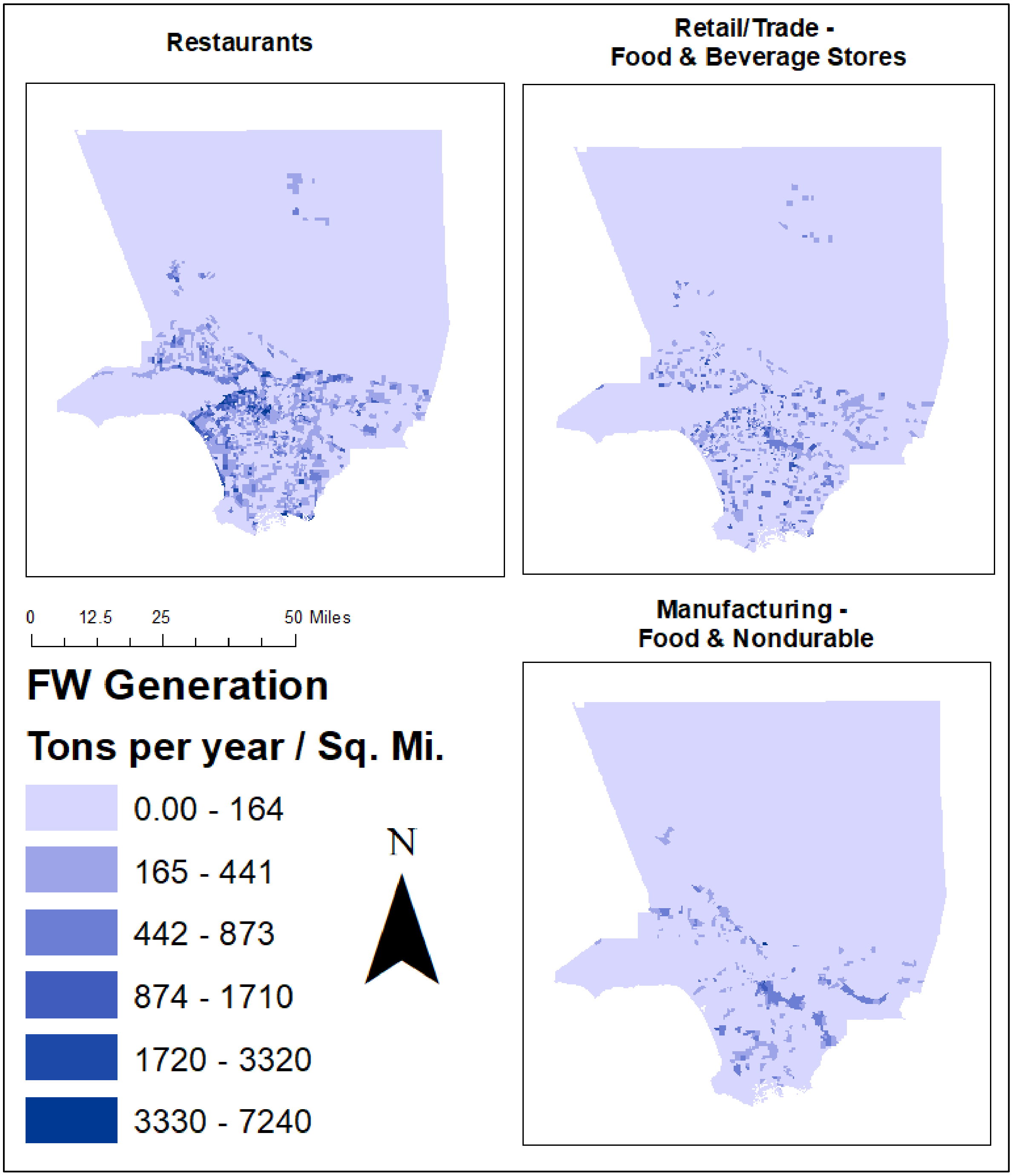

Figure 16. *Census tract-level food waste generation for Restaurants, Retail/Trade – Food & Beverage Stores, and Manufacturing – Food & Nondurable industry groups.*

Comparison to CalRecycle Data

The FWG created in this study can be compared to the FW generation values released by CalRecycle in their Waste Characterization Tool (WCT). Like the FWG, the FW values of the WCT are derived from CalRecycle's TPEPY values established in the 2014 Generator-Based Disposal Study. There are two major differences between the employment data used to create the FWG and the WCT datasets: the source of data and the spatial unit. While the FWG was created using 2018 employment data from ESRI BA, the WCT uses a special employment dataset from 2014 created by the California Employment Development Department (EDD) specifically for CalRecycle. To protect the confidentiality of individual businesses, the CalEDD dataset has suppressed the data of specific municipalities if there are less than 3 businesses in that industry *or* if a single employer is responsible for over 80% of employment in that city (CalRecycle 2019). The amount of FW generation suppressed by each of these reasons may vary significantly; however, it is not possible to determine this volume from the CalRecycle data alone. The waste data available in the WCT is meant for general municipal planning, and therefore comes at the spatial scale of the Census designated City; hence, this study's use of ESRI BA data provides finer spatial scales and includes matching data on the number of businesses within the space which is unavailable in the WCT.

Despite the differences in reference year and data suppression, the CalRecycle WCT dataset has an overall higher estimated FW generation, 1,085,628 tons/year, compared to the FWG's estimate of 1,046,706 tons/year, a difference of 38,922 tons/year (3.7%). Industry specific differences in FW generation between the two datasets range from 52,517 tons/year more in the WCT dataset (not_cl) to 33,071 tons/year more in the FWG (rt_oth). The average difference between the two datasets for each industry is 4,579 tons/year more FW in the WCT dataset (SD: 24,511) than the FWG. **Table 5** shows the comparison between the FW generation estimates found in the WCT and the FW geography's estimated FW generation by industry. Differences in estimated FW generation between the data released by CalRecycle and the FWG can be explained by differences in employee counts among the industries due to different reference years (2014 in WCT, 2018 in FWG); differences in employee counts due to the source data; as well as data suppression in the WCT to protect employer's privacy. It is also likely that methodological differences to create the initial employment datasets used to generate the FW data are the primary reason for the differences between the CalRecycle WCT and the FWG developed in this study.

Table 5. *Industry comparison between employment and FW generation between the FWG and the CalRecycle Waste Characterization Tool (WTC). Negative numbers indicate more FW in the WCT than in the FWG.*

Keyword	CalRecycle Industry Group	Employees		Employee Difference	FW Generation (tons/year)		FW Gen Difference
		FWG	*WCT*		*FWG*	*WCT*	
rests	Restaurants	315649	329646	-13997	285576	298240	-12664
rt_f_b	Retail Trade - Food & Beverage Stores	94763	88889	9098	146794	137696	5874
rt_oth	Retail Trade - All Other	391318	286463	33072	123424	90352	104855
m_food	Manufacturing - Food & Nondurable Wholesale	99732	140109	-40377	81331	114259	-32928
art_r	Arts, Entertainment, & Recreation	108003	78539	20840	76390	55550	29464
s_prof	Services - Professional, Technical, & Financial	490291	525313	-35022	66471	71220	-4749
med_h	Medical & Health	422586	414893	7693	53662	52685	977
ed	Education	370618	273616	97002	50098	36986	13112
s_mgmt	Services - Management, Administrative, Support, & Social	300087	596350	-296263	45513	90446	-44933
s_rep	Services - Repair & Personal	167088	88809	78279	44234	23511	20723
hotel	Hotels & Lodging	62987	39607	23380	30828	19386	11442
not_cl	Not Elsewhere Classified	63625	268349	-204724	16322	68840	-52518
pub_ad	Public Administration	215791	120846	94945	11488	6434	5054
d_w_t	Durable Wholesale & Trucking	173335	175074	-1739	10067	10168	-101
m_el	Manufacturing - Electronic Equipment	56651	33384	23267	2395	1411	984
m_oth	Manufacturing - All Other	69109	275614	-206505	2120	8454	-6334
	All Industries	3401633	3735501	-333868	1046713	1085638	-38925

To compare the spatial differences in FW generation between the two, the points of the FWG were aggregated to the city level to match the spatial resolution of CalRecycle's WCT data. The difference between overall FW generation estimates in the WCT and the FWG is visualized in **Figure 17(A)**, which shows the difference in FW generation for all industries between the two datasets. Overall, the WCT and FWG estimates appear to be very similar, as the municipalities with large differences between the two datasets are generally smaller in area. In general, the WCT appears to overestimate FW (blue) in more populated areas while underestimating FW (red) in more commercial/industrial areas of the county when compared to the FWG. Looking at industry specific differences between the WCT data and the FWG, more pronounced spatial patterns can be observed which may help explain the overall FW map. **Figure 17** shows the comparison between CalRecycle dataset and the FWG for rt_f_b (**B**), rests (**C**), and m_food (**D**). The rests and rt_f_b industry groups look very similar to that of the overall FW generation, which is unsurprising given these two industries make up the largest percentage of overall FW generation. These two sectors show slightly more FW in the CalRecycle dataset for the city of Los Angeles, the largest city in the county by area (not including unincorporated area). This is unsurprising given the specificity of the FWG, which was estimated on much smaller geographic units within the City of LA and had to be averaged out to make this map for comparison. The relationship between a municipalities size and differences in FW between the two datasets appears to be true in the opposite direction as well, as the FWG generally shows higher FW in smaller cities, as it is more accurate at fine spatial scales.

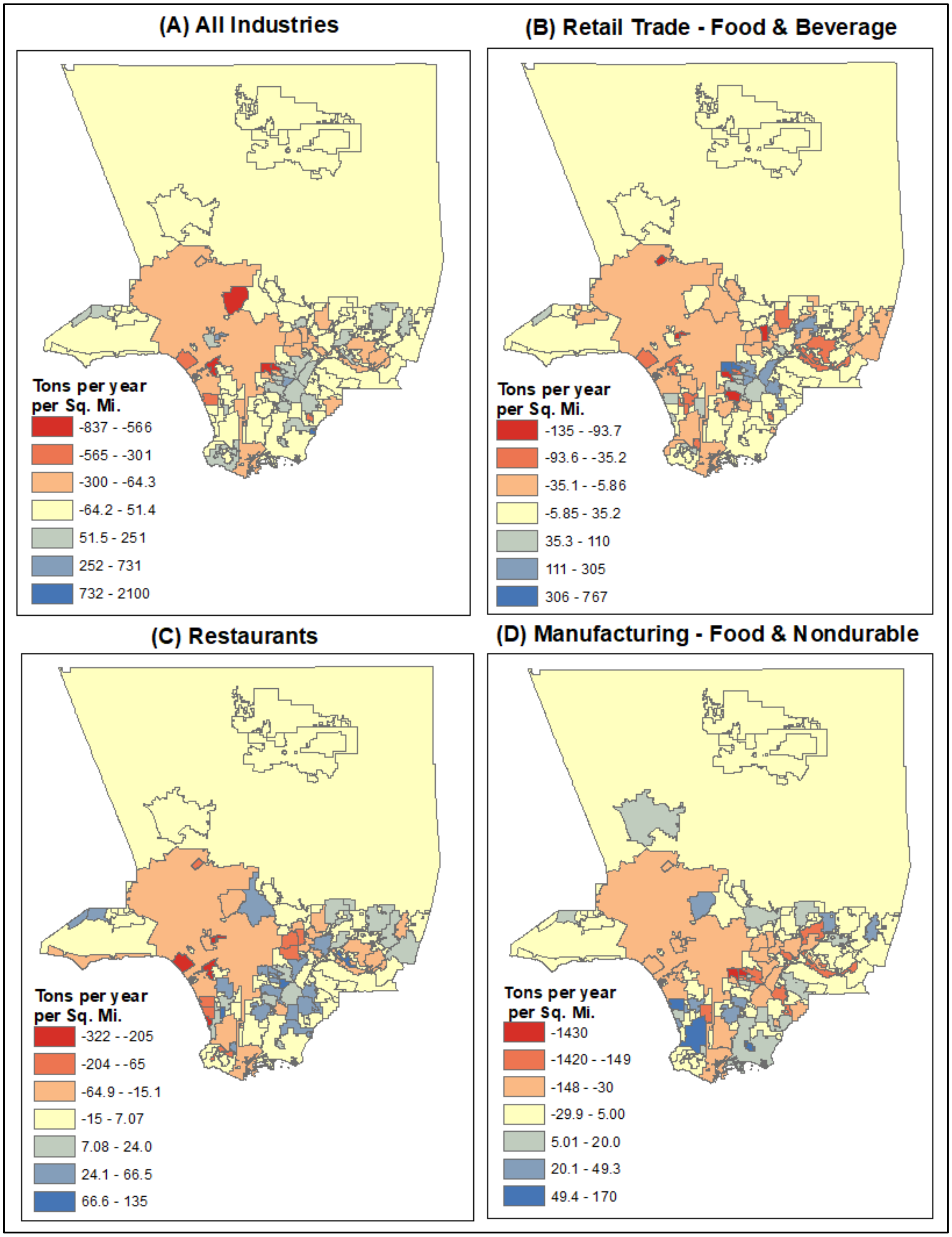

Figure 17. *Differences in food waste generation between the CalRecycle WCT dataset and the FW Geography for All Industries at the city level* ***(A)*** *and Retail/Trade – Food & Beverage Stores* ***(B),*** *Restaurants* ***(C),*** *and Manufacturing – Food & Nondurable* ***(D)*** *industry groups. Cities with negative values have more FW in the CalRecycle WCT dataset than in the FWG.*

The suppression of data in the employment data underlying the WCT may also explain some of the differences between the CalRecycle waste estimates and the FWG on an industry basis. It is not possible to determine which of the two reasons CalRecycle has suppressed an industry's data for a municipality, yet there are clear patterns of differences in FW generation within municipalities associated with suppressed data. The most general pattern associated with data suppression is that all the jurisdictions that have suppressed data for a specific industry have less FW in the WCT estimation than in the FWG, meaning that a significant amount of FW might be missing from the CalRecycle WCT estimations for these industries. An industry-specific example of potential losses of FW due to suppressed data is that from educational institutions where data from 734 institutions in 35 cities have been suppressed in the WCT. While it is not possible to determine the exact amount of FW suppressed within the education sector as we do not know which institutions have had their data suppressed, there is a difference of 13,110 tons/FW generated per year between the FWG and the WCT, with the FWG being the higher of the two. With the amount of uneaten food from trays alone at K-12 schools estimated to be as high as 65 g per pupil per day (Wilkie, Graunke, and Cornejo 2015), this data suppression may conceal a significant volume of FW that should be diverted for treatment. While outside the scope of this study, the potential impacts and possibilities for reduction of food waste from the education sector deserves more attention in future studies.

Discussion

The method of data disaggregation and reaggregation to create 16 industry groups that match CalRecycle TPEPY values presented in this study created a tract-level FW geography that is more spatially refined than the FW generation values released by CalRecycle in the WCT. By incorporating zoning data and generating points that represent FW generators, this tract-level FW data is transformed into the Food Waste Geography (FWG) of Los Angeles County. Shown in **Figure 14**, the FWG is a dataset consisting of 273,023 points representing FW generating businesses from 16 industry groups that together generate 1,046,706 tons FW/year. When combined with a road network, the FWG can be considered as a graph and can be used with routing, location-allocation, and clustering models as described in the Literature Review. While the granularity of the FWG matches the scale requirements for siting a decentralized network of containerized ADs, the large number of points in the FWG means that using it often requires an unreasonable amount of time for the models to find a solution. By systematically reducing the number of points in the FWG, the problem size can be reduced enough to utilize the models discussed above within a reasonable computation time. More importantly, intentionally reducing the number of points in the FWG can make it more accurately depict the FW supply chain by representing the geography of FW discard instead of FW production. Thus, careful aggregation of nodes within the FWG more closely mimics the physical location of collection containers, trash bins, and other discard points, i.e., the physical location where food becomes waste and enters the waste supply chain. This section will discuss techniques for strategically reducing the size of the FWG through point exclusion and aggregation for faster runtime and geographic accuracy.

Point Exclusion

Individual Points by FW Generation

The simplest method to reduce the number of points in the FWG is to simply remove FW generator points that do not produce enough waste to require collection services. Individual business exemptions to SB1383 are granted on a case-by-case basis and are based on the total volume of solid waste generated, as of September 2020, the threshold is 2 cubic yards of solid waste (CalRecycle 2021). Since the FWG is developed using FW generation values and not total waste values, removing individual FW generator points from the FWG that would be exempt from SB1383 is not possible. **Figure 18** shows the amount of FW lost when groups of FW generator points with the lowest FW generation are removed from the FWG. If the 204,770 points with the lowest FW generation are removed, the FWG can be reduced to 25% of the original size while still capturing 75% of the total amount of FW generated, keeping Los Angeles county within the 75% FW diversion goal of SB1383. Assuming 100% FW capture from the remaining FW generators, this result supports CalRecycle's current practice of allowing individual exemptions to the organics diversion rule and even supports broad exemptions to individual businesses based solely on FW volume. Removing low FW generating businesses from the FWG is also a reasonable option from a modelling perspective as it essentially weights the models towards higher FW generating businesses without significantly altering the amount of FW captured by the model. While ultimately all organic waste will need to be diverted from landfills to comply with SB1383, this trade-off curve can help establish minimum FW thresholds for required FW treatment.

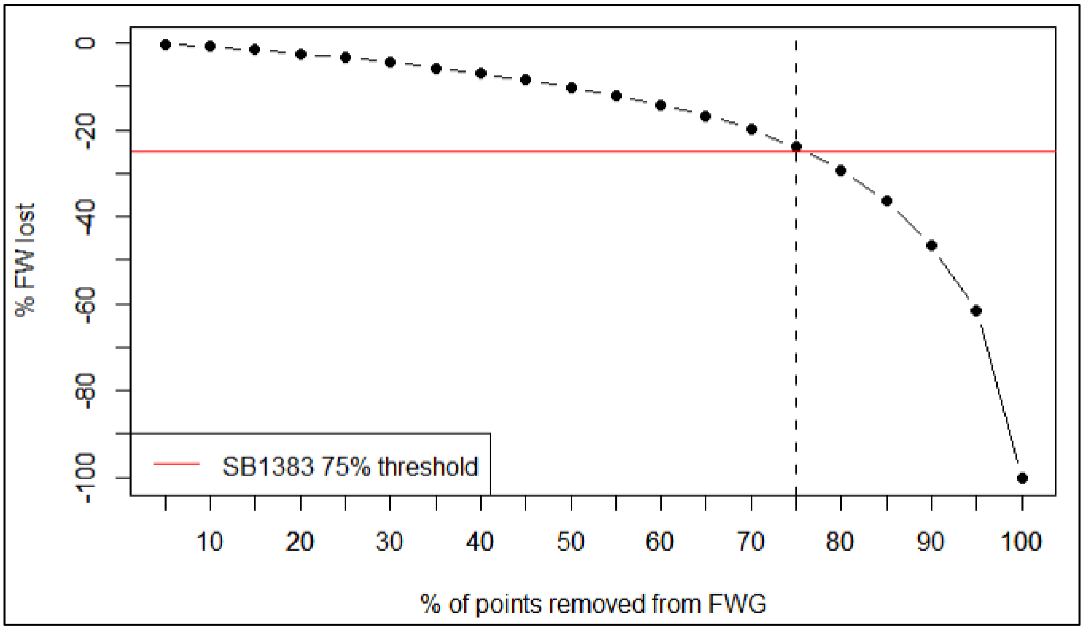

Figure 18. *Trade off between FWG size reduction and FW loss from the FWG when removing groups of FW generators with the lowest individual FW generation. The red line indicates the 75% waste diversion target mandated by SB1383.*

Individual Points by Spatial Location

Exemptions from SB1383 are also granted to rural areas at the county, city, or census tract level based on population density. As the largest county in the state, Los Angeles County does not qualify for a county waiver; however, 70 rural Census tracts within the county could be exempt as they have a population density of less than 50 people per sq mile (HF&H Consultants 2018). These census tracts are shown in **Figure 19,** and within these tracts there are 2,249 business points (0.8% of total) that generate 6,736 tons of FW per year (0.6% of total). Also indicated on **Figure 19** is the city of Rolling Hills, which consists of a single census tract, that may also be eligible for a citywide low population waiver as it disposes less than 5,000 tons of waste and has a population of less than 5,000 people (HF&H Consultants 2018); however, it is not currently listed as an exempt jurisdiction. Removing points within these areas from the FWG will have little effect on the runtime of the models as it does not significantly reduce the size of the FWG, but it is likely to improve the quality of the final solution of mean-based models as they are sensitive to spatial outliers. More importantly, by removing these points from exempt census tracts, the FWG more accurately simulates real world conditions for the implementation of SB1383.

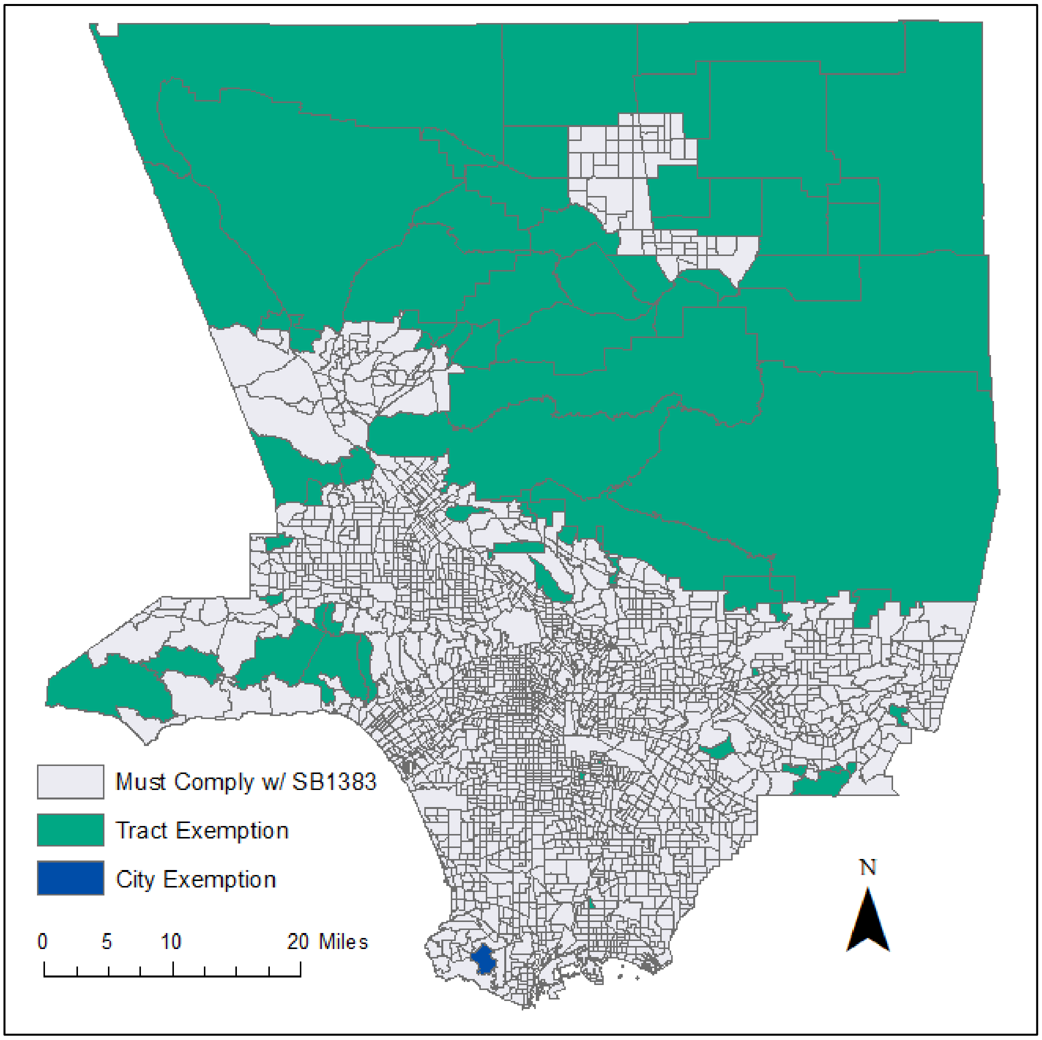

Figure 19. *Census tracts with less than 50 people per sq. mile in Los Angeles County, which are eligible to receive a low-population waiver from SB1383. Also shown is the City of Rolling Hills which includes one eligible census tract and may also be eligible for a city-level low population waiver.*

Entire Industries by TPBPY Value

As it has been shown in **Figure 18**, almost 75% of points can be removed from the FWG while only reducing the amount of FW in the FWG by 25%. Therefore, a simpler solution from a regulation perspective may be to strategically add or remove entire industries from the FWG rather than individual businesses. Doing so would better simulate real world policy and management scenarios as CalRecycle has specific industries to target for FW capture under SB1383 including restaurants, grocery stores, and food wholesalers, and other high FW generating industries. For modelling a spatially optimized system of

FW treatment facilities, capturing as much FW from the fewest number of FW generators as possible should be the primary goal, as this maximizes FW treatment while minimizing VMT. To assess these two goals, a Tons Per Business Per Year (TPBPY) value was calculated for each industry by dividing the total FW generation by the number of businesses for that industry, these are shown in **Table 6**. Also indicated are TPBPY groups, which are used to aggregate points later in the discussion. The overall TPBPY value for all industries in Los Angeles County is 3.834 (SD: 9.527) and industry specific TPBPYs range from 0.417 (m_oth) to 19.427 (rt_f_b). By utilizing the TPBPY value, industries can be prioritized for FW capture to meet the FW treatment goals of SB1383 while minimizing GHG emissions associated with collection and hauling of this waste.

Table 6. *Calculated TPBPY Values for each industry and TPBPY group. Group A have a TPBPY value greater than 5, Group B is industries with TPBPY value between 1 and 5, and Group C is industries with a TPBPY value less than 1.*

Keyword	CalRecycle Industry Group	TPBPY	Group
rt_f_b	Retail Trade - Food & Beverage Stores	19.427	A
hotel	Hotels & Lodging	15.562	A
rest	Restaurants	11.309	A
m_food	Manufacturing - Food & Nondurable Wholesale	10.867	A
art_r	Arts, Entertainment, & Recreation	10.214	A
ed	Education	5.143	A
rt_oth	Retail Trade - All Other	2.921	B
pub_ad	Public Administration	2.880	B
not_cl	Not Elsewhere Classified	2.570	B
med_h	Medical & Health	2.165	B
s_mgmt	Services - Management, Administrative, Support, & Social	1.508	B
s_prof	Services - Professional, Technical, & Financial	1.398	B
s_rep	Services - Repair & Personal	1.283	B
m_el	Manufacturing -Electronic Equipment	1.017	B
d_w_t	Durable Wholesale & Trucking	0.610	C
m_oth	Manufacturing - All Other	0.417	C

Using the TPBPY value, as opposed to only the amount of FW generated, to prioritize industries for FW collection combines the waste collection maximization and VMT minimization goals of modelling a system of ADs for FW treatment. By ordering industries by TPBPY value and sequentially adding them to the FWG, a trade-off curve between the cumulative number of FW generators vs. the amount of FW added to the FWG can be established to help balance these competing goals. This trade-off curve is shown in **Figure 20(A)** as well as trade-off curves with industries ordered by total FW **(B)** and by the number of businesses in the industry **(C)**. As shown in **Figure 20(A)**, prioritizing FW collection from industries in *Group A*, the highest TPBPY group, will capture 64% of the total FW in Los Angeles County from 22% of the points within the space, assuming 100% FW diversion from each business. Taking the top 7 industries by TPBPY, which adds rt_oth from *Group B*, brings the cumulative FW captured over the 75% threshold for SB1383 while using 37% of the points in the overall FWG. Selectively adding industries to the FWG based on FW generated will reach the 75% threshold from 50% of the points (**Figure 20(B)**). Adding industries based on the number of businesses in the industry and prioritizing industries with the fewest businesses first to minimize collection points, will reach near the 75% threshold using 42% of the points (**Figure 20(C)**). While all three methods are ways to maximize FW capture while minimizing the number of collection points, the TPBPY value encompasses both modelling goals, while also identifying the best industries for FW collection. This result supports the CalRecycle's tiered rollout of SB1383 regulation, which targets specific industries for FW and organic waste diversion based on waste generation volume. However, these results suggest that modification of these tiers based on number of businesses within each industry may result in lower GHG emissions as using the TPBPY value to prioritize industries reaches the 75% FW treatment threshold of SB1383 with the fewest number of points.

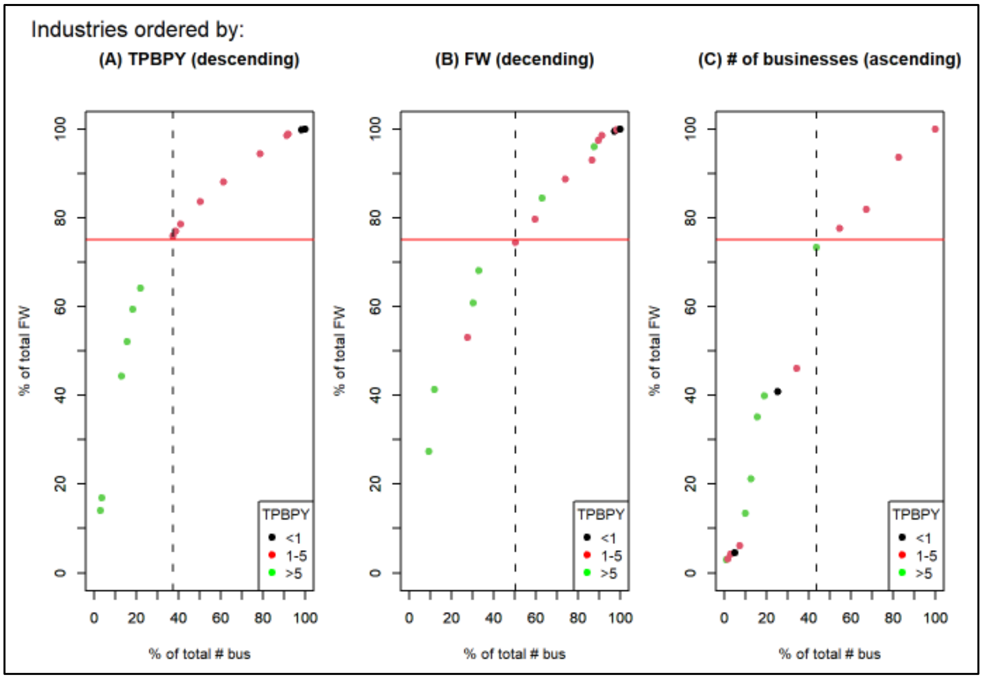

Figure 20. *Number of food waste generator points (in % of total number in FWG) vs. the amount of FW (in % of total in FWG) when selectively including industries for FW diversion under SB1383. Three different decision schemes are shown:* ***(A)*** *Industries with highest TPBPY are included first* ***(B)*** *Industries with highest FW are included first.* ***(C)*** *Industries with the lowest number of FW generators are included first.*

Point Aggregation

Point exclusion and aggregation can each simplify the FWG for faster analysis; however, point aggregation has the advantage of also helping the FWG more closely mimic the reality of FW generation, discard, and disposal. The FWG simulates the geography of FW production, which occurs at every business within the county. In many cases, businesses will share a collection bin, especially if they are located within the same parking lot, mall, or shopping area and generate small amounts of FW. By strategically aggregating instead of removing points, the FWG can more appropriately model the FW supply chain by simulating this geography of FW discard at waste collection points. It is important to note that point aggregation introduces aggregation error to the problem as it changes the representation of points from their original positions and may not reflect the real world. While this is a problem for researchers working with point data derived from remote sensing, field collection, or other spatially explicit methods, this is less of a concern for the FWG which was generated at random. In essence, the

FWG *is* data aggregation, as the randomly generated points are an aggregation of the tract-level dataset derived from employment counts and CalRecycle TPEPY values. Therefore, the simplest method of data aggregation is to generate a fraction of the required number of points in each tract and then distribute the full amount of FW equally among them as in the methods described above (**Figure 21**). While this method will reduce the size of the FWG by a predictable fraction, it also increases the weight each point, making the models more sensitive to spatial outliers.

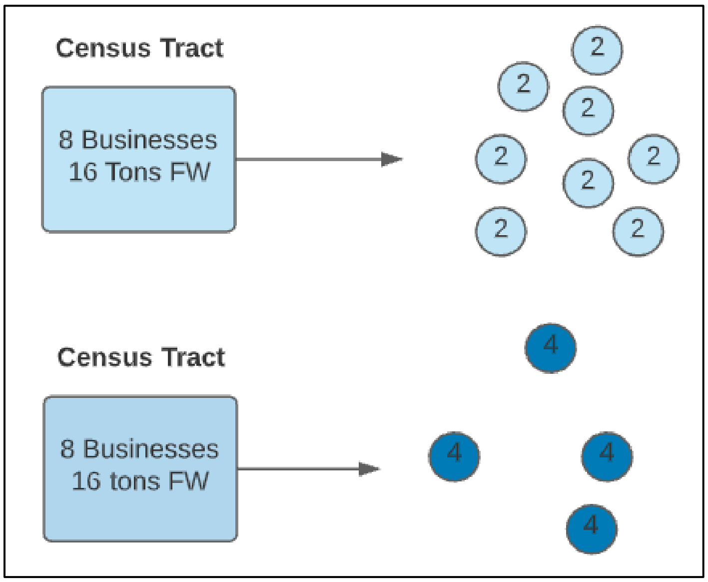

Figure 21. *Aggregation of tract level data to points by creating a point for all food waste generators in the tract (top) and by creating a fraction of points with equal total food waste generation (bottom).*

Using SCAG Zoning Data

By taking advantage of the fine spatial resolution of the SCAG zoning layer, which delineates individual parcels of land, the real-world situation of shared collection bins between FW generators can be modeled. To do so, FW generator points falling within the same parcel are combined following a set of rules (**Figure 22**). The largest reduction in points using this method can be achieved by combining all points from all industries that are found in the same parcel (**Figure 22(B)**), which reduces the FWG to 86% of the original problem size (38,384 points). To target industries with high FW generation, FW generator points of the same TPBPY group within the same parcel can be combined (**Figure 22(C)**), which reduces the FWG to 60,792 points, a 78% reduction in problem size. Realistically, businesses of similar type are more likely to share a collection bin, so the parcel-based aggregation could be done on an industry basis (**Figure 22(D)**). Aggregating businesses of the same industry located within the same parcel would reduce the FWG by 60%, bringing the FWG down to 111,603 points. Other aggregation schemes can be created based on FW generation, parcel size, industry group, or some other factor associated with the FW generator. Using the SCAG zoning layer for point aggregation is advantageous over simple distance-based methods, such as aggregating K nearest neighbors within a specified distance threshold, because it accounts for the real-world spatial layout of Los Angeles County. This includes land-use zoning that affects the clustering of FW generator points as well as areas that do not have FW generation, such as infrastructural restrictions including roads and highways, or areas conserved for wildlife preservation and recreation. The three methods of aggregation by parcel described here are simple examples and the rules of this parcel-based aggregation can be expanded as needed to add additional nuance to the FWG based on real-world factors.

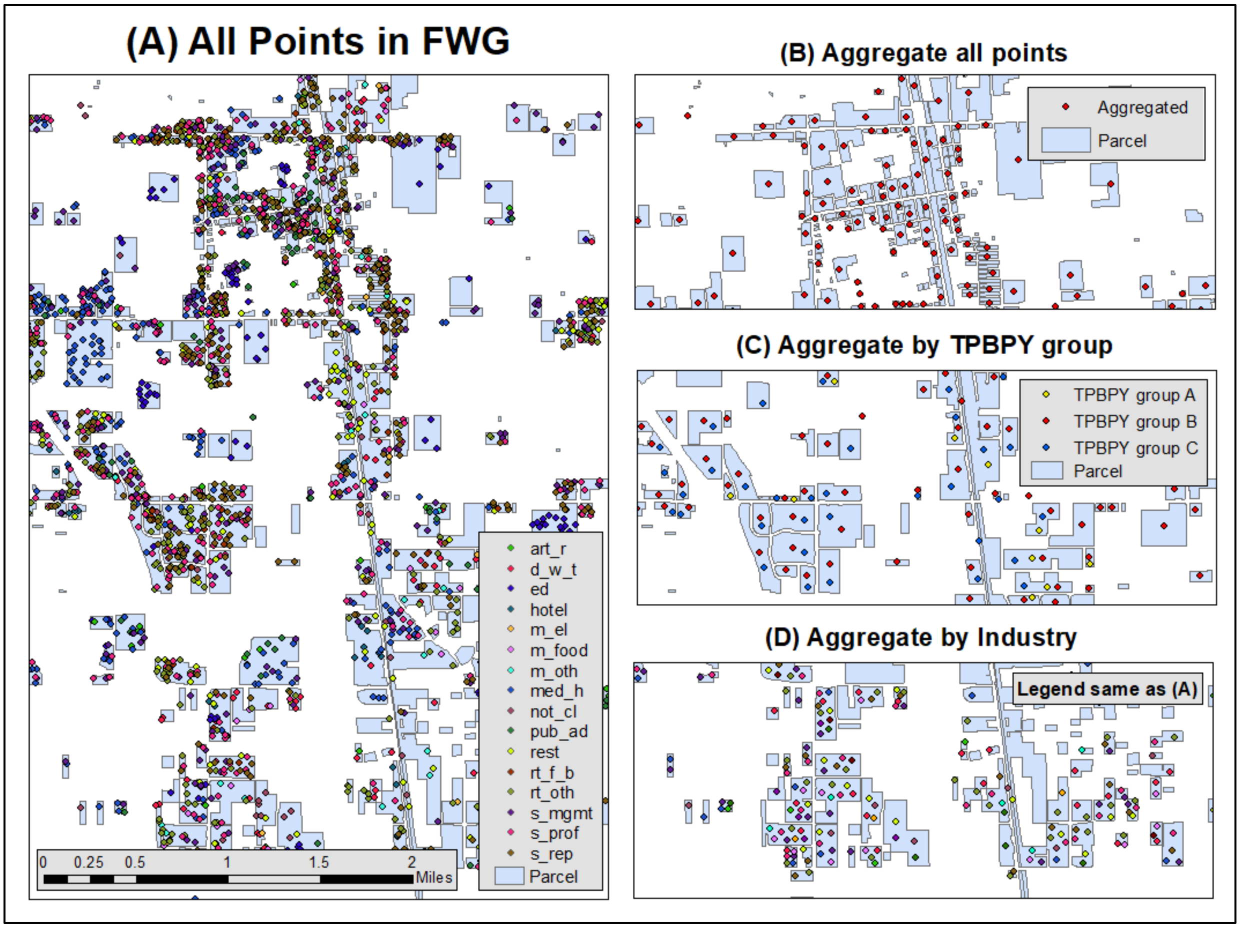

Figure 22. *Aggregation of food waste generators based on SCAG zoning layer, geographic areas on the left (A) and right (B,C,D) are the same.* ***(A)*** *Random generation of all food waste generator points is constrained within SCAG zoning layer.* ***(B)*** *All points in a parcel are aggregated together,* ***(C)*** *points of the same TPBPY group are aggregated within each parcel, and* ***(D)*** *points of the same industry within each parcel are aggregated.*

Discussion Summary

Using the FWG to plan a decentralized network of ADs for FW treatment requires several factors to be considered. With over 200,000 points, the time it takes to solve a model that uses the FWG as an input is a significant consideration as model runtime is a function of the number of points used as an input. Multiple models may need to be employed to leverage the specific strengths and weaknesses of unsupervised clustering, location allocation, and routing models to devise a network of ADs for FW that minimized GHG emissions. Strategically manipulating the FWG to reduce the number of points may help the models find a solution faster and, more importantly, will also help the FWG more accurately mimic the geography of FW discard in Los Angeles County. Removing points with low FW generation or removing points from low-populated census tracts can help mimic exemptions to SB1383, but these methods have a minimal effect on reducing the solve time of the models. The overall goal of using GIS to optimize locations of ADs for FW is to maximize FW captured (reducing GHGs associated w/ final disposal) while minimizing the number of points to collect from (minimize GHG associated w/ collection/hauling). Calculating the Tons Per Business Per Year (TPBPY) value for each industry brings together both goals and can help identify industries to target for FW diversion. Using TPBPY values alone is a non-spatial method of reducing the size of the FWG and is indiscriminate of the spatial arrangement of FW generators from each industry, so point aggregation may also be used to reduce the number of points in the FWG. Utilizing the highly specific SCAG zoning layer in point aggregation helps ensure spatial specificity and TPBPY values can be utilized with this method to provide direction. By randomly placing all the FW points first, then spatially aggregating them by parcel, the FWG can be "customized" to fit the waste diversion goals of the SB1383 and utilized with spatial models within GIS to create an optimal system of FW infrastructure.

Conclusion

This study addresses the significant challenge of implementing SB1383, an aggressive organics waste diversion policy in California, and is a first step towards the development of a decentralized network of containerized, small-scale anaerobic digestors for food waste. Understanding the geography of FW production in Los Angeles County at a spatial scale that matches the operational scale of the ADs is necessary to ensure high levels of FW capture and treatment while minimizing GHG emissions associated with FW collection and transportation. Anaerobic digestion is an excellent option for FW treatment as it reduces GHGs from the landfill and generates beneficial outputs such as biogas and a nutrient-rich digestate that can be used as fertilizer. These digestors can be built at a range of scales, with small-scale systems having the potential to be placed within urban areas as close to the point of FW generation as possible. Improved spatial alignment between FW generation and treatment can reduce VMT and GHG emissions associated with collection and hauling. Given the need for new infrastructure to treat increased organics diversions, SB1383 provides a "blank slate" for planning new forms of decentralized waste infrastructure. With spatial modeling, the size and placement of the ADs can be determined to ensure this new infrastructure is spatially optimized to achieve the highest possible reductions in GHGs associated with food waste disposal relative to 2014 levels.

The methods proposed in this study can inform the planning of this new infrastructure by developing a set of points representing FW generators known as the FWG. The FWG can be used as an input to node-based models such as routing, location allocation, and clustering models to plan the network of ADs. While CalRecycle releases FW production data through its WCT, these data are at the city level, and are not suitable for use as a model input. By combining the TPEPY values from CalRecycle with Census tract-level employment counts from ESRI Business Analyst, less-aggregated FW generation data can be estimated. Disaggregation of the employment dataset to 3-digit NAICS codes was required to match the production-oriented industry groups of the ESRI dataset to the waste-oriented industry groups of the CalRecycle TPEPY values. This methodology is an important contribution of this study as the industry groups used by CalRecycle are not directly comparable to similar industry groups used by other datasets. Another novel method of this study is the use of zoning data to constrain the aggregation of tract-level FW data to point level data, which more closely simulates the “real world” FW landscape. This layer can also be used to apply spatial specificity to point aggregation by modelling the geography of FW discard as FW generators within the same mall, shopping area, etc. that are likely to share a collection bin can be aggregated together. Finally, developing the FWG separately for each industry, then combining into one, allows for the strategic targeting of industries in modelling to achieve the 75% reduction in FW in landfills required by SB1383.

The results of this study show overall FW generation at the Census-tract level as well as by industry. When compared to the dataset released by CalRecycle at the city level, we observed some deviation in estimates that can be explained by differences in reference year, spatial level, and data suppression in the CalRecycle dataset. While it is not possible to determine the amount of FW suppressed in the CalRecycle dataset using the FWG, data suppression may be significant in industries such as education which generates a relatively large amount of FW per employee and has a large number of suppressed businesses in the CalRecycle dataset. Further research into the effect of data suppression on the CalRecycle dataset is needed.

The results of this study also highlight the practical challenges of using GIS to model real-world situations, where the needs of collecting FW from all businesses must be balanced with limitations in solve-time. To balance these needs, the FWG should be systematically reduced in size to collect and treat as much FW from the fewest number of points as possible. The TPBPY value was developed to capture both of these competing goals and select specific industries for targeted FW capture.

The FWG developed in this study can be used with GIS models for a top-down approach to planning a network of ADs for FW. Not considered in this study are “bottom-up” operational/logistics challenges to siting the ADs once the optimal locations are found through spatial modelling. One such concern is the permitting process to build and operate an AD once the location has been selected by the model. Related to this are questions about who shall operate these facilities and collect the waste. Many of these concerns can be mitigated through strategic partnerships between FW generators and the waste service providers to collaboratively work on siting AD facilities to minimize collection and hauling of AD feedstock.

The use of the beneficial outputs from the AD, especially the nutrient rich digestate, is another factor that needs to be considered. In the case of the digestate, scarcity of farmland and other agricultural areas in urban spaces may limit opportunities for its productive utilization. Further research into the effects of transportation of this digestate to rural/agricultural areas is needed to fully model the impacts of this proposed systems on GHG emissions. However, the use of the digestate as fertilizer is an opportunity to increase the productivity of urban farms in the area and develop infrastructure for a circular economy of food. Despite planning and operational challenges of the proposed AD system, the blank slate provided by SB1383 is an opportunity for California to rethink their waste management infrastructure to incorporate the principles of the circular economy and move towards a sustainable agricultural system as a whole.

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Appendix

Table A.1 *CalRecycle Industry Groups and their assigned SCAG zone codes*

Keyword	CalRecycle Industry Group	Code	Description
art_r	Arts, Entertainment, & Recreation	1230	Other Commercial
		1232	Commercial Recreation
		1240	Public Facilities
		1246	Other Public Facilities
		1250	Special Use Facilities
		1253	Other Special Use Facilities
		1310	Light Industrial
		1312	Motion Picture Lots
		1810	Golf Courses
d_w_t	Durable Wholesale & Trucking	1300	General Industrial
		1310	Light Industrial
		1311	Manufacturing, Assembly, & Industrial Services
		1340	Wholesaling & Warehousing
		1410	Transportation
		1500	Mixed Commercial & Industrial
ed	Education	1260	Educational Institutions
		1261	Preschools/Day care
		1262	Elementary Schools
		1263	Middle Schools
		1264	High Schools
		1265	Colleges & Universities
		1266	Trade/Professional Schools
hotel	Hotels & Lodging	1230	Other Commercial
		1233	Hotels & Motels
		1620	Commercial Oriented Residential/Commercial Mixed
m_el	Manufacturing -Electronic Equipment	1310	Light Industrial
		1311	Manufacturing, Assembly, Industrial
m_food	Manufacturing - Food & Nondurable Wholesale	1300	General Industrial
		1310	Light Industrial
		1311	Manufacturing, Assembly, Industrial
		1313	Packing houses & Grain elevators
		1340	Wholesaling & Warehousing
		1500	Mixed Commercial and Industrial
m_oth	Manufacturing - All Other	1300	General Industrial
		1310	Light Industrial
		1311	Manufacturing, Assembly, Industrial
		1320	Heavy Industrial
		1321	Heavy Manufacturing
		1322	Petroleum Refining & Processing
		1324	Major Metal Processing

		1325	Chemical Processing
med_h	Medical & Health	1200	General Commercial
		1210	General Office Use
		1211	Low to Medium Major Office Use
		1212	High Rise Office Use
		1230	Other Commercial
		1240	Public Facilities
		1244	Major Medical Health Care Facilities
		1250	Special Use Facilities
		1252	Special Care Facilities
pub_ad	Public Administration	1240	Public Facilities
		1241	Government Offices
		1242	Police and Sherriff Stations
		1243	Fire Stations
rest	Restaurants	1200	Commercial & Services
		1220	Retail Stores/Commercial Services
		1221	Regional Shopping Center
		1222	Retail Centers
		1223	Retail Strip Development
		1230	Other Commercial
		1233	Hotels & Motels
		1265	Colleges & Universities (1260 not included)
		1411	Airports (1410 not included)
		1500	Mixed Commercial/Industrial
		1600	Mixed Residential/Commercial
		1610	Residential Oriented Mixed
		1620	Commercial Oriented Mixed
rt_f_b	Retail Trade - Food & Beverage Stores	1220	Retail Stores/Commercial Services
		1221	Regional Shopping Center
		1222	Retail Centers
		1223	Retail Strip Development
		1310	Light Industrial
		1311	Manufacturing, Assembly, Industrial
		1500	Mixed Commercial/Industrial
		1600	Mixed Residential/Commercial
		1610	Residential Oriented Mixed
		1620	Commercial Oriented Mixed
rt_oth	Retail Trade - All Other	1220	Retail Stores/Commercial Services
		1221	Regional Shopping Center
		1222	Retail Centers
		1223	Retail Strip Development
		1310	Light Industrial
		1311	Manufacturing, Assembly, Industrial
		1500	Mixed Commercial/Industrial
		1600	Mixed Residential/Commercial
		1610	Residential Oriented Mixed
		1620	Commercial Oriented Mixed
s_mgmt	Services - Management, Administrative, Support, & Social	1200	General Commercial
		1210	General Office

		1211	Low to Medium Office Use
		1212	High Rise Office Use
		1213	Skyscrapers
		1220	Retail Commercial Services
		1221	Regional Shopping Center
		1222	Retail Centers
		1223	Retail Strip Development
		1240	Public Facilities
		1245	Religious Facilities
		1250	Special Use Facilities
		1253	Other Special Use
		1600	Mixed Residential/Commercial
s_prof	Services - Professional, Technical, & Financial	1200	General Commercial
		1210	General Office
		1211	Low to Medium Office Use
		1212	High Rise Office Use
		1213	Skyscrapers
		1220	Retail Commercial Services
		1221	Regional Shopping Center
		1222	Retail Centers
		1223	Retail Strip Development
		1420	Communication Facilities
		1500	Mixed Commercial/Industrial
		1600	Mixed Residential/Commercial
		1610	Residential Oriented Mixed
		1620	Commercial Oriented Mixed
s_rep	Services - Repair & Personal	1220	Retail Commercial Services
		1221	Regional Shopping Center
		1222	Retail Centers
		1223	Retail Strip Development
		1500	Mixed Commercial/Industrial
		1600	Mixed Residential/Commercial
		1610	Residential Oriented Mixed
		1620	Commercial Oriented Mixed
not_cl	Not Elsewhere Classified	2100	Cropland, improved pastureland
		2110	Irrigated Cropland, improved pasture
		2120	Non-irrigated Cropland
		2200	Orchards & Vineyards
		2300	Nurseries
		2400	Dairy & Intensive Livestock
		2500	Poultry Operations
		2600	Other Agriculture
		1330	Extraction
		1331	Mineral Extraction other than Oil & Gas
		1332	Mineral Extraction – Oil & Gas
		1400	Transportation, Communication, Utilities
		1410	Transportation
		1411	Airports
		1412	Railroads

		1415	Bus Terminals & Transit Centers
		1417	Harbor Facilities
		1430	Utility Facilities
		1431	Electrical Power Facilities
		1432	Solid Waste Disposal Facilities
		1436	Water Transfer Facilities

Table A.2 *Land area available for each industry. The area for All Industries does not add up to 100% of the total area for individual industries as multiple industries can be assigned the same zoning code.*

Industry	**Area (sq. mi.)**
Arts, Entertainment, & Recreation	45.275
Durable Wholesale & Trucking	71.422
Education	42.018
Hotels & Lodging	4.732
Manufacturing -Electronic Equipment	44.376
Manufacturing - Food & Nondurable Wholesale	70.374
Manufacturing - All Other	69.445
Medical & Health	51.84
Not Elsewhere Classified	201.811
Public Administration	14.808
Restaurants	90.475
Retail Trade - Food & Beverage Stores	103.678
Retail Trade - All Other	103.678
Services - Management, Administrative, Support, & Social	107.347
Services - Professional, Technical, & Financial	94.819
Services - Repair & Personal	59.301
All Industries	486.914