Estimating Commercial and Residential Food Waste Generation at County Scale

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Abstract

A majority of food waste in the United States is generated by businesses and homes. Leading efforts in food waste diversion have been implementations of municipal or county-level policies. However, estimates of food waste generation are typically conducted at the national scale. Cities, counties, and states have examined waste characterization of municipal waste streams. Yet there is no consistent methodology employed in the research and no empirical model estimating waste generation for all counties across the country. The model presented in this paper combines a county-level aggregate of waste producing businesses with a county-level estimate of how explanatory factors of household waste vary across space. A dataset is produced which contains food waste generation estimates for all 3,142 counties and county equivalents, as well as categorized estimates of residential waste, commercial waste, and waste generation by business type. The county dataset is tested for global and local spatial autocorrelation, and its spatial patterns are discussed in comparison to spatial patterns of food insecurity. A model of food waste generation at county scale will aid the creation of food waste diversion policies in local governance, while also revealing spatial patterns which are useful for a broader understanding of regional trends.

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1. Introduction

Projections of future agricultural production, land use, economics, and demographics present a worldwide, interdisciplinary challenge. There must be enough land to feed a growing world population (Lambin and Meyfroidt 2011). Simultaneously, there needs to be enough food of different types to adequately satisfy the world's nutritious needs and shifting dietary preferences (Aleksandrowicz et al. 2016). There must also be minimal land use change to preserve non-cultivated natural habitats while also preserving agriculture land used for fuels or fibers (Steffan-Dewenter et al. 2007). Food waste is an inefficiency in its essence and its reduction is a commonly cited tactic in the global approach to answer these challenges (Lipinski et al. 2013). In 2011, it was estimated that food loss and waste constituted one-third of all food produced, globally: approximately 1.3 billions tons annually (FAO 2011). In an intuitive sense, lost or wasted food equates to the waste of the inputs used to produce the food, such as land, water, and fertilizer. The valuation of these annual costs are $1 trillion economically, $700 billion environmentally, and $900 billion socially (FAO 2020). Due to the wide range of impacts associated with food loss and waste, research on food waste reduction is a crucial study area in social sciences.

In the United States, up to two-fifths of all food produced is lost or wasted, which corresponds to $165 billion being spent annually to produce 240 pounds of food waste per person (Buzby et al. 2014; Gunders and Bloom 2017). The Natural Resources Defense Council (NRDC) estimates that a 15% decrease in food loss would be enough to feed over 25 million food insecure Americans. Around one-quarter of all freshwater in the United States is used for lost and wasted food, and landfilled food represents about one-quarter of annual methane emissions (Gunders and Bloom 2017). Food loss and waste simultaneously correspond to 21% of landfill volume and 18% of cropland, requiring 19% of the nation's fertilizer usage (ReFED 2020).

In every step of the food supply chain, loss or waste is possible. Beginning in production, food loss can occur from improper harvesting practices, a crop's failure to meet aesthetic or quality standards, or sudden changes in market demand. From the farm, food loss can occur from pestilence, disease, or spoiling from improper handling, storage, or transport. Additional loss can ensue as the food undergoes processing. Food is wasted in markets due to product expiration, quality control, and item damage. Food scraps from unfinished meals are common at locations which provide food, such as restaurants, schools, hospitals, and hotels. In a household, food waste includes expired or undesired products, meals incorrectly cooked or prepared, food scraps, and uneaten leftovers (Lipinski et al. 2013; Parfitt et al. 2010). In the United States, it is estimated that 83% of food loss and waste occurs in the retail and household stage of a product's "life cycle". To decrease food waste, there is a need for policies which target consumer-facing businesses, in addition to attitudinal changes and education campaigns (ReFED 2020).

The United States Environmental Protection Agency (EPA) has published a "food recovery hierarchy" which defines and prioritizes several food waste mitigation strategies. The strategy of highest preference is the reduction of waste at its source. Organizations are urged to audit their waste and make adjustments as necessary to reduce their generation of food waste. The EPA encourages that the remainder of food waste is donated to groups which combat food insecurity and hunger, presuming that the food is edible and fit for human consumption. If the waste does not meet those standards, the next highest priority is the diversion of waste to feed animals. If that is not possible, food waste can be used in industrial processes such as anaerobic digestion, rendering, and biodiesel production. When none of those options are viable, composting is the next-most preferred alternative. Composting has environmental benefits in terms of water retention, carbon sequestration, less reliance on chemical fertilizers, and methane emission mitigation. The least preferred strategy for food waste disposal is allowing the waste to be deposited at a landfill (EPA 2020a; Papargyropoulou et al. 2014).

For businesses in the United States, self-reported adherence to the food recovery hierarchy is dependent on business type. An industry-led survey found food manufacturers were able to recycle 96.8% of their waste. Food retail and wholesale businesses were able to recycle 54.3% and donate 18.1% of their waste. Restaurants were able to recycle or donate just 6.2% of their waste, with the rest being landfilled (Alliance 2014).

According to the EPA, about 94% of household food waste in the United States is landfilled or incinerated (EPA 2019a). In 2019, there were approximately 185 full-scale composting facilities in the United States, excluding universities and correctional facilities (Goldstein 2019). In 2017, curbside composting was available to 5.1 million households in 326 localities across 20 states and drop-off programs were available to an additional 6.7 million households in 318 localities across 15 states. Even in areas with access to curbside composting, some households choose not to participate (Streeter and Platt 2017).

Waste collection for businesses and homes is a functionality of municipal governance. Therefore, the trend of waste diversion policies occurring in new communities across the country is the result of local laws rather than federal mandates. Moreover, it is imperative for local governments to be able to gain access to local-level statistics on food waste in order to expand waste diversion efforts to their jurisdictions. Ultimately, greater information will lead to policies which decrease the prevalence of food waste nationally.

1.1 Definitions

Definitions are provided to better clarify the meaning of various key terms used throughout this paper. The definitions also provide critical distinctions between terms, such as food loss and food waste.

- *Food loss* refers to food which is disposed of before reaching a food retailer, wholesaler, or any other food provider. This includes waste during production, transport, and processing of food (FAO 2011). The concept of food loss is excluded from this paper, as manufacturing and processing losses are conceptualized as potential food waste diversion (EPA 2019b).
- *Food waste* refers to food which is never consumed but was produced for human consumption. However, not all food waste is edible at the time of disposal (FAO 2011; EPA 2019b). In this paper, quantities of food waste are measured in tons (short tons).
- *Generation* of waste is the dual consideration of waste disposal and waste diversion. Waste generation quantifies the amount of waste produced at a given business or home. In contrast, waste characterization studies of landfills only consider waste disposal. These are two different methodologies for quantifying food waste (Alliance 2014).
- *Residential Food Waste* represents waste generated from households. It is interchangeable with the terms “household waste” “consumer waste” or “at-home waste” which are also used in this paper.

- *Commercial Food Waste* represents waste generated from non-households. It is interchangeable with the terms "retail waste" or "away-from-home waste" which are used in this paper, and "ICI (Industrial, Commercial, and Institutional)" which was used by the EPA and the NRDC in the reports which greatly influenced this paper.
- *County* refers to the one of the 3,142 counties and county-equivalents in the 50 states and the District of Columbia. For conciseness, all 3,142 counties and county-equivalents will be referred to as "counties" without explicitly mentioning county-equivalents.

2. Literature Review

The production and consumption of food are often spatially distant. Analysis of imports and exports has shown complex agricultural trade networks between nations (MacDonald et al. 2015). The food supply chain within the United States is equally complex. A spatial examination of food flows between origin and destination counties has found that food flows were quite often inter-state or even inter-regional, with nine "core" counties that were essential to food logistics (Lin et al. 2019). In contrast, it has been estimated that half of American grocery store consumers live within two miles of three supermarkets (Ver Ploeg et al. 2012). A study of five cities found Americans travel farther to sit-down restaurants, although still at an average of 3.3 miles from their residence (Liu et al. 2015). Since the food supply chain is much more spatially complex prior to reaching consumer-facing businesses, it is much harder to derive policy implications for food loss and waste reduction with spatial analysis of waste generation. However, the spatial simplicity of retail food waste generation allows for clearer opportunities for policy interventions.

At a national level, the quantification of food waste from households and businesses varies. The United States Department of Agriculture has estimated that 66.5 million tons of food is wasted nationally every year (Buzby et al. 2014). The food waste think tank ReFED has estimated that households and "consumer-facing businesses" generate 52 million tons of waste annually (ReFED 2020). The EPA has estimated that food waste represented 15.2%, or 40.71 million tons, of total municipal solid waste in 2017 (EPA 2019a).

At a subnational spatial scale, the amount of literature explicitly aiming to quantify food waste is minimal. Italian researchers have conducted research on spatio-temporal patterns of urban food waste by province, modeling values and interpreting spatial autocorrelation results (Cerciello et al. 2019). No such equivalent has been published for the United States. However, the Natural Resources Defense Council (NRDC) has modeled city level food waste generation estimates for three American cities (Denver, Colorado, Nashville, Tennessee, and New York City, New York) based on waste generated in a sample of participating households and businesses. In addition, the report shared methods on how to calculate industrial, commercial, and institutional (ICI) waste per waste generating location, as well as factors which influence household food waste. The report calls for further research in other cities, to investigate trends from aggregated data, which is in agreement with the motivation of this paper (Hoover and Moreno 2017).

Indirect measures which quantify food waste exist at the state, county, and city level. The amount of food waste is calculated through the analysis of landfill composition. States such as Connecticut, Delaware, Indiana, Minnesota, Rhode Island, and Vermont have quantified the statewide amount of food entering the municipal solid waste stream in waste characterization reports (EPA 2020b). California and Illinois have measured waste generation, a more comprehensive measure in comparison to municipal solid waste characterization (California 2014; Illinois 2015; Alliance 2014). Waste characterization studies of landfills have been published for counties such as Sonoma County, California, Boulder County, Colorado, Alachua County, Florida, Johnson County, Kansas, Montgomery County, Maryland, Mecklenburg County, North Carolina, and King County, Washington. Additional waste characterization studies have focused on cities such as Phoenix, Arizona, Palo Alto, California, San Francisco, California, Minneapolis, Minnesota, Austin, Texas, and Seattle, Washington (Sandhei 2020).

3. Methodology

Multiple data sources at varying spatial scales were used to measure consumer food waste at the county level across the United States in tons per year. The first is the EPA's Excess Food Opportunities Map (EFOM), an interactive map with an open-access dataset (EPA 2019b). The EFOM dataset contains food waste estimates and addresses for under 1.2 million institutions from eight different business types across all 3,142 counties in the United States. The eight categories of waste generating businesses are "correctional facilities," "educational facilities," "food banks," "healthcare facilities," "hospitality industry," "food manufacturing and processing facilities," "food wholesale and retail," and "restaurants and food services." Each facility location (except food banks) listed in the EFOM dataset has upper and lower bound estimates (in tons per year) based on formulae from published literature, such as waste as a function of revenue per year or students per year, for example (EPA 2019b). Using the PivotTable feature in Microsoft Excel, I was able to aggregate the lower and upper bounds for each business type to the county level.

The stated goal of the Excess Food Opportunities Map is to quantify the potential for waste to be diverted from landfills. Given the hierarchy of food waste, this means the data does not reflect the edibility of the estimated food waste. In addition, the dataset is missing an unknown amount of locations and has a null value rate of 2.24% for each location's annual tonnage estimate.

Table Name	**Null Count**	**Total Count**	**Null rate**
Restaurants and Food Services (Part 1)	*7371*	*324696*	--
Restaurants and Food Services (Part 2)	*8308*	*324621*	--
Restaurants and Food Services (Total)	15679	649317	2.41%
Correctional Facilities	0	5268	0%
Educational Institutions	2831	125676	2.25%
Food Manufacturers and Processors	6649	59914	11.10%
Food Banks	154	316	48.73%
Food Wholesale and Retail	67	236384	0.028%
Healthcare Facilities	615	7490	8.21%
Hospitality Industry	79	80233	0.099%
TOTAL	**26074**	**1164598**	**2.24%**

(Table 1: Null occurrence)

There are an additional 6763 institutions with "NULL" in the county field, 713 institutions from the hospitality industry, 757 food manufacturers or processors, 1645 restaurants or food services, 3648 food wholesalers or retailers. These locations correspond to an estimated 205,617 tons of food waste per year, which is 0.72% of the total.

The EFOM dataset differs from the NRDC report of Denver, Nashville, and New York City discussed previously; the EFOM dataset does not include residential waste. The NRDC report relies on kitchen diaries from participating businesses and households in order to quantify total food waste at a city level, while the EFOM dataset only estimates commercial locations of food waste (Hoover and Moreno 2017). Therefore, estimates of residential food waste must be derived from the NRDC findings.

The NRDC report does not state an equation for residential food waste as it does for ICI food waste sources, but the document does provide information on which factors serve as explanatory variables for residential food waste. Table 1 of Appendix H of the NRDC report contains detailed explanations of the correlation of demographic variables to household food waste in kitchens participating in the survey. One factor, household size, is statistically significant across all three cities at the 10% significance level. Both household maximum age and household average age are statistically significant in two cities. The results indicate that smaller households and older households tend to waste more food (Hoover and Moreno 2017). These findings are consistent with a variety of published literature from both the USA and UK (Parfitt et al. 2010). With values from the NRDC report Table 50, I interpreted the relationship between household size and household food waste to be decreasing exponentially. It can be inferred from Table 50 that the decrease from a 1 person household to a 2 person household is larger than the decrease from a 4 person household to a 5 person household, meaning the relationship is non-linear. Fitting the report's values, the household size equation is $\hat{y} = -0.0625x^2 + 3.0625$, where $\hat{y}$ is household food waste in weekly pounds per person per household, and x is the size of the household measured by the number of occupants.

The United States Census Bureau's American Community Survey publishes household occupancy characteristics (Census Table S2501) which contains estimates of household size, subdivided into 1 person households, 2 person households, 3 person households, and 4 or more person households. The table also quantifies the total number of households and average size of households for each geography. I used the 2018 5-Year Estimate with all US counties as the selected geography. To determine the average number of people living in 4-or-more person households per county, I used Equation 1. S_x is the unknown value in persons per household, H_{tot}, H_1, H_2, H_3, and H_x are the number of total households, households with 1 occupant, 2 occupants, 3 occupants, and 4-or-more occupants, respectively, and S_{avg} is the average number of people per household for the county.

$$S_x = \frac{(H_{tot} * S_{avg}) - (H_1 + 2 * H_2 + 3 * H_3)}{H_x} \quad \text{(equation 1)}$$

I then used the household size equation to determine the amount of food waste from each household. Multiplying the result by the number of households and number of occupants and converting from pounds per week to tons per year, I arrived at a total figure representing yearly household waste at the county level. For the few counties with a 4-or-more person household average household size greater than 8.75, the household waste was limited to 0.005 tons per year to prevent the household size equation from producing negative results. The exact "floor" of food waste in terms of household size requires further research.

I used similar methods for modeling household age. Table 51 from the NRDC report was used to construct an equation relating age to household food waste: $\hat{y} = 0.0137x + 1.5648$, where x is the age, in years, and $\hat{y}$ is the pounds per person per week. The US Census Bureau American

Community Survey's published 5-year median age estimates for 2018 were used (Census Table B01002), with all US counties as the selected geography. Total annual household food waste, in tons per year, was derived by entering the county median age estimate into the age-waste formula, multiplying by the county's population, and converting from pounds per week to tons per year.

Both estimates of annual household waste at the county level were divided by 0.66 to account for underreporting, which is consistent with the underreporting correction implemented in the NRDC report (Hoover and Moreno 2017). The two estimates were summed, with household size weighted twice as much as median age due to the significance across all three cities in the NRDC report compared to only two for household age. The result of the weighted average calculation was a single value, representing the sum of a county's annual residential food waste.

3.1 Sensitivity Analysis

The EPA EFOM dataset and NRDC report share similar away-from-home waste categories.

EFOM Table Name *(EPA 2019b)*	**NRDC Category Equivalent(s)** *(Hoover & Moreno 2017)*
Correctional Facilities	Correctional Facilities
Educational Institutions	K-12 Schools; Colleges & Universities
Food Manufacturers and Processors	Food Manufacturing & Processing
Food Banks	*(none)*
Food Wholesale and Retail	Grocers & Markets; Food Wholesalers & Distributors
Healthcare Facilities	Health Care
Hospitality Industry	Hospitality (Hotels)
Restaurants and Food Services	Restaurants and Caterers
(none)	Events & Recreation Facilities

(Table 2: EFOM and NRDC comparison)

This allows for comparisons between NRDC estimates and estimates from the EFOM-based model presented in this paper. The three cities in the NRDC report correspond to counties well; all three have consolidated city-county governance to some extent, meaning NRDC city estimates can be directly compared to modelled county estimates for all three cities. Davidson County encompasses Nashville, Denver is a county-equivalent city, and New York City is divided into five counties, Bronx County, Kings County, New York County, Queens County, and Richmond County. In order to provide a measure of uncertainty based on published literature, I conducted sensitivity analysis on the parameters. I compared the NRDC city-level estimates by category, found in Table 60 of the NRDC report, to the EFOM county-level upper bound and lower bound estimates, using EFOM table names and the categorical equivalences in Table 2.

The objective of determining the parameters in this way was to minimize the amount of error across all three cities. A desirable parameterization was set for each business category when the average error of the three cities was lowest, within reason. Table 3 shows the upper and lower bound manipulations as well as the percent error for each city, calculated with Equation 2. Note that the term "sum" refers to the sum of the upper and lower bound estimates.

Category	**Parameterization**	**Denver % error**	**New York % error**	**Nashville % error**
Correctional	One half the lower bound	-34.77%	-4.65%	56.93%
Manufacturing	One third of sum	-9.10%	-39.17%	21.56%
Retail	One quarter of sum	-21.36%	226.67%	-39.12%
Healthcare	1.5 times the upper bound	-15.35%	-15.47%	10.77%
Hospitality	One half the sum	-24.13%	-28.53%	11.53%
Education	Two fifths the sum	-1.29%	-0.33%	-6.91%
Restaurant	Upper bound	-11.06%	23.96%	-34.51%
Overall error		-13.40%	24.98%	-12.23%

(Table 3: Sensitivity Analysis)

$$Error = \frac{Modeled\ value - Report\ value}{Report\ value} * 100\% \quad \text{(equation 2)}$$

The overall error represents the sum of the away-from-home waste, the at-home waste, and a correction for missing data compared to the NRDC totals listed in Table 62 of the NRDC report. The correction for missing data is a 111.11% increase of the calculated away-from-home total. This also accounts for the exclusion of events and recreation facilities mentioned previously, which represent 1-2% of the waste in the three cities. The average error of the three overall errors is 0.22%, which I determined to be sufficiently minimal.

3.2 Assumptions

It is necessary to enumerate the assumptions made in the building this empirical model. First, it is assumed that the amount of at-home food waste can be explained solely by household size and median age. This assumption is based on the regression analysis findings of the NRDC report and past literature, although it remains unclear if race, income, or poverty can explain patterns of food waste as well. In addition, the most cited research on this topic is at least a few decades old (Parfitt 2010). Similarly, more work can be done to establish if the relationship between household size is non-linear and median age is linear, as assumed in the model. In terms of using the NRDC report to specify model parameters, it is assumed that Denver, Nashville, and New York City have away-from-home food waste rates that are representative of the country. Rurality could potentially be an unaccounted factor contributing to error in the away-from-home estimates. These concerns are addressed in section 5.1 of this paper. Moreover, the model assumes waste-producing locations excluded from the Excess Food Opportunities Map database are distributed evenly across the United States.

Finally, there is a lack of reliable data related to quantifying food waste from locations outside the scope of both the EFOM database and the NRDC report such as airports, stadiums, and workplaces. It is assumed that waste from these locations represents a minute portion of total, county level waste. The lack of "Events & Recreation Facilities" locations in the EFOM database led to their exclusion from this paper's model as well.

3.3 Workflow

The first action after downloading the EFOM dataset was to tidy the data across the numerous Microsoft Excel spreadsheets, partially using the "find and replace" functionality to manipulate text in the "county" column. Next, I used the "PivotTable" feature to create one record per county, with the count of locations and sums of lower bound and upper bound estimates. I then used Excel to join spreadsheets together using matching text in the "county" field across the away-from-home subcategories into a single away-from-home spreadsheet. I used a new column to convert the business category estimate sums into a single estimate for the county, previously described in greater detail. The at-home food waste calculations, sensitivity analysis, and creation of a final data product were also a result of Excel functionalities.

The shapefile (.shp) included in this paper's data product was created with Esri's ArcMap 10.6 software by joining a comma separated values (.csv) file with the data to a Census Bureau county-level shapefile with all fields removed except the Federal Information Processing Standards (FIPS) code, which works as a unique identifier for each county.

4. Results

There is a data product (compressed as a .zip file) which accompanies this paper. The .zip file “fw_slobotsky2020.zip” contains a “readme.txt” file which explains the contents of the data product and provides metadata for each of the files. The product contains Microsoft Excel files with commercial and household calculations described in the methodology section. The results featured in this section comes from the “fw.csv” file, and the spatial data comes from “CountyLevelEstimates.shp.”

4.1 Example of Suggested Data Interpretation

Prince George’s County, Maryland, can be used as an example to demonstrate the contents of the “fw.csv” file. Columns and values are shown in Table 4. Note that away-from-home count and estimate columns are produced side by side for viewing convenience.

FIPS	24033		
County	Prince George's County, MD		
Pop	906202		
Cor_Est	39.91366	Cor_Count	3
Edu_ Est	6630.221	Edu_Count	281
FB_Est	0	FB_Count	0
Hea_Est	810.7709	Hea_Count	7
Hos_Est	4290.381	Hos_Count	134
Man_Est	2290.9	Man_Count	125
Res_Est	32469.77	Res_Count	1603
Ret_Est	20355.66	Ret_Count	576
AFHFW	66887.62		
AHFW	70147.4		
TOTAL	144467		
TotPerCap	0.15942		

(Table 4: Prince George’s County, MD, results)

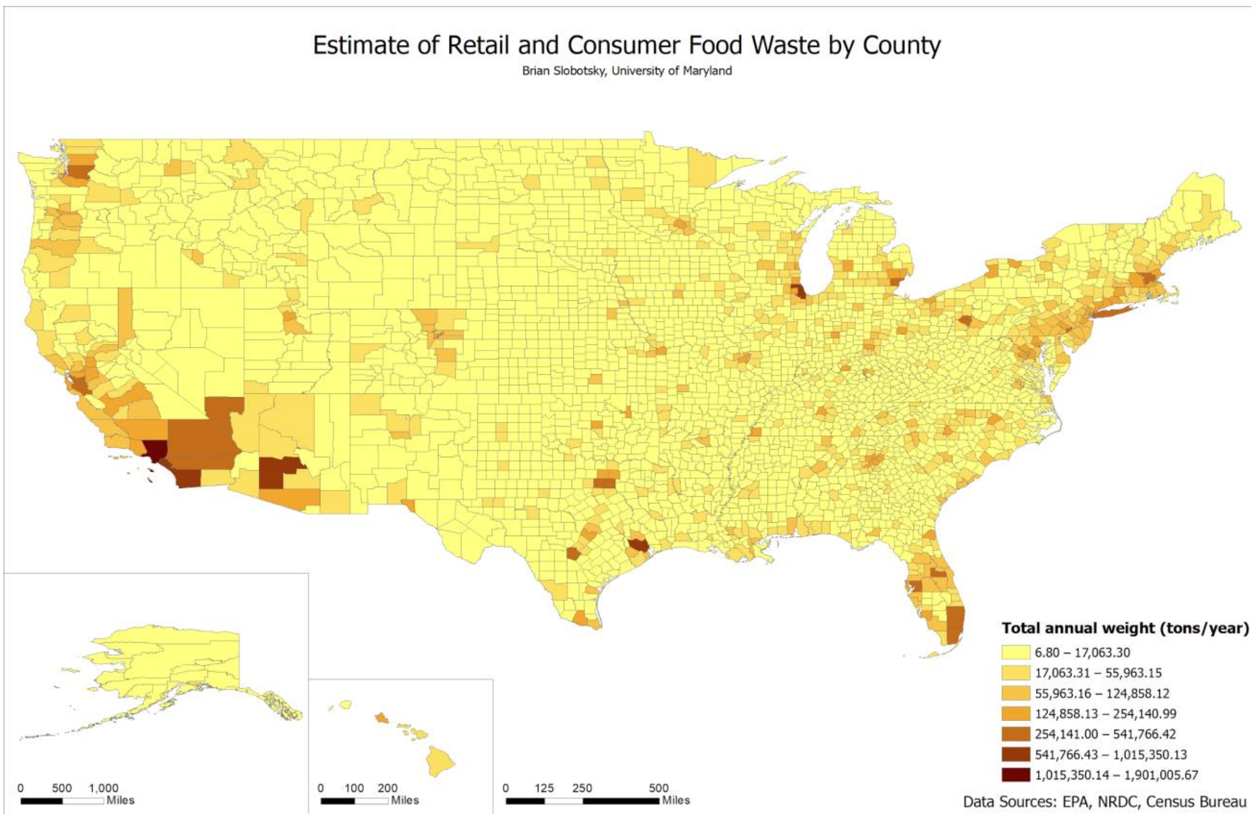
The total amount of annual commercial and residential waste generation in Prince George's County is estimated to be 144,467 tons according to the model. The commercial, away-from-home food waste (AFHFW) is the sum of the business category estimates listed above. The residential, at-home food waste (AHFW) is the result of the at-home food waste modeling process documented in the methodology. It is critical to note that the away-from-home and at-home subtotals do not sum to the total. The away-from-home subtotal is adjusted in the calculation of the total to account for missing data, which was previously shown to be prevalent. The value of the remainder should be interpreted as waste from other sources, including from outside the given subcategories.

A breakdown of waste by origin shows that residences in Prince George's County represent nearly half (48.56%) of the total waste generation. Restaurants are the second largest generator of food waste in the county at 22.48%. Food wholesale and retail institutions, including markets and grocery stores, are the third largest, at 14.09% of the total. Constituting smaller shares, educational venues represent 4.59%, the hospitality industry contributes 2.97%, food manufacturing and processing institutions represent 1.59%, healthcare institutions represent 0.56%, and correctional facilities represent 0.03%. There is no data for any food banks in the county. The remaining 5.14% represents all other waste-producing locations excluded from the dataset.

Prince George's County has a population of 906,202, which makes the per capita estimate of consumer and retail waste about 0.16 tons per person per year. Feeding America estimates that 120,230 people in the county are food insecure (Gundersen et al. 2019). Per food insecure person, there are 1.20 tons of edible and inedible food waste generated per year in Prince George's County. Because Feeding America's food insecurity estimate by county is not publicly available, it was not included in the final dataset, but it will be used subsequently in this paper.

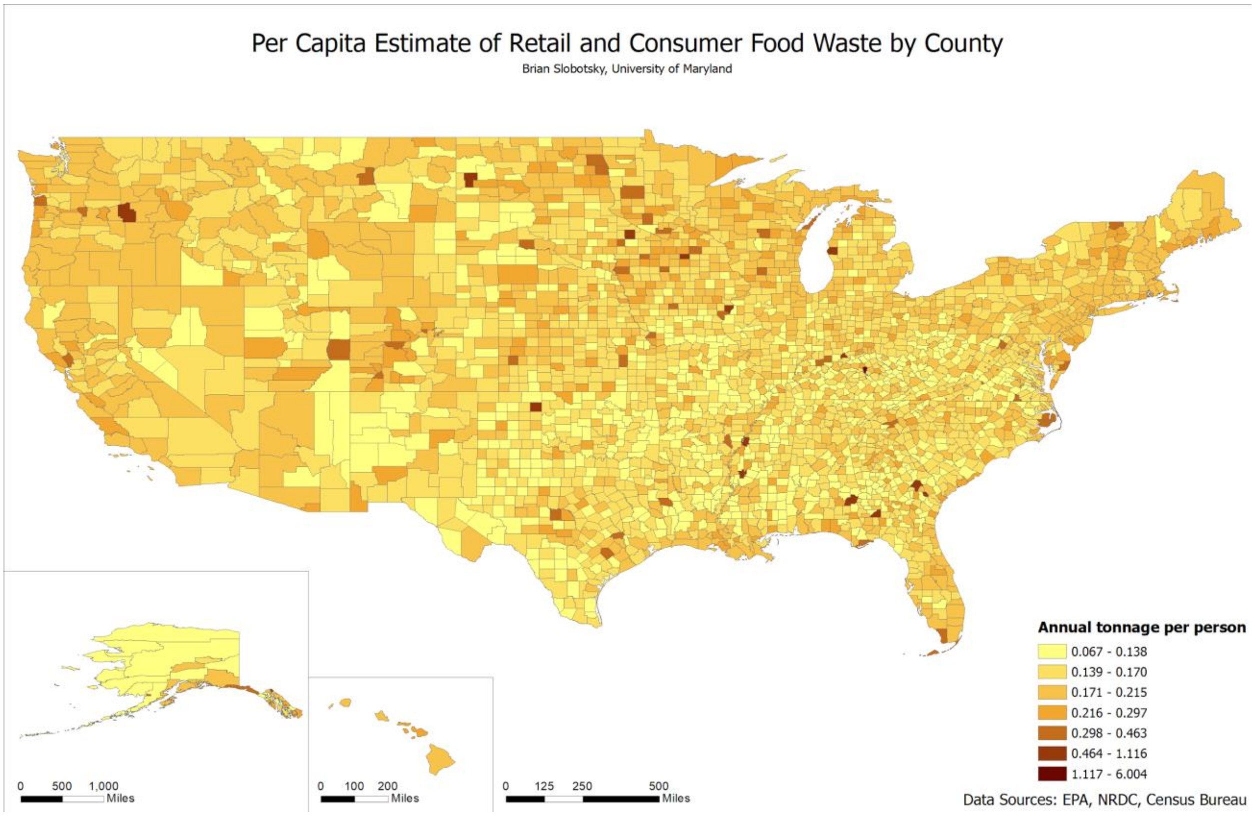
4.2 Data Visualizations

The following maps were created using Esri's ArcMap software. The data has been classified using a natural breaks classification. Please note each map has different legend values, meaning multiple maps cannot be compared equally based on color patterns.



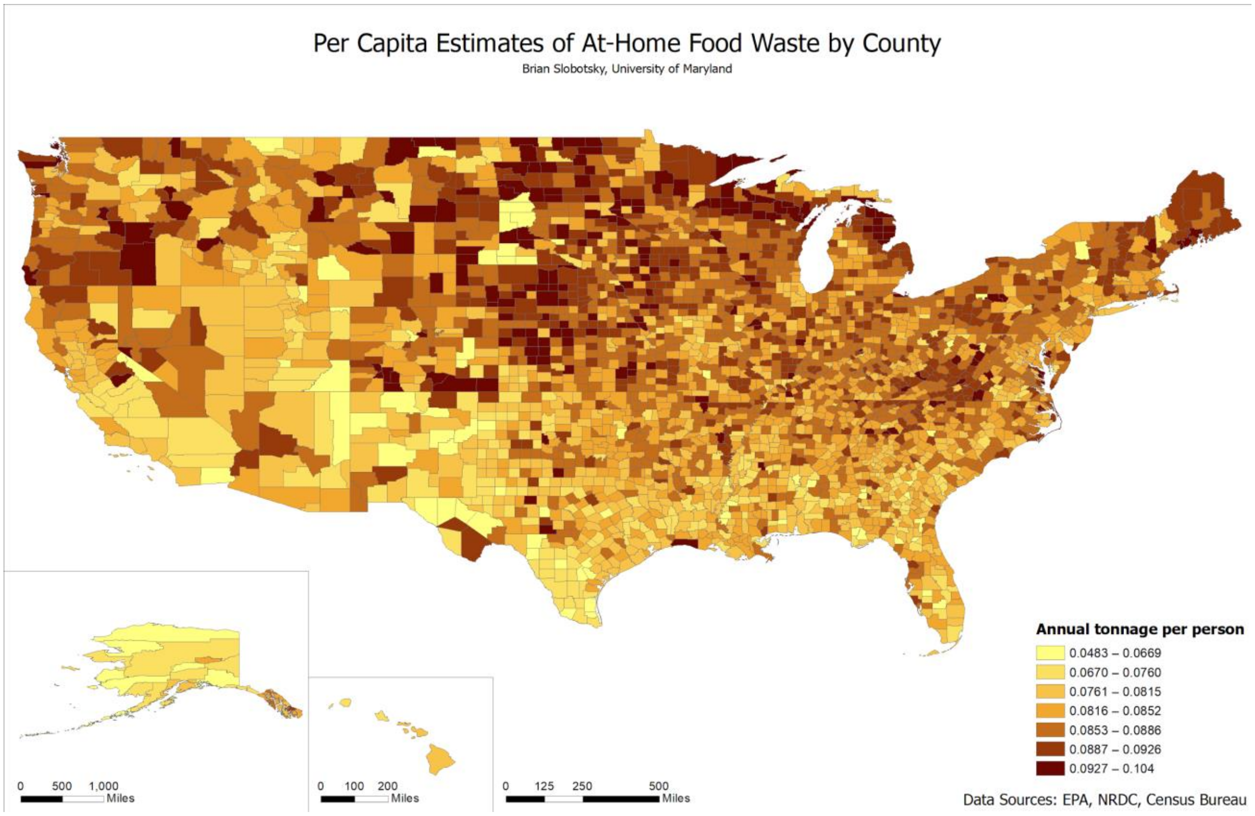
(Figure 1)

Figure 1 shows the total estimate of retail and consumer food waste by county, measured in tons per year. This closely parallels a county map of population in the United States, which is why maps which show per capita estimates are more informative of large scale patterns across the country rather than total estimates.



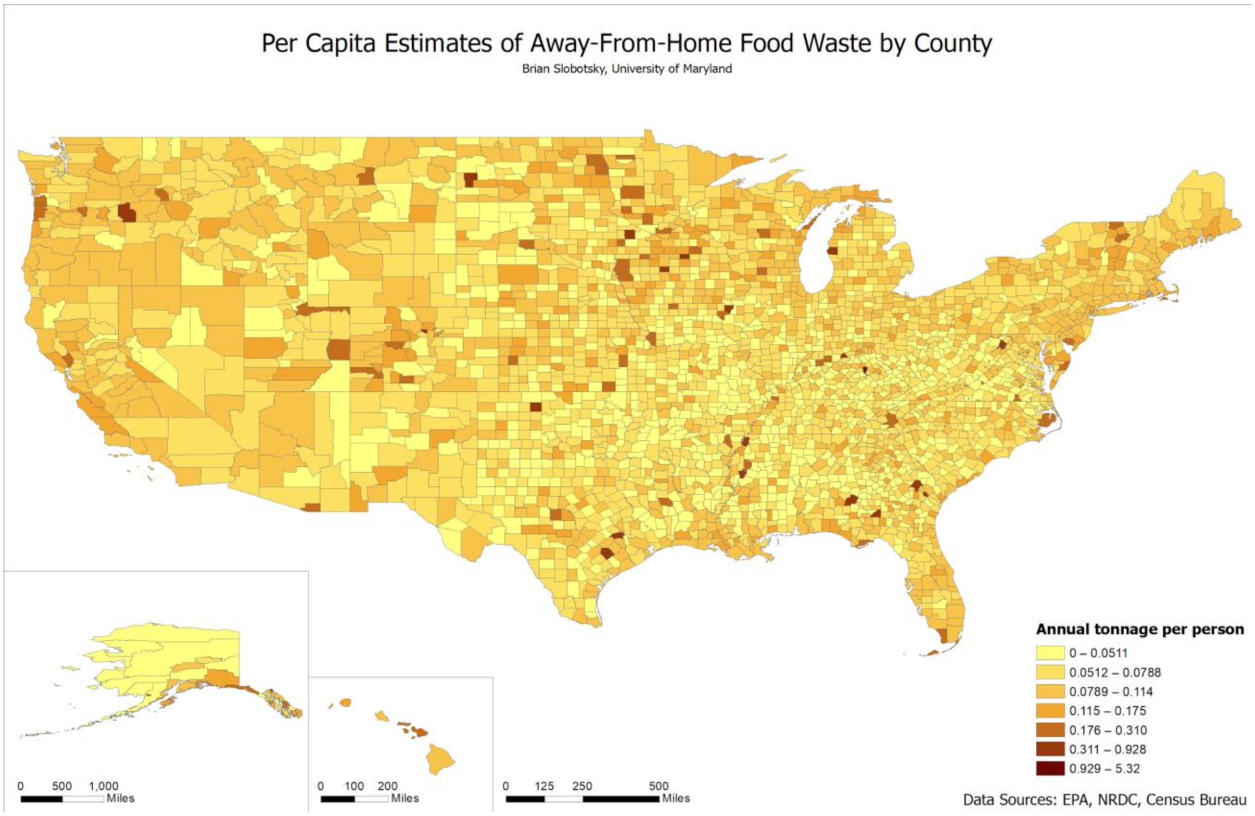
(Figure 2)

Figure 2 shows the total estimate of retail and consumer food waste by county, per capita, measured in tons per year per person.



(Figure 3)

Figure 3 shows household food waste by county per capita, measured in tons per year per person.



(Figure 4)

Figure 4 shows commercial food waste by county per capita, measured in tons per year per person.

4.3 Spatial Autocorrelation

It is useful to understand how the model's estimated values of waste generation vary spatially. To accomplish this with spatial data analysis one must check for spatial autocorrelation. With ArcMap, I was able to compute global Moran's I calculations for the total retail and consumer food waste estimate and the per capita waste estimate, seen in Table 5. Additional calculations, for the at-home and away-from-home estimates, are available in Table 7 in the Appendix. I decided to check the results by using one contiguity-based conceptualization and one distance-based conceptualization of space. Queen contiguity, known as "contiguity edges corners" in

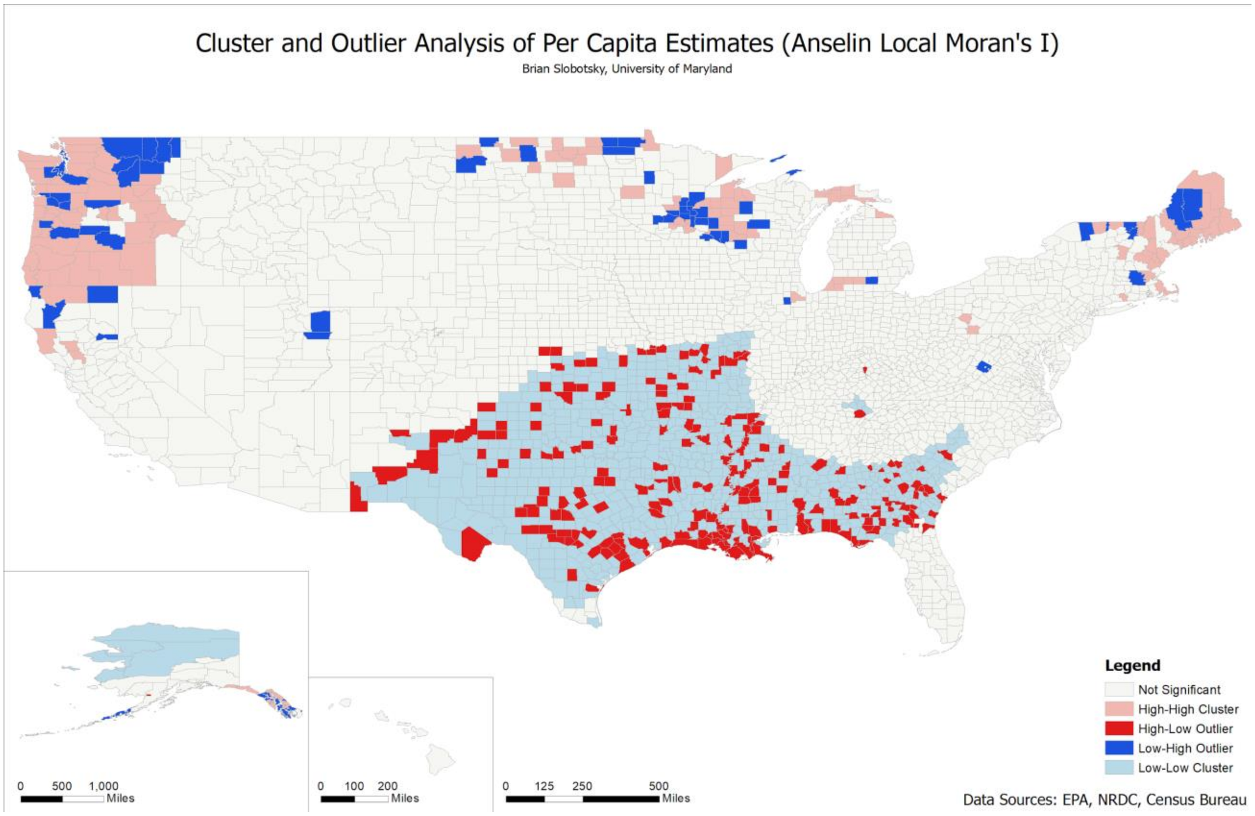
ArcMap, was used. A distance of 493681.2925 meters (306.76 miles) was used, which was selected automatically by an ArcGIS built-in algorithm. The global Moran's I values and z-scores are listed in Table 5.

	Contiguity		Distance	
Estimate	*Moran's I*	*z-score*	*Moran's I*	*z-score*
Total	0.281996	28.46374	0.030598	27.10489
Per Capita	0.016471	2.601546	0.003588	5.005487

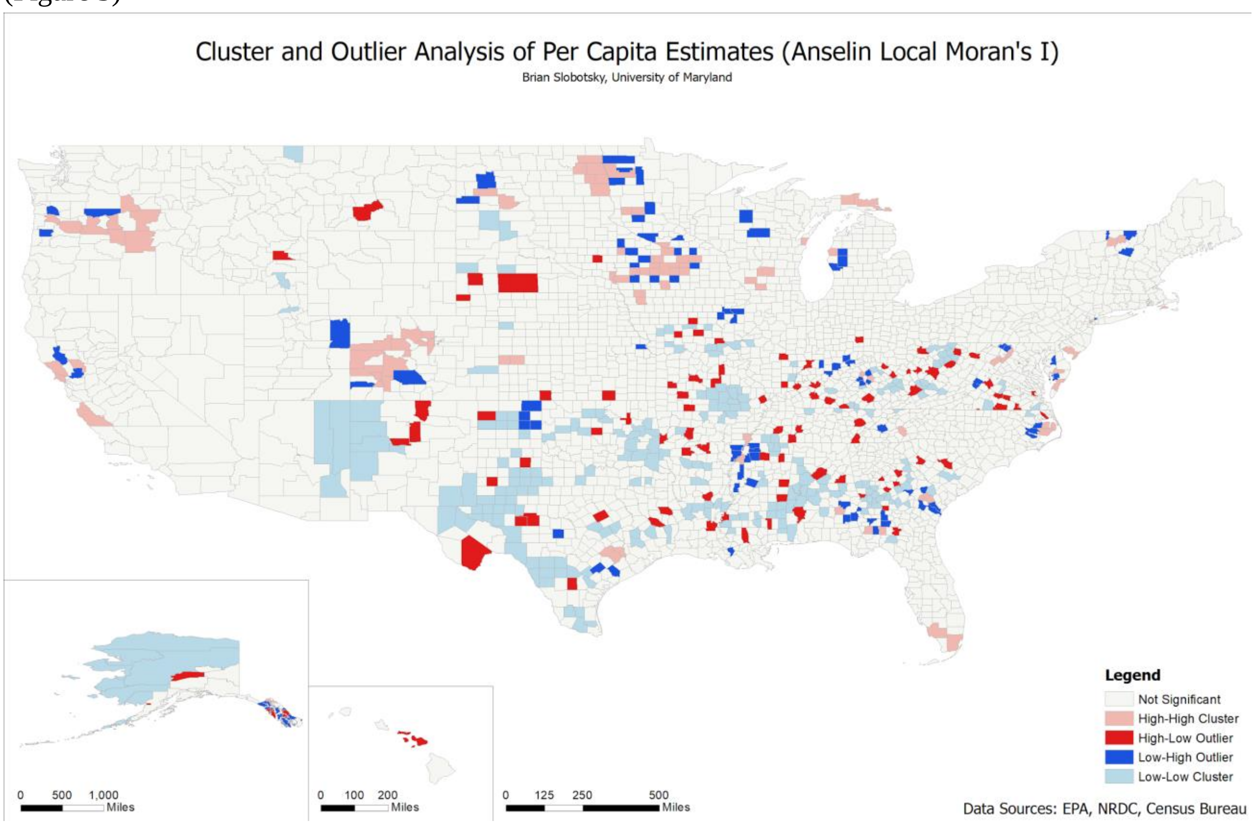
(Table 5: Spatial autocorrelation results)

The z-score for each test of spatial autocorrelation was above 2.58, meaning that the results are very statistically significant, with a p-value < 0.01. We can conclude that spatial autocorrelation exists within the data. At-home and away-from-home total estimates also exhibit spatial autocorrelation, per results in Table 7. The positive sign for each Moran's I value indicates that the data exhibits spatial clustering. Thus, total and per capita estimates of retail and consumer food waste generation at the county level show patterns of statistically significant clustering.

To know more about where these patterns occur, local indicators of spatial autocorrelation are key. Anselin Local Moran's I, known in ArcGIS as "cluster and outlier analysis," was used on per capita estimates to visualize where clustering is occurring. Both distance and contiguity conceptualizations were used again, in Figure 5 and Figure 6, respectively. An interpretation of these results is shared in section 5.2 of this paper.



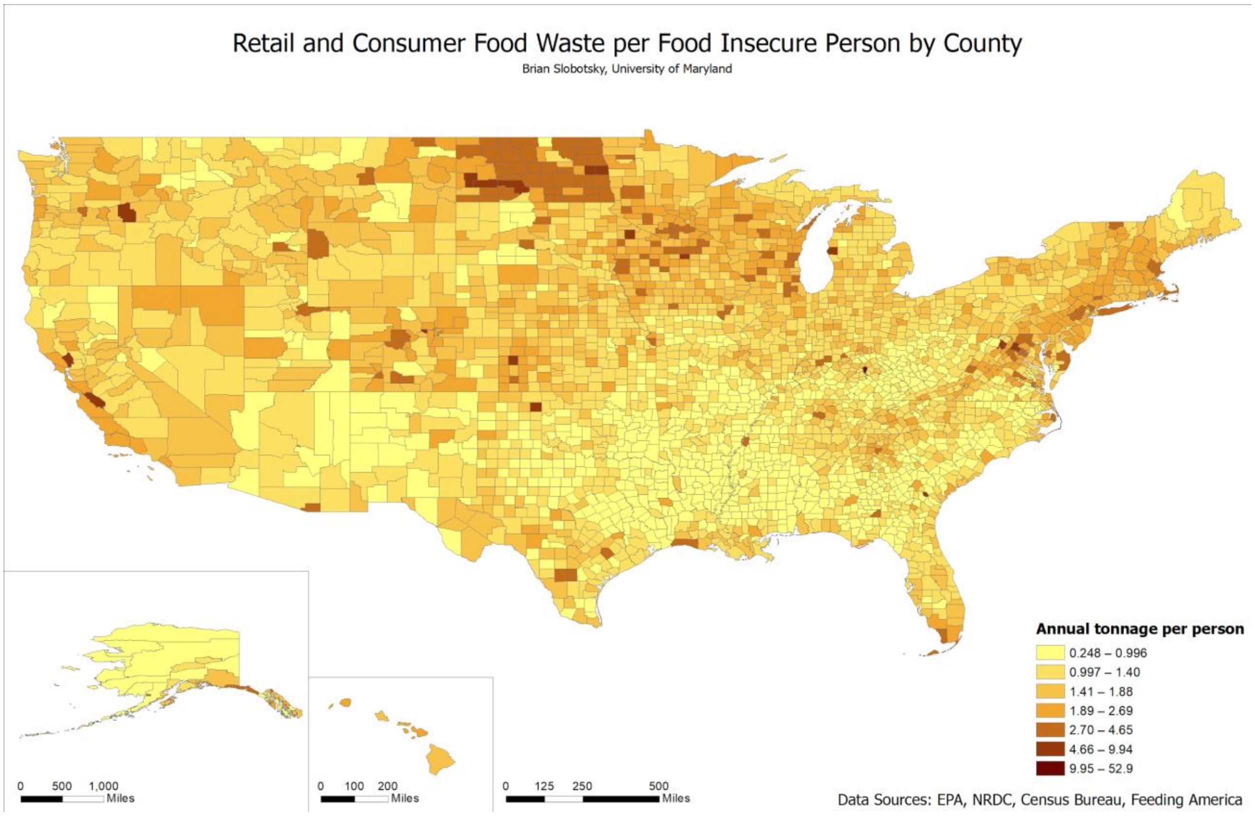
(Figure 5)



(Figure 6)

4.4 Comparison to Food Insecurity

The organization Feeding America created Map The Meal Gap, a data product which provides a county-level estimate of food insecurity (Gundersen et al. 2019). With permission, I have used the Map The Meal Gap data to visualize food waste per food insecure person in Figure 7.



(Figure 7)

Figure 7 shows the total estimate of retail and consumer food waste by county, per food insecure person, measured in tons per year per person. Two additional versions of this map, showing away-from-home waste and at-home waste per food insecure person, are respectively shown in Figure 10 and Figure 11 in the Appendix.

5. Discussion

5.1 Model Evaluation

It is necessary to check how the model performs in relation to existing county waste estimates. Many states have performed statewide waste characterization surveys; most methodologies do not align with the approach taken in the NRDC paper (EPA 2020b; Hoover and Moreno 2017). Two states, California and Illinois, have performed broad waste surveys from the standpoint of waste generation. In addition, both states have published data at the county level. For California only, that includes classification of residential and commercial estimates by county (California 2014; Illinois 2015). Thus, these county estimates can be compared to estimates from this paper's data product. The statewide estimate percent error and median and average county percent errors are listed in Table 6.

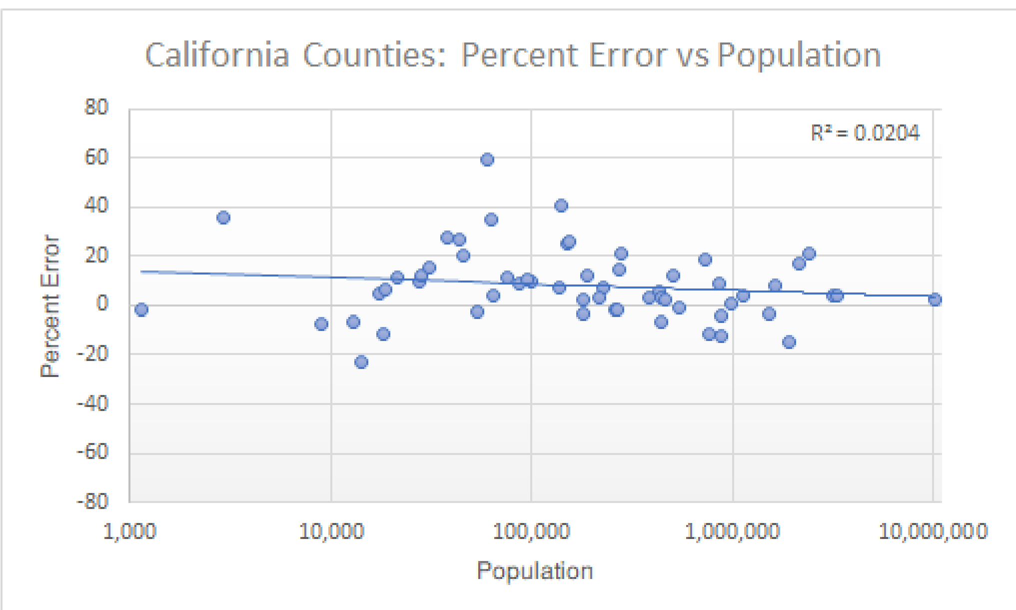
	California			Illinois		
Error Measure	Commercial	Residential	Total	Commercial	Residential	Total
Statewide	-8.28%	5.97%	3.60%	2.75%	7.18%	9.41%
County Median	-6.12%	4.61%	6.09%	—	—	2.19%
County Average	3.21%	5.46%	8.08%	—	—	1.35%

(Table 6: California and Illinois model evaluation)

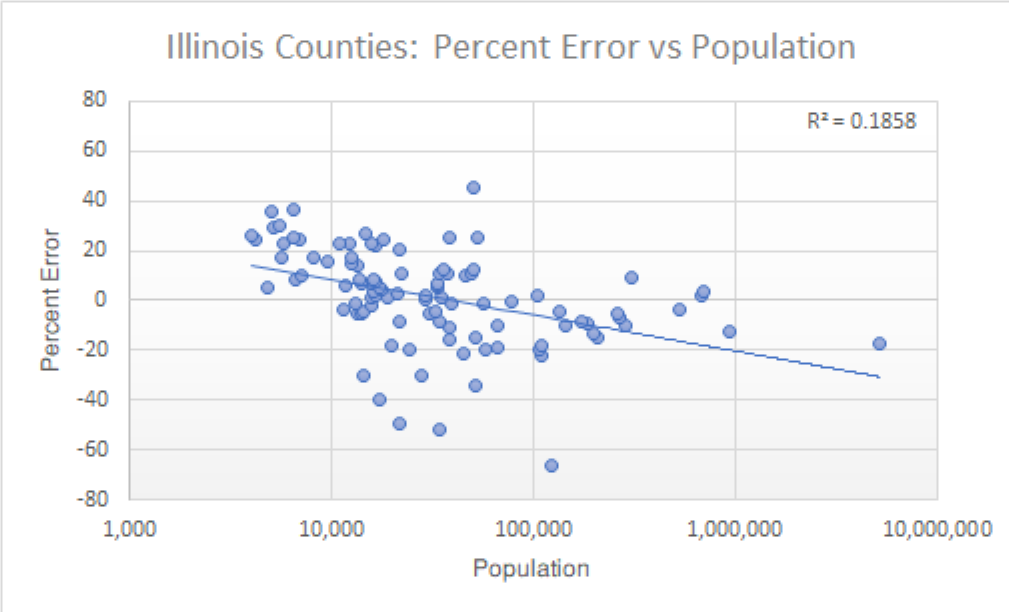
Percent errors were calculated using the Equation 2 error formula. California's waste characterization classifies waste from multi-family facilities as commercial, while similar waste would be classified as residential in the NRDC report. This discrepancy was accounted for in the error figures above. California suppresses waste data from certain industries in counties with low population due to data privacy, which is not accounted for in the error table. It is assumed that temporal changes are insignificant; The California data is from 2014, the Illinois data is from 2015, and the model's underlying NRDC values are from 2017 and EPA estimates are from

2019. Overall, all errors were calculated to be less than 10%. County-level error figures for both states are available as Tables 8 and 9 in the Appendix.

One of the assumptions of the model in this paper is that Denver, Nashville, and New York City are representative of trends across the country. The model assumes that the specifications tailored to the seven populous, urban counties which encompass the three cities are informative for the country's other 3,135 counties. To test that assumption, I have used the California and Illinois data to plot the model's percent error against population (on a logarithmic scale) for each county in both states, seen in Figure 8 and Figure 9. A logarithmic trendline and R^2 calculation is provided for context.



(Figure 8)



(Figure 9)

The California data shows a very weak relationship between error and population. Therefore, it is unlikely that a county's population influences the amount of error in California's modeled values, with the previously-stated data suppression as a noteworthy caveat. However, Illinois shows somewhat of a trend, where model overestimation decreases with an order-of-magnitude increase in population. Compared to the Illinois report, the 16 least populous counties in Illinois are all overestimated, while 13 of the 16 most populous counties are underestimated. The inconsistency between these two states could be a result of methodology differences or inherent geographical differences. More research is needed to be able to definitively settle whether the data product in this paper adequately serves counties with lower populations.

Further research on the assumptions of this model will be key. In addition to urban-rural differences, more data is needed on how median age and household size influence waste generation at the county level and the linearity of those relationships. Also, it is important to confirm the assumption that race, income, or poverty are not factors in the production of food waste. It is unknown how well this model predicts residential and consumer food waste generation in the handful of counties which solely contain American Indian reservations. Furthermore, the model can be improved by incorporating more waste-generating locations in future studies of commercial and industrial food waste. Background literature on waste generation estimates from corporate offices, airports, and recreational facilities such as movie theaters, bowling alleys, theme parks, and stadiums is needed. Overall, conducting a nationwide waste generation study at the county level in a sample of counties which vary by race, income, population, and geographical location would be a crucial step towards validation of the model presented in this paper.

5.2 Spatial Distribution

It is apparent that consumer and residential food waste generation is higher in counties with higher populations. Therefore, the spatial pattern of total food waste from commercial and residential sources resembles the spatial pattern of population in the United States. The maps of local spatial autocorrelation in Figures 5 and 6 present some information about the spatial patterns of food waste generation per capita. It appears that the Pacific Northwest (Washington and Oregon), Midwest (North Dakota, Minnesota, Wisconsin), and Northern New England (Vermont, New Hampshire, Maine) contain clusters of high values. In addition, the South (from New Mexico to Georgia and as far north as Missouri and Kansas) displays clusters of low values. These Southern states tend to generate less waste than Northern states both at-home and away-from-home. More research is needed to determine whether this pattern is indicative of regional trends and attitudes.

In terms of food waste generation per food insecure person, the same trends are apparent. It is important to note that these figures do not consider edibility of food waste. States such as Iowa, Minnesota, Wisconsin, (and North Dakota especially), as well as states in the Northeast and California show higher quantities of waste per food insecure person in comparison to states in the South. As seen in Figures 10 and 11 in the Appendix, this spatial pattern is driven by at-home food waste, which exhibits a similar spatial distribution. According to Feeding America's Map The Meal Gap, the region with the greatest food insecurity is the South (Gundersen et al. 2019). In conclusion, the spatial distributions of food waste and food insecurity are inversely related; regions with low food waste have high food insecurity, and vice versa.

5.3 Model utility

Legislation targeted at the diversion of food waste has historically been more successful with local and state governments. Curbside composting is available in only a few communities across the United States thanks to municipal lawmakers (Streeter and Platt 2017). Similarly, food recovery programs usually operate in a single geographic area. The dataset created in this paper will hopefully be an asset to county and state governance in the pursuit of greater waste diversion. This model is designed to be a tool for measurement in order to lead to successful management. By providing local governments with waste generation estimates, change can develop without the help of federal policymaking.

In addition, the data product can help improve the logistics of food waste diversion in accordance with the hierarchy of food waste reduction. Organizations such as food recovery groups can utilize the estimate of total food waste in a given county and decide to take action, expand to new areas, or scale their efforts more efficiently. Moreover, groups are aided by the data's breakdown into estimates classified by business type. Likewise, this allows for markets to open across the country which can link generators of food waste to recipients of food waste. A food waste equivalent of food hubs, which would aim to connect businesses selling excess food to hunger-relief groups or compost firms, would lower waste being sent to landfills and lower food insecurity. A future intermediary of this sort could find great use in local spatial trends as it relates to their economic viability.

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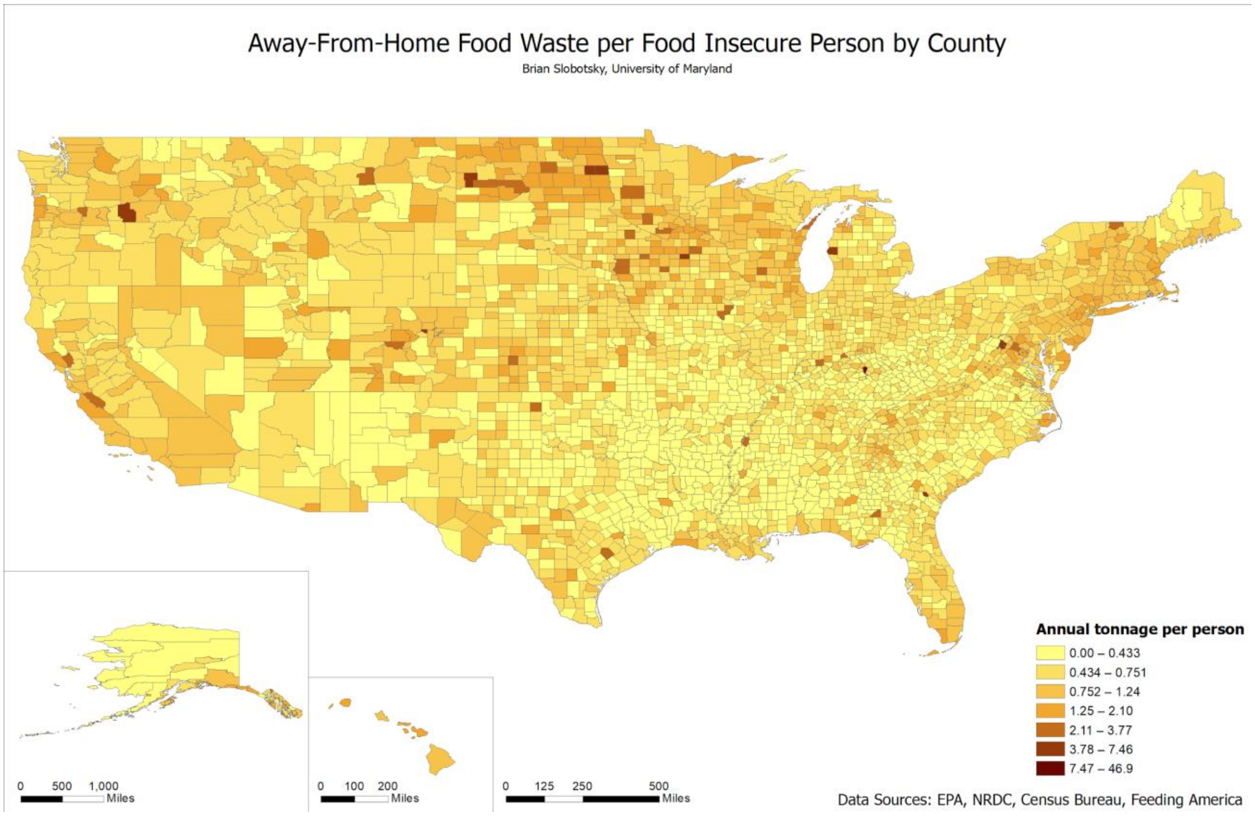
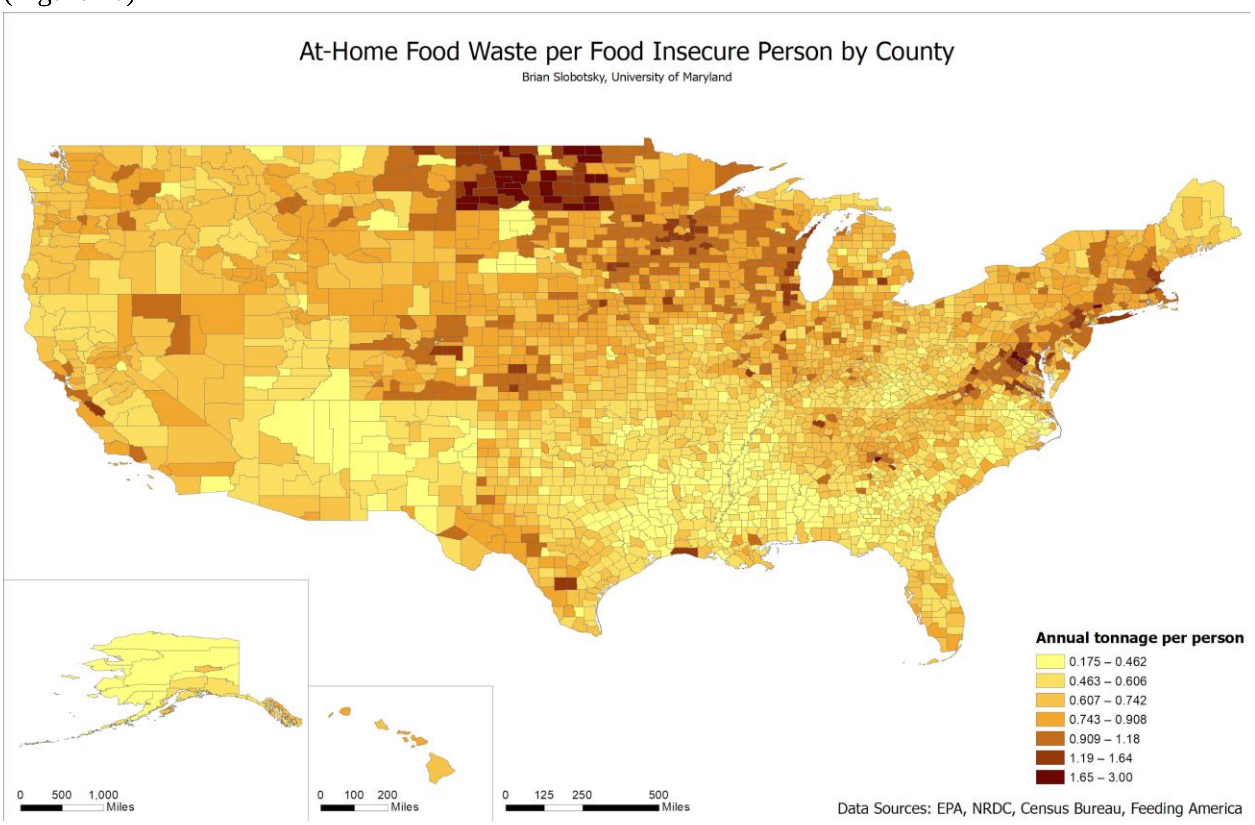
7. Appendix

Table 7: Global spatial autocorrelation results for at-home and away-from home figures

	Contiguity		Distance	
	Moran's I	z-score	Moran's I	z-score
AHFW	0.299216	30.01245	0.032556	28.65664
AFHFW	0.266774	27.03225	0.028888	25.69632



(Figure 10)



(Figure 11)

Table 8: California county error values

County	Commercial Percent Error	Residential Percent Error	Total Percent Error	Population
Alameda County, CA	6.80%	-4.33%	8.34%	1643700
Alpine County, CA	71.90%	-43.13%	-1.86%	1146
Amador County, CA	17.88%	24.30%	27.72%	37829
Butte County, CA	-0.12%	2.00%	6.84%	227075
Calaveras County, CA	10.23%	18.82%	20.43%	45235
Colusa County, CA	3.43%	5.03%	11.43%	21464
Contra Costa County, CA	-5.14%	2.02%	3.68%	1133247
Del Norte County, CA	6.07%	2.98%	10.05%	27424
El Dorado County, CA	-5.56%	20.13%	11.93%	186661
Fresno County, CA	-8.47%	-1.13%	0.48%	978130
Glenn County, CA	6.64%	5.51%	12.12%	27897
Humboldt County, CA	-6.99%	11.98%	7.08%	135768
Imperial County, CA	-14.67%	-1.25%	-3.57%	180216
Inyo County, CA	-24.48%	-5.28%	-11.73%	18085
Kern County, CA	-19.69%	3.21%	-4.55%	883053
Kings County, CA	23.27%	9.90%	25.46%	150075
Lake County, CA	-6.13%	3.59%	3.91%	64148
Lassen County, CA	5.78%	12.97%	15.20%	31185
Los Angeles County, CA	-8.06%	3.60%	2.74%	10098052
Madera County, CA	30.86%	5.00%	26.13%	155013
Marin County, CA	-15.38%	5.17%	-1.45%	260295
Mariposa County, CA	-8.54%	8.28%	4.82%	17540
Mendocino County, CA	-2.43%	8.99%	8.64%	87422
Merced County, CA	-14.56%	1.40%	-2.12%	269075
Modoc County, CA	-23.25%	-0.54%	-7.63%	8938
Mono County, CA	-29.37%	-25.98%	-23.09%	14174
Monterey County, CA	-0.63%	-1.41%	5.97%	433212
Napa County, CA	42.70%	-0.05%	40.99%	140530
Nevada County, CA	-12.06%	23.88%	9.62%	99092
Orange County, CA	-13.03%	16.54%	3.84%	3164182
Placer County, CA	-13.82%	14.64%	3.49%	380077
Plumas County, CA	-6.11%	7.99%	6.21%	18699
Riverside County, CA	6.82%	23.53%	20.85%	2383286
Sacramento County, CA	-18.93%	4.34%	-3.34%	1510023
San Benito County, CA	68.51%	16.34%	59.49%	59416
San Bernardino County, CA	-0.56%	26.56%	17.37%	2135413
San Diego County, CA	-11.19%	11.41%	3.75%	3302833
San Francisco County, CA	-19.33%	-16.37%	-12.49%	870044
San Joaquin County, CA	18.26%	3.95%	18.38%	732212
San Luis Obispo County, CA	12.43%	15.53%	21.31%	281455
San Mateo County, CA	-23.16%	-6.26%	-11.22%	765935

Santa Barbara County, CA	-20.20%	0.53%	-6.79%	443738
Santa Clara County, CA	-27.86%	-7.70%	-14.48%	1922200
Santa Cruz County, CA	5.51%	10.23%	14.49%	273765
Shasta County, CA	-13.15%	8.82%	2.27%	179085
Sierra County, CA	218.46%	3.96%	35.44%	2930
Siskiyou County, CA	30.33%	10.27%	26.52%	43540
Solano County, CA	-7.39%	3.72%	3.31%	438530
Sonoma County, CA	6.27%	3.33%	12.20%	501317
Stanislaus County, CA	-15.43%	6.76%	-0.63%	539301
Sutter County, CA	3.41%	4.88%	10.13%	95872
Tehama County, CA	61.93%	-1.55%	34.84%	63373
Trinity County, CA	-23.81%	-2.65%	-6.98%	12862
Tulare County, CA	-7.30%	1.73%	2.44%	460477
Tuolumne County, CA	-28.96%	21.36%	-2.23%	53932
Ventura County, CA	-12.38%	27.77%	8.82%	848112
Yolo County, CA	-6.96%	2.56%	3.00%	214977
Yuba County, CA	3.80%	8.87%	11.32%	75493

Table 9: Illinois county error values

County	Percent Error	Population
Adams County, IL	-10.18%	66427
Alexander County, IL	36.76%	6532
Bond County, IL	7.46%	16712
Boone County, IL	25.55%	53606
Brown County, IL	8.16%	6675
Bureau County, IL	7.08%	33381
Calhoun County, IL	5.14%	4858
Carroll County, IL	-4.61%	14562
Cass County, IL	17.28%	12665
Champaign County, IL	-14.52%	209448
Christian County, IL	5.27%	33231
Clark County, IL	1.47%	15836
Clay County, IL	13.71%	13338
Clinton County, IL	11.12%	37628
Coles County, IL	-14.61%	51736
Cook County, IL	-16.93%	5223719
Crawford County, IL	1.50%	19088
Cumberland County, IL	23.21%	10865
De Witt County, IL	3.64%	16042
DeKalb County, IL	2.13%	104200
Douglas County, IL	-17.98%	19714
DuPage County, IL	-12.48%	931743
Edgar County, IL	4.28%	17539

Edwards County, IL	25.63%	6507
Effingham County, IL	-52.00%	34174
Fayette County, IL	-8.40%	21724
Ford County, IL	-5.26%	13398
Franklin County, IL	-1.02%	39127
Fulton County, IL	1.28%	35418
Gallatin County, IL	29.17%	5157
Greene County, IL	-1.43%	13218
Grundy County, IL	12.17%	50509
Hamilton County, IL	17.44%	8221
Hancock County, IL	24.42%	18112
Hardin County, IL	26.33%	4009
Henderson County, IL	24.09%	6884
Henry County, IL	10.90%	49464
Iroquois County, IL	-30.12%	28169
Jackson County, IL	-19.37%	58551
Jasper County, IL	16.03%	9598
Jefferson County, IL	-15.59%	38169
Jersey County, IL	10.59%	22069
Jo Daviess County, IL	-49.54%	21834
Johnson County, IL	15.10%	12602
Kane County, IL	-3.99%	530839
Kankakee County, IL	-21.92%	111061
Kendall County, IL	-65.99%	124626
Knox County, IL	45.34%	50999
Lake County, IL	3.59%	703619
LaSalle County, IL	-18.38%	110401
Lawrence County, IL	8.16%	16189
Lee County, IL	10.42%	34527
Livingston County, IL	12.59%	36324
Logan County, IL	0.56%	29207
Macon County, IL	-20.01%	106512
Macoupin County, IL	9.87%	45719
Madison County, IL	-6.97%	265670
Marion County, IL	-10.46%	38084
Marshall County, IL	5.89%	11794
Mason County, IL	8.67%	13778
Massac County, IL	-29.95%	14430
McDonough County, IL	-5.13%	30875
McHenry County, IL	9.55%	307789
McLean County, IL	-8.35%	173219
Menard County, IL	22.56%	12367
Mercer County, IL	22.90%	15693
Monroe County, IL	6.22%	33936
Montgomery County, IL	2.25%	29009

Morgan County, IL	-8.10%	34426
Moultrie County, IL	26.47%	14703
Ogle County, IL	-33.80%	51328
Peoria County, IL	-9.36%	184463
Perry County, IL	2.72%	21384
Piatt County, IL	22.28%	16427
Pike County, IL	-1.89%	15754
Pope County, IL	24.53%	4249
Pulaski County, IL	17.23%	5611
Putnam County, IL	22.94%	5746
Randolph County, IL	-4.61%	32546
Richland County, IL	6.54%	15881
Rock Island County, IL	-10.02%	145275
Saline County, IL	-19.51%	24231
Sangamon County, IL	-13.29%	197661
Schuyler County, IL	9.64%	7064
Scott County, IL	35.34%	5047
Shelby County, IL	20.15%	21832
St. Clair County, IL	-4.93%	263463
Stark County, IL	29.72%	5500
Stephenson County, IL	-21.65%	45433
Tazewell County, IL	-4.49%	133852
Union County, IL	4.92%	17127
Vermilion County, IL	-0.71%	78407
Wabash County, IL	-3.85%	11573
Warren County, IL	-39.55%	17338
Washington County, IL	7.07%	14155
Wayne County, IL	1.70%	16487
White County, IL	-4.83%	14025
Whiteside County, IL	-1.11%	56396
Will County, IL	1.88%	688697
Williamson County, IL	-19.13%	67299
Winnebago County, IL	-9.96%	286174
Woodford County, IL	24.96%	38817