15 (2022) 200113

Contents lists available at ScienceDirect

Resources, Conservation & Recycling Advances

journal homepage: www.sciencedirect.com/journal/Resources-Conservation-and-Recycling-Advances

"A cluster-based spatial analysis of recycling boundaries aligning anaerobic digestion infrastructure with food waste generation in California"

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ARTICLE INFO

Keywords:
Food waste
Anaerobic digestion
Greenhouse gasses
Transportation
Circular economy
Recycling boundary
Spatial analysis
GIS

ABSTRACT

In 2016, California passed Senate Bill (SB) 1383 to reduce short-lived climate pollutants, including methane gas. Towards this end, the law specifically mandates a 75% reduction of organic waste, including food waste (FW), from landfills by 2025. However, current infrastructural capacity to treat this diverted organic waste is limited throughout the state, so new facilities will need to be built to treat these valuable waste flows. The purpose of this study is to investigate ideal size and scale of new facilities that maximize FW treatment and minimize GHG emissions. To do so, this study uses a case study of Los Angeles County to model a decentralized network of small-scale, containerized anerobic digestors (ADs) for treatment of FW in the region. A spatial FW dataset developed for this study is used with a novel iterative-descent clustering model to simulate potential "FW-sheds" of ADs using Geographic Information Systems (GIS). Monte Carlo simulation was used to generate a range of model results and a GHG analysis of FW collection is used to compare systems of two different AD capacities. The results of this analysis show that food waste is ideal for recycling at relatively small spatial scales as hauling burden of FW is reduced in these systems. The proposed infrastructure modeling approach is a first step of developing a zero net energy infrastructural solution that promotes a circular economy of food in direct response to SB 1383 and, more broadly, global climate change.

1. Introduction

Landfills are one of the largest "super-emitters" of methane in California, contributing to over 41% of statewide point-source methane emissions (Duren et al., 2019). These emissions are primarily generated through the anaerobic decomposition of organic waste, which is the largest component of municipal solid waste (MSW) disposed in landfills (34%). Of the total organic waste, food waste (FW) is the largest component, contributing to 44% of organic wastes and 15% of all wastes disposed of in California in 2018 (CalRecycle, 2020). To combat these emissions, California Senate Bill (SB) 1383 calls for the diversion of 75% of organic waste from landfills by 2025 as part of a larger mandate to reduce greenhouse gas (GHG) emissions in the state. The bulk of FW currently headed to landfill is expected to be diverted towards compost or anaerobic digestion (AD) facilities for recycling. Current infrastructural capacity is insufficient to treat this increased tonnage of FW directed towards these systems (CalRecycle, 2019). Therefore, the implementation of SB 1383 presents a unique opportunity to transform organic waste management by providing a near "blank slate" to build out a circular economy infrastructure that seeks to recycle, rather than dispose, organic material.

In designing new waste systems under the circular model, a key question that emerges is the ideal spatial scale of (re)circulation. Several case studies have analyzed recycling systems to determine ideal operational scale, such as eco-industrial parks in Japan (Chen et al., 2012), recycling firms in Texas (Lyons, 2008), and non-hazardous solid wastes in Brussels (Zeller et al., 2019). These studies reveal key linkages between waste material type, generation rates, and transportation costs in determining the ideal spatial scale for recycling systems. In their analysis of plastics recycling in the Tokyo Metropolitan region, Chen et al. (2014) use spatial location-allocation techniques to determine the optimal number, capacity, and locations for new recycling centers that maximize economic return. Their findings indicate that the spatial density of waste and the ratio of unit transportation costs to unit treatment costs are the key determinants of what they call "resource recycling boundaries". While these case studies are not specifically focused on organic wastes, their results indicate that FW is likely ideal for recycling at a local scale given its high density of generation in urban

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https://doi.org/10.1016/j.rcradv.2022.200113

Available online 1 September 2022

areas and its stringent transportation requirements (i.e. spoilage, pest, and odor issues limit its ability to be stored). These general results are corroborated by Rijal and Lin (2021) who specifically focus on FW in their study of recycling boundaries for low-value materials (LVMs). They develop “convenient equations” to determine recycling radii of LVMs, based on the amount of material collected, cost of transportation, and cost of treatment. Their results showed that the spatial density of FW is the most important factor affecting the size of the recycling radius. While they correct for population density in their calculations, their equations assume a homogenous distribution of FW generation within municipal boundaries. This represents an important limitation of this approach, considering that commercial waste generators are point-sources of waste that tend to be heterogeneously distributed within and between municipal boundaries. By taking a highly granular geographic approach, the current study overcomes these limitations and represents a novel evaluation of recycling boundaries for new organic waste treatment technologies under a circular economic framework in a (simulated) real-world setting.

The organic waste treatment considered in this study is AD which is widely used to treat some types of organic wastes, however its specific use for treatment of FW is limited. California currently has over 140 wastewater treatment facilities using AD technology (Breunig et al., 2017), but only 15 existing standalone AD facilities (with 16 more pending) currently accept organics from municipal sources (Dewey, 2021). Therefore, while statewide AD capacity is increasing, local (county) AD capacity is limited in twenty-three counties (Breunig et al., 2017). Meanwhile, the physical area in which typical large-scale waste facilities can be built is limited in urban and peri-urban regions. Advancements in waste treatment technology, specifically the development of smaller scale, containerized, AD systems, represent an alternative option that can expand local capacity for FW treatment while being more easily integrated into the urban landscape in these regions. Current examples of small-scale digestors exist in Oxnard, California and at the University of California, Davis, with treatment capacities of 10, 000 and 55,000 tons of FW/year, respectively. Given their potential to align with the high spatial density of urban FW generation, the introduction of small-scale ADs for FW can supplement existing infrastructural capacity to manage the substantial increase in organic waste diversion mandated by SB 1383. Further, designing the network to explicitly minimize hauling burdens can simultaneously reduce the environmental impact (i.e. fossil fuel use and GHG emissions) as well as the health impacts (i.e. air pollution) associated with transportation of FW for treatment.

A fundamental element to reducing these hauling burdens is the location of the ADs relative to the location of FW generation, which determines the minimum Vehicle Miles Traveled (VMT) for FW collection trucks travelling between them. Routing models can be used to directly reduce VMT by manipulating the collection route (Sahoo et al., 2005), however the need for increased treatment capacity due to SB 1383 means the location of waste facilities themselves can be optimized to reduce hauling burden. Location-allocation models are a class of algorithms that choose the optimal set of ADs from a larger set of potential AD sites that satisfies some objective, usually to minimize total transport cost or maximize waste collection within a defined service area. Various location-allocation techniques have been used to optimize circular waste treatment/waste to energy systems either from a waste-treatment perspective (Nithya et al., 2012; Yalcinkaya, 2020) or energy generation perspective (Comber et al., 2015; Fraccascia et al., 2021), differentiated by the demand function being satisfied. While location-allocation models are widely-used tools for planning, possibly due to their inclusion in popular GIS software, other approaches to facility siting that identify natural clusters of high waste generation in which to locate facilities are increasingly used to help minimize hauling burdens of waste systems. For example, both Hohn et al. (2014) and Laasasenaho et al. (2019) use kernel density methods to locate areas of high woody biomass feedstock in which to locate energy generation plants in Southern Finland. Clustering techniques that leverage the power of artificial intelligence in data-mining are also used. Examples include hierarchical clustering to localize location-allocation or multi-criteria analysis (Jesus et al., 2021; Laasasenaho et al., 2019), k-medoid clustering(Kaundinya et al., 2013), and k-means clustering which has substantial advantages in computation time for large datasets (Gomes et al., 2007; Mohamed Sultan and Mativenga, 2019). Given the large number of new AD facilities needed to comply with SB 1383 as well as the flexibility in siting of the proposed containerized ADs, these unsupervised clustering models are well suited to our exploratory analysis of FW generation and subsequent AD location.

In this assessment, we ultimately want to understand how the spatial distribution of FW aligns with small-scale AD technology and its potential to mitigate GHGs through reduced waste hauling and optimal treatment capacity allocation. We use a novel spatial clustering model within Geographic Information Systems (GIS) to simulate a potential infrastructure pathway reliant on a decentralized network of containerized ADs. A use-case for this model is demonstrated that generates equal-sized clusters of FW in which to place ADs in Los Angeles County, California. The GHG emissions associated with FW collection are used as a performance metric as this is the stage of the FW supply chain most affected by the size of the recycling boundary. By comparing this hauling burden between large and small capacity ADs we advance our understanding of the relationship between the geography of FW production and the ideal scale of FW recirculation. Thus, the analysis can help to inform the identification of the ideal operational scale for an expanded network of AD treatment facilities in California that promotes a circular economy of food.

1.1. Study area

The study area is Los Angeles (LA) County, California, the largest county in the state by population (over 10 million people) as well as the largest generator of MSW. In 2018, LA County disposed 10,098,794 tons of waste from commercial sources, contributing to 28.1% of total statewide tonnage (CalRecycle, 2020). Assuming the LA County MSW has the same composition as the statewide average, then 34% (over 3433,000 tons/year) of this waste would be organic waste and subject to the SB 1383 diversion mandate. Most of the county’s population resides in the southern half of the region, with some pockets of high-density generation in the northern half. Almost bisecting the county is the Angeles National Forest, which covers over 700,000 acres and has essentially no commercial FW generators. Given the contrast between high population density (and high density of FW generation) in the south, and the dispersed clusters of FW generation in the north, LA County is an ideal study area for evaluating the spatial distribution of small-scale ADs for FW treatment relative to the FW generation landscape.

A novel spatial dataset called the “FW Geography” (FWG) was created to model the spatial distribution of FW from commercial businesses within the study area at the point-level scale. In California, the Department of Resources Recycling and Recovery (CalRecycle) has estimated the Tons Per Employee Per Year (TPEPY) of FW generated by 17 industries across the state through surveys of waste haulers and waste generators (CalRecycle, 2020, 2015). The FWG was developed using TPEPY values from the 2014 Generator-Based Waste Characterization Study (CalRecycle, 2015), the most recent statewide waste characterization study that differentiates waste generation rates into industry groups. These values were combined with spatial, Census tract-level employment data from ESRI’s Business Analyst (BA) software extension (*ESRI ArcGIS Pro*, 2019) to produce FW disposal data at the Census-tract level. Significant processing of these datasets was needed to match the production-oriented industry groups of ESRI BA data with the 17 waste-oriented industry groups utilized by CalRecycle based on North American Industry Classification (NAICS) codes. This process is shown in **Figure S.1** and 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.

To more closely mimic FW generation in the real world, the areal, tract-level FW data was aggregated to points which were spatially constrained to commercial areas within each tract using parcel-level zoning/land-use data from the Southern California Association of Governments (SCAG, 2020). Additionally, Census tracts with a population density of less than 75 people/sq. mile or located within unincorporated areas of the county were excluded from the FWG, as these regions were assumed to have a low-population density waiver from CalRecycle and not required to divert their waste under SB 1383 (HF&H Consultants, 2018). Removing these low-population Census tracts from consideration excludes less than 1% of the estimated FW from the FWG and greatly improves the performance of the clustering model by removing spatial outliers. The final FWG is shown in Fig. 1 and consists of 272,177 points representing FW generators across 17 industries that in total dispose of an estimated 802,723 tons of FW in landfills per year. This dataset is available in a Github repository located at https://github.com/lmabe/FWADA-Model.

2. Methods

This study assesses potential GHG emissions from the adoption of a decentralized network of small-scale ADs for commercially generated FW in Los Angeles County, California. A novel spatial clustering model, called the Food Waste/Anaerobic Digestor Allocation (FWADA) model, was developed that takes the desired AD capacity and the location of FW generation (Fig. 1) as inputs and returns equal-sized clusters of FW generation points in which to place ADs. Two scenarios of cluster size (10,000 and 55,000 tons/year) are evaluated that differ by scale of AD deployment as both tested capacities have demonstrated commercial viability. The AD networks derived by the FWADA model are compared by their hauling requirements, which is assessed in terms of estimated GHG emissions derived from VMT and the weight of FW transported. The following sections describe the function of the FWADA model's iterative-descent clustering algorithm, the method of GHG accounting used for assessment, and obtaining the results of the model using Monte Carlo simulation.

2.1. FWADA model clustering algorithm

The goal of a decentralized network of ADs is to maximize FW treatment while minimizing systemic GHG emissions by placing ADs near the source of FW generation to reduce VMT for collection. Since the ideal recycling boundary is dependent on the density of waste generation, unsupervised K-means clustering can be used to find "natural clusters" of high-density FW generators in which to place ADs. As an unsupervised method, K-means clustering is best suited for exploratory situations where no current FW-specific infrastructure exists. This clustering algorithm finds a user-specified number of clusters in which the total within-cluster sum of squared distances (T.WSS) from the FW generation points to the ADs located at the cluster centers is minimized. However, the algorithm only takes the spatial location, not production intensity, of the FW generators into account leaving some ADs in the solution allocated FW outside their optimal capacity range. Therefore, the FWADA model was developed to generate clusters of FW generators

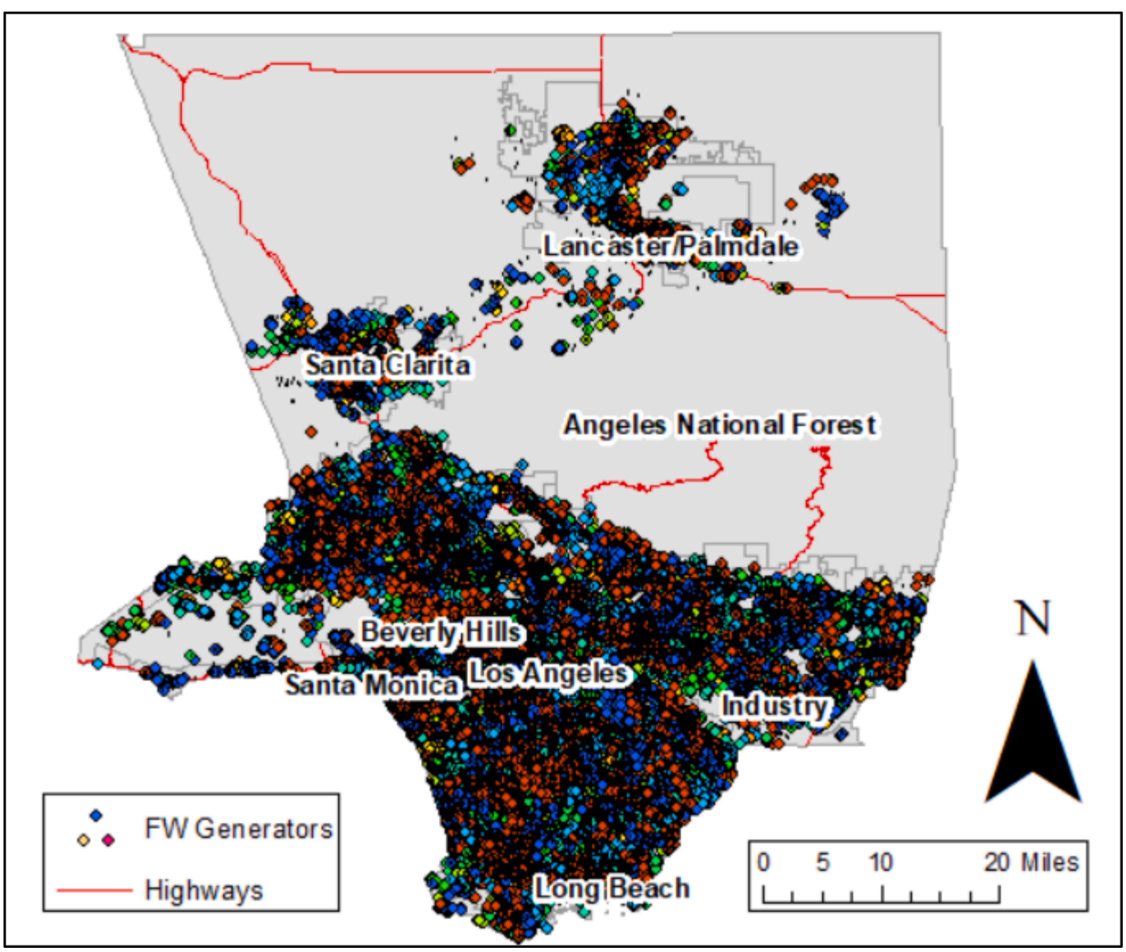

Fig. 1. The "Food Waste Geography" (FWG) dataset used created for this study. The FWG is a spatial point dataset which models the location of food waste generation from 272,177 commercial businesses across 17 industries in Los Angeles County, California that in total dispose of 802,723 tons of FW/year.

that produce relatively equal amounts of FW to optimize FW treatment capacity for each AD. In this analysis, K-means is used to establish the initial clusters of FW, which are then further modified with AD capacity constraints introduced with the FWADA algorithm. While the modeling goal of K-means (minimize T.WSS therefore reducing total VMT) is *global* in scope, the scope of the FWADA algorithm is on a *local* per-cluster basis, iteratively modifying clusters to equalize the distribution of FW between clusters.

This equalization step is an important for the analysis of recycling boundaries. The factors that influence GHG emissions for collection are the weight of FW being transported (determined by the capacity of the AD) and the VMT of the collection truck hauling said waste. Since larger ADs require more FW to be collected, VMT is also influenced by the size of the AD. By holding the capacity of the AD within a model run fixed, the spatial variation of FW within the study area is the primary influence on the physical size of any single cluster in the FWADA model's solution. Doing so also allows for better comparisons between larger and smaller scale systems as these are the main independent variable. From a modeling perspective, however, the equalization of FW within clusters is difficult using traditional spatial modeling techniques thus requiring the development of the iterative-descent FWADA model to modify K-means derived clusters.

To initialize the FWADA model, the user-specified K parameter of the unsupervised K-means model is set 81 and 15 clusters, respectively, which is the minimum number of ADs needed at each capacity to digest all FW in the FWG. Following the establishment of these clusters, the FWADA model then works in three stages to equalize FW distribution among clusters using an iterative algorithm that corrects a single cluster at a time until all ADs have been allocated FW within an optimal range of 70–100% of their capacity. Summarized in Fig. 2, different spatial processes are utilized within each of the three stages to change the size of the clusters by reclassifying FW points to different ADs based on the current volume of FW in the target cluster relative to adjacent clusters (**Table S.1**). We developed a method of establishing adjacency between point-based clusters that produced consistent results for the purposes of our model. The following paragraph gives a general description of the FWADA model. For more detailed information, a Github repository containing the R code for the FWADA model, as well as informational files that detail the spatial processes to establish adjacency, modify clusters, and assess GHG emissions are available at https://github.com/lmabe/FWADA-Model.

The first stage of the FWADA model reduces the size of clusters that have a greater volume of FW than available AD capacity. Starting with the largest cluster, the model reduces the amount of FW allocated to its AD by reclassifying FW points along its boundaries to neighboring ADs. Alternately, if the target AD is especially large, defined as being allocated FW over 140% of its capacity, the cluster is bifurcated. This is achieved by dividing the cluster in half, perpendicular to its line of principal direction, leaving both resulting ADs above a minimum 70% capacity. By locating an additional AD within the study area, this splitting operation adds global surplus AD capacity which may be used in later stages of the iterative algorithm. The second stage of the model removes small clusters with total FW less than 70% of AD capacity by redistributing their FW to adjacent ADs. This stage starts with the smallest cluster to minimize the number of iterations, since the process in turn brings the neighboring ADs closer to 100% full. During this stage, some ADs may be left overfilled if surplus capacity in neighboring ADs is unavailable to absorb excess FW. Overfilled clusters are revisited in the final stage which attempts to reduce their size in case neighboring AD capacity became available in later iterations. The model stops when all ADs have been allocated FW between the optimal operating range of 70–100% of capacity, or after a prespecified number of iterations. Due to the spatial arrangement of the FW in the FWG, some ADs may be left slightly overfilled. While ideally, all ADs have some surplus capacity, this is not a big concern in practice as existing AD facilities deal with fluctuations in feedstock quantity by increasing the through rate of FW resulting in slightly decreased biogas generation.

2.2. Greenhouse gas emissions analysis

Systemwide (global) GHG emissions of collection and hauling are the key performance metric for the clustering analysis, which are calculated as the sum of per-cluster (local) hauling GHGs. The GHGs associated with hauling of waste is a function of the Vehicle Miles Travelled (VMT) of the collection route and the weight of the FW being hauled. Minimizing these impacts can be done through ideal placement of, and allocation of FW to, ADs within the study area. Given the large number of FW generating businesses within the study area, we prioritized speed of computation over optimality of route when estimating VMT for each cluster established by the FWADA model (Lawler, 1976). The Euclidean Nearest Neighbor route constructor algorithm, the simplest algorithm, was used to estimate VMT and no further post-hoc optimization of the route was performed. Technical details of this algorithm and other time-saving computation methods used are included in the code found in the Supplemental Information. Therefore, while the calculated route is not exactly reflective of the potential real-world situation, given the relative uncertainty in the placement of individual FW generator points in the FWG, it still adequately models a FW collection route that can be used as a rough estimate of VMT for the purposes of this study.

The calculated VMT is used to estimate GHG emissions associated with weekly collection and hauling of FW by typical commercial organics recycling trucks. We modelled a diesel-powered collection vehicle with an average fuel efficiency of 4.4mpg (Sandhu et al., 2015). Capacity limitations to the trucks, which may require multiple return trips to the AD, were ignored as the collection trucks were assumed to have a capacity of 25,000lbs (12.5 tons) of FW (Scranton Manufacturing Co., Inc., 2022). These truck specifications were used with emissions factors for CO_2, CH_4, and N_2O for heavy duty diesel trucks from the US EPA (EPA, 2016) to generate emissions factors in terms of kg CO_2e per kg/mile. To account for increasing volume of FW collected as the truck moves along its route, the weekly weight of FW allocated to each AD was divided in half, modeling a linear relationship between FW collected and VMT travelled. Improvements to this method that include the varying distance between and/or weight of FW at each FW generator along the collection route would obtain a more accurate absolute GHG value, however given the uncertainty of the route using the nearest neighbors method described above, this was not included. The weekly collection emissions estimations for each cluster were then multiplied by 52 to obtain yearly values that match the temporal scale of the FWG.

2.3. Obtaining FWADA model results

The FWADA model was used to obtain clusters of FW at two different AD scales: 10,000 tons/year and 55,000 tons/year capacities. Since the FWADA model uses the unsupervised K-means algorithm to generate initial clusters, the result is highly dependent on the initial random cluster centers used to begin the K-means algorithm. Therefore, Monte Carlo simulation ($n = 1000$) was used to generate a distribution of results to address this model uncertainty. For each iteration of the Monte Carlo simulation, the GHG emissions and other summary statistics of each individual cluster is calculated and then summarized to a total value for the entire study area; these values are referred to as local and global results, respectively. A method of measuring the area of each cluster using the convex hull was developed as part of these summary statistics. The mean and standard deviations of the global values are used to summarize the entire Monte Carlo simulation in the Results section. GHG emissions are reported in terms of MT GWP100 CO_2-eq/year for the entire study area which allows for direct comparisons of the environmental effects of the overall proposed AD system between 10k-ton and 55k-ton operational scales.

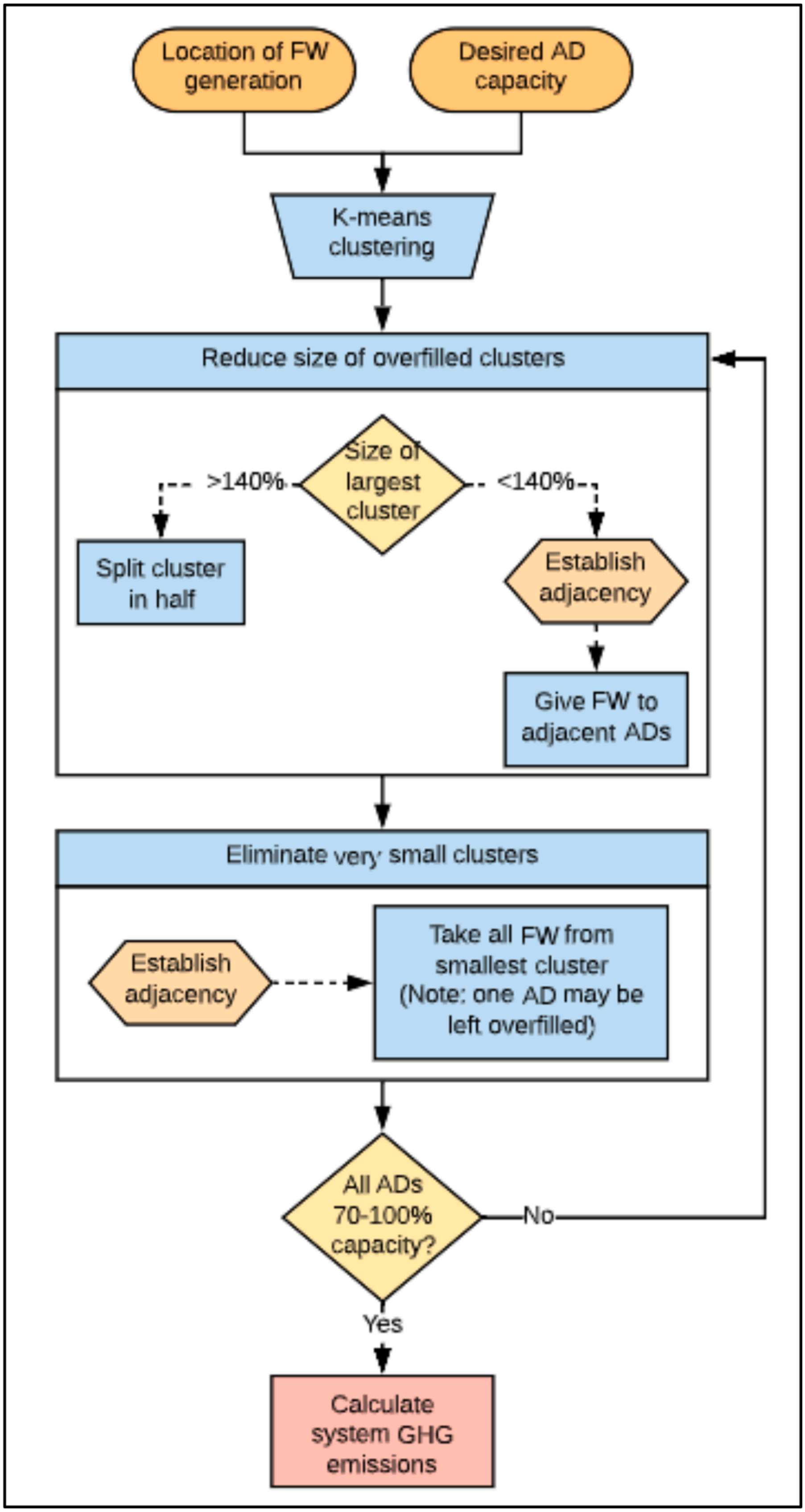

Fig. 2. General framework of the FWADA model.

3. Results

Two AD operational capacities are evaluated using the FWADA model which are referred to as 10k-ton (10,000 tons FW/year) and 55k-ton (55,000 tons FW/year) ADs in this section. Fig. 3 shows the clusters derived by one run of the FWADA model for both capacities; these maps represent average performing AD networks and are not necessarily the most optimal result. Instances of non-compact clusters that may increase VMT can be seen on both maps. For example, both maps have general overlap between clusters near the highly populated Beverly Hills area. These results are not unexpected, given that adjacency function assumes a uniform density of FW generators and these errors occur near areas at the extreme ends of the FW population density spectrum. Improvement of the FWADA model's adjacency function would decrease instances of these clusters and generate more optimal results.

Comparing the two maps shown in Fig. 3 shows the clear relationship between operational scale and spatial scale of FW recirculation as the size of 10k-ton clusters are physically smaller than those of 55k-ton clusters. Shown in Table 1, the average area of clusters for 10k-ton ADs is 36.05 miles^2 with 3179.88 FW generators while for 55k-ton ADs, 17,858.19 FW generators are needed to make cluster with an average area of 180.64 miles^2. Both maps show that the size of the FW recycling boundary is dependent on the AD's location relative to the concentration of FW generation within the study area. For example, for both tested capacities, the geographical size of the clusters is much larger in the north than in the more densely populated south. This result is consistent with other studies that observe that the size of the recycling boundary is dependent on the density of waste generation. Given the regional variability of FW generation within the study area, future modeling work could address this observation by developing models that generate heterogenous networks of ADs with varying capacities. Such a system could fully optimize the FW treatment infrastructure for Los Angeles County, however it is outside the scope of this study.

Summary statistics of the FWADA model solutions are shown in Table 1, which reports average values for entire Monte Carlo simulation. The minimum number of 10k-ton ADs needed to treat the FWG is 81 ADs that are filled to 99.10% of their capacity while for 55k-ton systems, 15 ADs at 97.30% capacity are needed. To account for the spatial variation of FW generation quantities, the FWADA model may need to place more

Table 1
Summary statistics of selected indicators of FWADA model performance. Values represent the average (standard deviation) for the Monte Carlo simulation (n = 1000). * = significantly different @ 0.95.

Mean (sd)	Unit	10k-ton ADs	55k-ton ADs
Number of ADs	ADs	85.61* (1.53)	15.26* (0.60)
Avg. FW per AD	% of AD capacity	93.80* (1.69)	95.76* (3.69)
Avg. SD of FW per AD	% of AD capacity	9.35* (1.26)	10.25* (2.87)
Total FW over AD capacity	% of FWG	0.69* (0.49)	1.59* (1.40)
Avg. per cluster Area	Sq. miles	36.05* (8.08)	180.64* (17.90)
Avg. per cluster FW generators	FW generators	3179.88* (57.17)	17,858.19* (687.33)

ADs within the space; after 1000 model runs the average number of ADs placed by the FWADA models is of 85.61 and 15.26 ADs for 10k- and 55k-ton ADs, respectively. Partial values in this result are due to the variation in Monte Carlo simulation results, for example in the 55k-ton systems the FWADA model placed and additional AD into the network 26% of the time. These additional ADs increase overall surplus capacity of the system, which is shown by the reduced average amount of FW to each AD, 93.80% for 10k-ton and 95.76% for 55k-ton ADs. Ideally, all ADs should be as close to 100% full to maximize FW treatment efficiency, but in practice the slightly reduced volume of FW allocated to ADs could be viewed as infrastructural flexibility to accommodate changes in FW generation due to seasonal, geographic, or market factors.

The standard deviation (SD) of FW allocated to each AD in a model solution is the primary global metric used to evaluate the FWADA model's ability to equalize FW between clusters. To allow for comparison across the two AD scales, Table 1 shows the average of this value for the Monte Carlo simulation as a percent of the AD's capacity. The amount of FW allocated to each cluster deviate 9.35% of AD capacity from the mean for 10k-ton ADs and 10.25% of AD capacity for 55k-ton ADs. Equalizing FW volumes across all ADs in a solution in turn maximizes FW treatment over the entire AD system. In total, only 0.69% (5600 tons/year) and 1.59% (12,700 tons/year) of the FWG is allocated

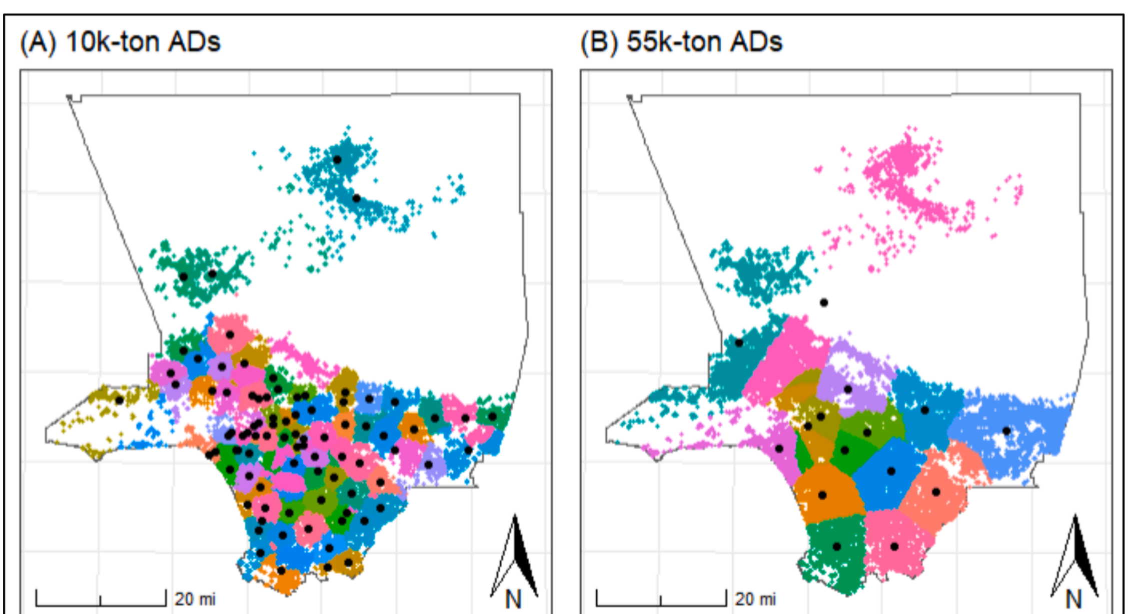

Fig. 3. Clusters of food waste generators produced by the Food Waste/Anaerobic Digestor Allocation (FWADA) model for **(A)** 10,000 tons/year capacity and **(B)** 55,000 tons/year capacity ADs. These solutions are for one run of the model in the Monte Carlo Simulation and represent an average model run based on total GHG emissions. ADs are located at the cluster centers, weighted by food waste.

to ADs over their capacity for 10k-ton and 55k-ton ADs respectively. In practical terms, this means that the two capacity scenarios are comparable as the FWADA model's ability to equally allocate FW to ADs is relatively unchanged between higher and lower AD capacities.

Fig. 4 compares VMT (**A/Top**) and collection GHGs (**B/Bottom**) between the tested AD capacities on a per-cluster local (**1/Left**) and systemwide global (**2/Right**) basis. The average per-cluster VMT for 10k-ton systems is 133 miles while for 55k-ton systems this value is 714 miles (Fig. 4.A.1). This 137.19% difference in local VMT contributes to the 187.217% difference in average local collection GHGs, with 117 MT CO_2e/year and 3544 MT CO_2e/year for 10k-ton and 55k-ton ADs respectively (Fig. 4.B.1). Despite the lower per-cluster VMT, 10k-ton ADs show a higher global VMT than 55k-ton ADs, with the average of the Monte Carlo simulation results being 11,383 MT CO2e/year for 10k-ton systems and 10,882 MT CO2e/year for 55k-ton systems (Fig. 4.A.2) However, it should be noted that the standard deviation of system VMT within the Monte Carlo simulation is much larger for the 10k-ton systems; 385.45 miles for 10k-ton ADs compared to 92.37 miles for 55k-ton ADs. Ultimately, the goal of the FWADA model is to locate ADs and allocate FW to them to reduce systemwide GHGs associated with collection and hauling. This value is shown in Fig. 4.B.2, where on average 10k-ton systems produce more than 5 times lower GHG emissions than 55k-ton systems, 9980 MT CO2e/year for 10k-ton systems compared to 53,912 MT CO2e/year for 55k-ton systems.

4. Discussion

This study is aligned with others that FW is ideal for recirculation at small scales as the 10k-ton AD networks had lower systemwide GHG emissions than 55k-ton ADs. Both AD capacities tested in this study are considered "small-scale" relative to current waste facilities, therefore the GHG analysis enables an evaluation of the potential benefits of decentralized FW infrastructure as well as the appropriate scale of AD deployment. We assume a best-case scenario in which all of the estimated 802,723 tons/year of FW in the FWG that is currently disposed of in landfills are diverted to the AD system. GHG emissions associated with FW collection are the key metric to this analysis as they function of VMT and the hauling burden, measured as weight of FW transported. Both factors are directly influenced by the location of ADs relative to FW generation and the capacity of the ADs. Therefore, the FWADA model was developed to investigate the relationship between AD size and GHG emissions by locating ADs near areas of high FW generation using AD capacity as the primary variable input.

A connection between the local and global scales can be seen when comparing the two AD capacities shown in Fig. 4. On one hand, 10k-ton ADs have an 81% lower per-cluster VMT than 55k-ton ADs, which is not surprising given that 139.54% more FW generators, on average, are needed to fill the larger ADs. However, when these are aggregated to the global scale, 10k-ton networks had a 4.5% increase in global VMT over 55k-ton systems as many more ADs are needed to treat all the FW in the FWG. Despite this slight VMT increase, the 10k-ton ADs have an 81.49% decrease in system GHG emissions from the 55k-ton ADs. This difference in global GHG emissions is proportionally equal to the change in per-cluster FW volumes between the two AD sizes. This result highlights the significance of material-specific transportation costs, measured here as weight of FW transported, for determining ideal recycling boundaries. In practical terms, simply reducing global VMT does not necessarily translate to decreased global GHG emissions if it results in larger volumetric FW hauling burdens for individual facilities. By evening the distribution of FW between individual clusters, the FWADA model also reduces this hauling burden in aggregate.

The comparison of VMT between the two systems makes one limitation to our approach apparent as economic costs for collection and hauling are some of the highest in the waste supply chain. The small increase in global VMT for 10k-ton ADs may have amplified impacts on the ability to develop such a system in the real world. Furthermore, the costs of building and operating the 10k-ton systems may also be increased, as more units need to be built and operated, reducing economies of scale that come with larger facilities. Given the connection between FW generation density and size of recycling boundary seen in the FWADA model cluster maps (Fig. 3), the development of AD networks of multiple capacities could also help balance the need for localized AD treatment while minimizing overall costs of the system. Future work that optimizes a small-scale AD system for a particular

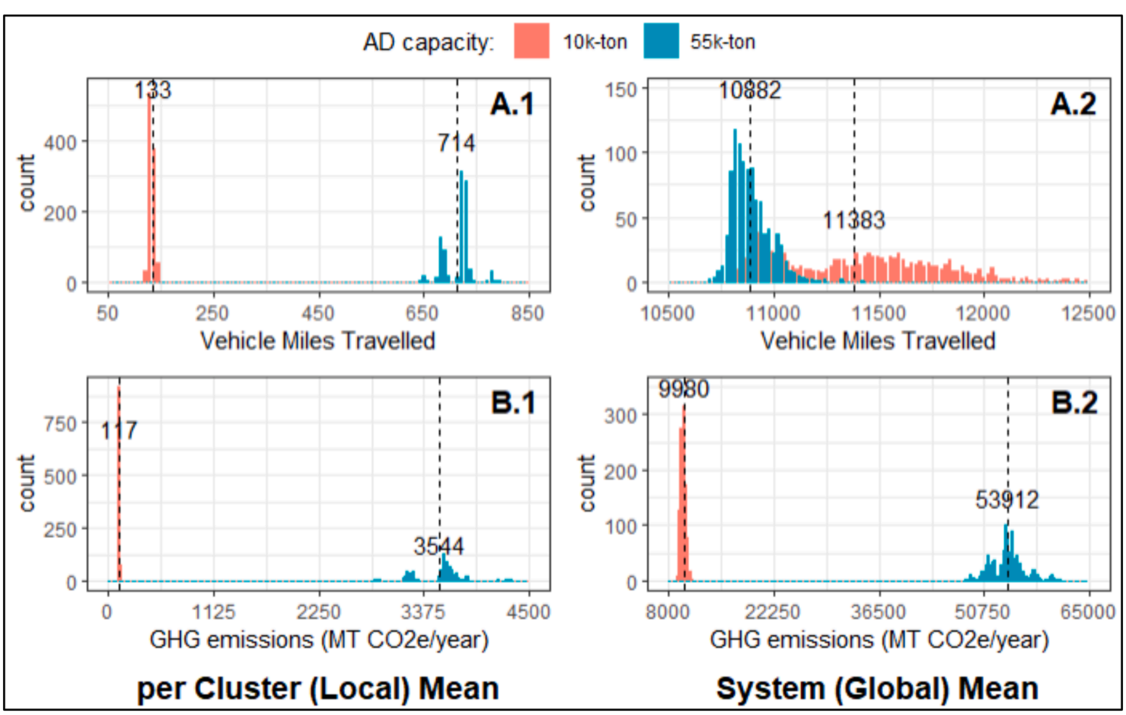

Fig. 4. Comparison between 10k-ton and 55k-ton AD systems for the Monte Carlo simulations ($n = 1000$) showing local/per-cluster (1) and global/system (2) means for Vehicle Miles Travelled (A) and collection GHG emissions (B).

municipality should include this economic component to determine the appropriate scale of AD deployment within a particular municipality.

The overarching policy implications of our analysis of FW recycling shows that SB 1383 is an opportunity to develop new waste infrastructure under a circular economy framework. The circular economy has become pervasive in recent policy circles in the U.S. as an umbrella term for a variety of practices that promote maximizing resource productivity and minimizing waste. Both tested AD capacities are considered small-scale relative to traditional waste management facilities, have proven commercial viability, and can be to be rapidly deployed throughout urban areas to treat localized FW catchments. Incentives to promote AD or other decentralized FW recycling infrastructure can be connected to initiatives within other arenas of food policy to address larger social and environmental issues. For example, small scale FW facilities present an opportunity to support alternative agriculture by high quality, nutrient-rich organic soil amendment that recirculates these nutrients back into food production. This AD digestate can be used to mitigate environmental concerns of larger farms, however the relatively small FW clusters shown in dense, urban areas present could promote it usage in community farms/gardens to address issues of hunger and nutrition in these areas. While the current market for AD digestate as a soil amendment is underdeveloped, specific policies promoting its use in alternative agriculture, and the expansion of urban agriculture in general, can increase the market demand for digestate and promote a circular economy of food within the state.

5. Conclusion

The small-scale ADs tested in this study are an opportunity to rethink traditional waste management systems that operate under economies of scale and “out of sight, out of mind” principles. Decentralized AD networks have the potential to reduce transportation costs and associated emissions when aligned to match the density of FW generation across the urban landscape. The GHG analysis utilized in this study suggests that smaller organic waste infrastructure can provide greater overall environmental benefits, as the 10k-ton AD systems generated by the FWADA model had greater environmental returns than the 55k-ton systems. Given that the 10k-ton AD networks had a higher global VMT, the GHG savings of the 10k-ton systems is primarily due to the high volumetric cost of FW transportation. Furthermore, the visual analysis of cluster maps generated by the FWADA model show geographically smaller FW catchments for ADs in more populated areas, which is consistent with other studies.

The buildout of waste infrastructure required for the implementation of SB 1383 in California presents an opportunity for municipalities to develop a circular economy of organic waste through the adoption of decentralized networks of small-scale ADs. This study is one of the first to investigate recycling boundaries specifically for FW and is one of the first to do so in a real-world policy setting. The FWG dataset was developed to simulate the FW generation of Los Angeles County within GIS and consists over 270,000 points representing FW generators from 17 industries. Focusing on commercially generated FW, which is subject to specific diversion mandates under the law, can potentially maintain high levels of source separation and divert much of the total quantity of organic waste that is needed to achieve 75% diversion. To compare GHG emissions of treating this diverted waste using decentralized AD systems, we developed a spatial clustering model, the FWADA model, which generates equal-sized clusters of FW generators in which to place ADs. One advantage of using unsupervised clustering methods is that they can help locate ADs within “natural clusters” of FW generation using the geography of FW generation as the main data input. Computationally, these clustering models are easy to use and the FWADA model’s iterative algorithm reduces the computation time when using the large FWG dataset. While the most optimal AD infrastructural solution may be outside the tested operational capacities (10k-ton/year & 55k-tons/year), we hope that the results of this comparative assessment provide a starting point for developing a greater understanding of the potential for new organic waste infrastructure technologies in California.

For this AD-enabled circular economy of FW to be successful, markets for food waste-derived digestate need to be established to absorb this nutrient-rich outflow from the AD process. Perhaps these efforts can be linked to other community development programs that promote urban food security through utilization in community farms and gardens. Since this digestate is produced in almost equal quantities as the input FW and has similar hauling requirements, its transportation and distribution within urban agricultural landscapes must be considered as part of the recycling boundary. Understanding the geography of FW generation and these potential digestate sinks is needed to inform strategies for designing an effective infrastructure network for FW treatment in California that promotes a truly circular economy of food at appropriate scales. While outside the scope of the present study, an analogous spatial analysis of digestate is an avenue for further research as it is an essential component in “closing the loop” of FW recycling.

CRediT authorship contribution statement

Lauren Mabe: Methodology, Software, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Sara A. Pace:** Conceptualization, Validation, Project administration. **Edward S. Spang:** Conceptualization, Validation, Writing – review & editing, Supervision, Funding acquisition.

Declaration of Competing Interest

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

Acknowledgements

The Authors would like to acknowledge the funding agencies that have supported this work, including the California Energy Commission (CEC Grant #EPC-17–018) and the National Science Foundation (NSF Grant # 2115405).

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.rcradv.2022.200113.

References

Breunig, H.M., Jin, L., Robinson, A., Scown, C.D., 2017. Bioenergy potential from food waste in California. Environ. Sci. Technol. 51, 1120–1128. https://doi.org/10.1021/acs.est.6b04591.
CalRecycle, 2020. 2018 Facility-Based Characterization of Solid Waste in California (No. DRR-2020-1666). California Department of Resources and Recovery.
CalRecycle, 2019. SB 1383 Infrastructure and Market Analysis (No. DRRR-2019-1652). California Department of Resources and Recovery.
CalRecycle, 2015. 2014 Generator-Based Characterization of Commercial Sector Disposal and Diversion in California (No. DRRR 2015-1543). California Department of Resources and Recovery.
Chen, X., Fujita, T., Hayashi, Y., Kato, H., Geng, Y., 2014. Determining optimal resource recycling boundary at regional level: a case study on Tokyo Metropolitan Area in Japan. Eur. J. Oper. Res. 233, 337–348. https://doi.org/10.1016/j.ejor.2013.01.054.
Chen, X., Fujita, T., Ohnishi, S., Fujii, M., Geng, Y., 2012. The impact of scale, recycling boundary, and type of waste on symbiosis and recycling: an empirical study of Japanese eco-towns. J. Ind. Ecol. 16, 129–141. https://doi.org/10.1111/j.1530-9290.2011.00422.x.
Comber, A., Dickie, J., Jarvis, C., Phillips, M., Tansey, K., 2015. Locating bioenergy facilities using a modified GIS-based location–allocation-algorithm: considering the spatial distribution of resource supply. Appl. Energy 154, 309–316.
Dewey, M., 2021. California anaerobic digestion projects accepting organics from the municipal solid waste stream (May 2021).
Duren, R.M., Thorpe, A.K., Foster, K.T., Rafiq, T., Hopkins, F.M., Yadav, V., Bue, B.D., Thompson, D.R., Conley, S., Colombi, N.K., Frankenberg, C., McCubbin, I.B.,

Eastwood, M.L., Falk, M., Herner, J.D., Croes, B.E., Green, R.O., Miller, C.E., 2019. California's methane super-emitters. Nature 575, 180–184. https://doi.org/10.1038/s41586-019-1720-3.

EPA, U.S., 2016. Inventory of U.S. Greenhouse Gas Emissions and Sinks 1990–2014.

E.S.R.I. ArcGIS Pro, 2019. Version 10.1. Environmental Systems Research Institute, Redlands, CA.

Fraccascia, L., Spagnoli, M., Riccini, L., Nastasi, A., 2021. Designing the biomethane production chain from urban wastes at the regional level: an application to the Rome Metropolitan Area. J. Environ. Manag. 297, 113328 https://doi.org/10.1016/j.jenvman.2021.113328.

Gomes, H., Ribeiro, A.B., Lobo, V., 2007. Location model for CCA-treated wood waste remediation units using GIS and clustering methods. Environ. Modell. Software 22, 1788–1795. https://doi.org/10.1016/j.envsoft.2007.03.004.

H.F.&.H. Consultants, 2018. SB1383 - low population waivers and exemptions [WWW Document]. URL https://hfh-consultants.com/blog/sb-1383-exempt/#_ftn1.

Hohn, J., Lehtonen, E., Rasi, S., Rintala, J., 2014. A Geographical Information System (GIS) based methodology for determination of potential biomasses and sites for biogas plants in southern Finland. Appl. Energy 113, 1–10.

de Jesus, R.H.G., de, Barros, M.V., Salvador, R., Souza, J.T., Piekarski, C.M., Francisco, A. C., 2021. Forming clusters based on strategic partnerships and circular economy for biogas production: a GIS analysis for optimal location. Biomass and Bioenergy 150, 106097. https://doi.org/10.1016/j.biombioe.2021.106097.

Kaundinya, D.P., Balachandra, P., Ravindranath, N.H., Ashok, V., 2013. A GIS (geographical information system)-based spatial data mining approach for optimal location and capacity planning of distributed biomass power generation facilities: a case study of Tumkur district, India. Energy 52, 77–88. https://doi.org/10.1016/j.energy.2013.02.011.

Laasasenaho, K., Lensu, A., Rintala, J., 2019. GIS-data related route optimization, hierarchical clustering, location optimization, and kernel density methods are useful for promoting distributed bioenergy plant planning in rural areas. Sustain. Energy Technol. Assessments 32, 47–57.

Lawler, E.L., 1976. Combinatorial Optimization. Holt, Rinehart and Winston.

Lyons, D.I., 2008. A spatial analysis of loop closing among recycling, remanufacturing, and waste treatment firms in Texas. J. Ind. Ecol. 11, 43–54. https://doi.org/10.1162/jiec.2007.1029.

Mohamed Sultan, A.A., Mativenga, P.T., 2019. Sustainable location identification decision protocol (SuLIDeP) for determining the location of recycling centres in a circular economy. J. Clean. Prod. 223, 508–521. https://doi.org/10.1016/j.jclepro.2019.03.104.

Nithya, R., Velumani, A., Senthil Kumar, S.R.R., 2012. Optimal location and proximity distance of municipal solid waste collection bin using GIS: a case study of Coimbatore city. WSEAS Trans. Environ. Dev. 8, 107–119.

Rijal, S., Lin, H.-.Y., 2021. A convenient method to determine recycling boundary for low-value materials in household waste: a case study of compostable food waste in Taichung City. J. Clean. Prod. 280, 124349 https://doi.org/10.1016/j.jclepro.2020.124349.

Sahoo, S., Kim, S., Kim, B.-.I., Kraas, B., Popov, A., 2005. Routing optimization for waste management. Interfaces (Providence) 35, 24–36. https://doi.org/10.1287/inte.1040.0109.

Sandhu, G.S., Frey, H.C., Bartelt-Hunt, S., Jones, E., 2015. In-use activity, fuel use, and emissions of heavy-duty diesel roll-off refuse trucks. J. Air Waste Manag. Assoc. 65, 306–323. https://doi.org/10.1080/10962247.2014.990587.

SCAG, 2020. SCAG annual land use - 2019 - Los Angeles County [WWW Document]. SCAG regional data platform. URL https://hub.scag.ca.gov/datasets/4e5649efefdb4aa79e8b585b22c13a34_0/about.

Scranton Manufacturing Co., Inc., 2022. Roto-Pac [WWW Document]. Organics automated side loader with dual-purpose performance. URL https://refusetrucks.scrantonmfg.com/automated-side-loader/roto-pac (accessed 1.14.22).

Yalcinkaya, S., 2020. A spatial modeling approach for siting, sizing and economic assessment of centralized biogas plants in organic waste management. J. Clean. Prod. 255.

Zeller, V., Towa, E., Degrez, M., Achten, W.M.J., 2019. Urban waste flows and their potential for a circular economy model at city-region level. Waste Manag. 83, 83–94. https://doi.org/10.1016/j.wasman.2018.10.034.