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Operational Carbon Footprint of the U.S. Water Sector's Energy Consumption

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OPERATIONAL CARBON FOOTPRINT OF THE U.S. WATER SECTOR'S ENERGY CONSUMPTION

THESIS

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Abstract

Responding to global climate change requires better accounting of greenhouse gas emissions (GHG) to develop targeted strategies for reducing carbon footprints. Energy demand is a major contributor to operational GHG emissions in the water sector; however, the United States struggles to track GHG emissions in this sector largely due to the absence of a centralized water database. Previously, research focused on estimating operational GHG emissions generated from direct energy sources (energy produced or combusted on site), omitting operational GHG emissions generated from indirect energy sources (energy produced off-site, i.e., electricity). Accounting of energy-related GHG emissions in the water sector have largely been conducted at single utilities or cities and rarely at a regional or country scale. In this study, we assess the carbon footprints of operational energy use for 76 wastewater utilities and 64 water utilities across the United States. Additionally, we investigate water-related GHG emissions at a sub-annual scale through three case cities to understand how GHG emissions change at the monthly scale. Per unit of water, indirect energy in the form of grid electricity is found to be the largest contributor of operational GHG emissions. We estimate the total drinking water and wastewater GHG emissions associated with electricity, biogas, natural gas, and fuel oil consumption across the United States to be 26.5×10^9 and 20.1×10^9 kg CO_{2e} respectively. We find the average GHG emissions per unit drinking water and wastewater emissions to be 0.463 kg CO_{2e}/ m^3 and 0.42 kg CO_{2e}/ m^3, respectively. The research provides insights into operational GHG emissions of the water sector and advances the understanding of temporal variations in the life-cycle of energy use.

To my wife, for her understanding, acceptance, and love of the crazy life we live. To my sister, for keeping me in check whenever my head is too full of hot air. To my parents, for supporting me through my decisions. And to my friends, for reminding me that it's normal to step outside my room every once and a while. I wouldn't be the person I am today without the support of everyone I meet and laugh with.

"Words are pale shadows of forgotten names. As names have power, words have power. Words can light fires in the minds of men. Words can wring tears from the hardest hearts." -Patrick Rothfuss

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Louis J. Zib III

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OPERATIONAL CARBON FOOTPRINT OF THE U.S. WATER SECTOR'S ENERGY CONSUMPTION

I. Introduction

In 2012, the United States' energy consumption of water and wastewater utilities was estimate between 1% to 4% of the total electricity generation of the United States (1–3). The current practice for tracking water-related greenhouse gas (GHG) emissions (carbon footprint) largely relies on accounting direct emissions, such as on-site electrical generation, natural gas, and anaerobic processes which produce biogas for energy consumption. However, indirect emissions associated with off-site electricity generation are often overlooked. Indirect emissions from electricity consumption are generally larger than direct energy emissions (4). While studies accounting for both direct and indirect GHG emissions from the water sector have been done in China (5) and Australia (6), there are no comparable studies for the United States. In this study, we capture direct emissions in the form of natural gas consumption, fuel oil consumption, and biogas consumption. We also capture indirect emissions in the form of electrical grid energy consumption.

Problem Statement

The energy-water nexus details the complex relationship and interactions between the energy and water sectors (7). Within the energy-water nexus, studies of emissions from water systems are important because they aid in detailing energy efficiencies related to water production (8), can assist in reaching GHG reduction goals (9), and quantify previously hidden GHG emissions (5). However, government

research and development for the water sector are limited when compared to the energy sector, driving a lack of modernization of water sector technologies aimed at improving water and energy efficiencies (10).

Research Objective and Questions

In this study, we build on previous work in the energy-water nexus to assess the direct and indirect GHG emissions produced by the treatment of drinking water and wastewater across the United States.

1. What are the GHG emissions associated with the operation of drinking water and wastewater treatment plants across the United States?
2. Do the make-up of GHG emissions for water and wastewater differ across different regions?
3. How do GHG emissions change within the year at drinking water and wastewater treatment plants?

Scope and Limitations

This research will be conducted through a sample of water and wastewater utilities across the United States, detailing their energy demands and computing specific GHG production in relation to water utilities. Additionally, there are minimal studies of the energy-water nexus and the intra-annual patterns associated energy demand and subsequent GHG emissions (11). Therefore, we also examine three specific cities to detail the intra-annual relation between GHG emission and water production. In this research, we quantify the GHG emissions associated with direct and indirect energy emissions as it relates to the United States' water sector through an input-output framework within the scope of the energy-water nexus. We

evaluate the indirect emissions (electricity) and direct emissions (biogas, fuel oil, and natural gas) associated with operational water production of a sample of 64 drinking water treatment utilities and 76 wastewater treatment utilities that represent 24% and 23% of the population respectively, then we extrapolated our findings to the national scale.

While this study is one of the first of its kind in the United States, it does have some limitations. First, the data used in the analysis are from the year 2012. Additionally, this study is not an exhaustive study showing current, real-time operational carbon footprints of all water and wastewater treatment plants. Rather, this study provides as snapshot of 2012 operational GHG emissions from a set of water and wastewater utilities to capture the regional trends across the United States. Extrapolations to the national scale are based on an assumption of a representative sample of data. While we are limited in our analysis of available water utilities by corresponding availability emission factor data, the impacts of operational GHG across the water utilities show that the water sector relies heavily on indirect energy sources. Despite these limitations, the sample size evaluated does represent a strong proportion of the overall population in the United States by detailing a majority of larger cities. With that said, it is likely that these estimates of emissions are conservative due to economies of scale that might dictate larger emissions for smaller water utilities.

An additional limitation is the lack of control in setting standardized boundaries on the treatment of water across the water utilities. Each utility uses different boundaries to determine and report their energy consumption for water treatment. While this limitation exists, our study still provides useful information in determining the amount of CO_{2e} that is produced by each utility. The standardization of boundaries can be established by centralized data collection

guidelines similar in scope as the guidelines set forth by the EIA. While these limitations exist, this study is the first of its kind to determine a range of operational GHG emissions within water and wastewater treatment plants. The conducted research allows for future researchers the ability to progress the accuracy and precision of determining GHG emissions created at water and wastewater treatment plants in the United States.

II. Literature Review

The purpose of this chapter is to gain understanding in the common methods to assess carbon footprints in the energy-water nexus as well as understand the scope and relationship that define the energy-water nexus.

Life Cycle Assessment, Input-Output, and Hybrid Frameworks

Detailing the carbon footprint of a system can be handled with two prevailing methods: Life Cycle Assessment (LCA) and Input-Output (I-O) (12). With the added complexity of water accountability being historically difficult to set boundaries on (13, 14), both methodologies have their advantageous and disadvantageous when detailing the carbon footprint in a national context.

Process-based LCA is a bottom-up approach (12) that has been widely used to quantify life cycle environmental impacts associated with urban water infrastructure (15–17). LCA can be a useful tool for comparing environmental impacts across multiple technologies (18, 19) or across a small sample of city utilities (20). While it can be useful for accounting for life cycle GHG emissions and associated climate change impacts, process-based LCA relies on accurate representations of components and energy systems to produce results, often relying on built models rather than real-time data to generate emissions for an analyzed system (e.g., 12, 19). Furthermore, to fairly compare environmental impacts across multiple treatment plants using LCA, the functional unit must be carefully chosen to acknowledge differences among plants (e.g., electricity sources, composition of influent, types of treatment) (21). Due to the data requirements, process-based LCA frameworks to view national infrastructure systems are possible, but would take tremendous resources to provide detailed and accurate results.

While LCA seeks to provide a comprehensive assessment of environmental impacts over a system's lifetime, input-output analysis (I-O) evaluates impacts at a specific point in time during a system's life; see Figure 1. The outputs, often GHG emissions, are calculated by a top-down approach (12) that utilizes aggregated factors coupled with individual consumption to produce current emissions. I-O has often been used when intricacies or complexities of the system prohibit the use of process-based LCA due to rigorous data requirements or large study scope (22). For example, Zhang et. al. used an I-O framework to detail operational direct and indirect GHG emissions of water utilities of Chinese cities and found that the operational direct and indirect GHG emissions produced were 41 billion kg CO_{2e} (5). Unlike LCA, I-O only accounts for operational GHG emissions (12), and excludes GHG emissions generated at other points in a system's life (e.g., construction, end of life).

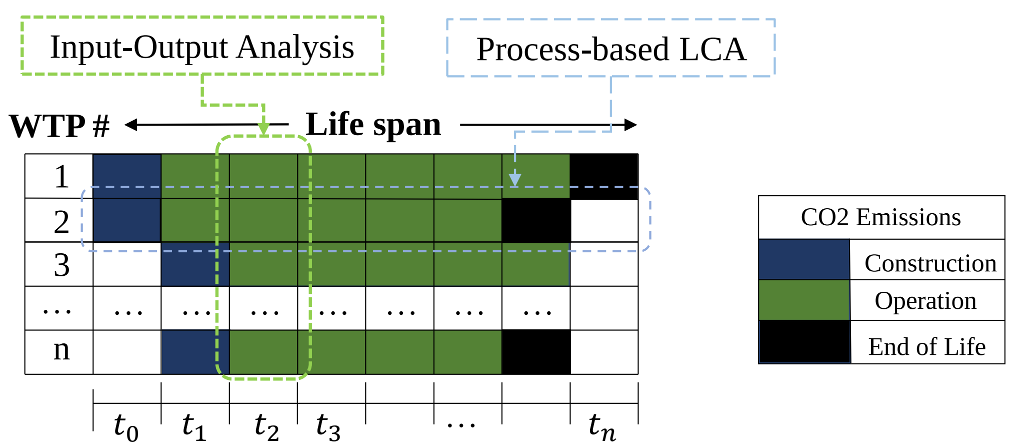

Figure 1. Scope of process-based LCA vs. I-O.

Process-based LCA views a single water utility's CO_{2e} emissions across the entire lifespan, while I-O assesses multiple water utility's CO_{2e} emissions during a specific operational timestep. Figure adapted from Zhang et. al. (5).

Recently, frameworks using both LCA and I-O have been used to analyze the life-cycle GHG emissions of renewable energy systems (23). Hybrid LCA frameworks combine process-based LCA and economic input-output LCA (EIO-LCA) in a way that maximizes the strengths of each approach (24). operational data and life cycle cost data for each water treatment utility. For example, hybrid frameworks have been used to explore future implementation of a technology (5, 23). While a hybrid framework could provide a more comprehensive assessment of each utility's emissions, acquiring the necessary life cycle inventory data from each of the many water treatment utilities is beyond the scope of this study. Therefore, the I-O framework was chosen to best facilitate the large-scale comparisons and analysis of the study.

Energy-Water Nexus

The energy-water nexus has been explored both by detailing the water use in the energy sector (e.g., 25–28) and the energy use in the water sector (e.g., 1, 5, 29–31). Previous assessments of the energy-water nexus includes managing limited water resources (7), adapting to increasingly uncertain conditions (32), water use efficiencies in urban environments (33, 34), and informing policy decisions at the city (35, 36), state (27), and regional (37) level. Investigating renewable energy sources (23, 38, 39), quantifying energy water intensities (40–42), and GHG interactions (43) within the energy-water nexus have further expounded scientific understanding of the interdependent resources. As global climate change continues to endanger water systems (44), analyzing the carbon footprint of emissions becomes important in managing climate change (45). Strategies for more efficient energy utilization of water have been explored in countries such as Australia (32), China (23), and the United States (46). While more detailed studies have been

conducted at the city level for carbon footprints of water treatment plants (5, 10, 18, 20, 34, 42, 47), there is minimal research that evaluates the operational GHG emissions from both drinking water and wastewater treatment plants on a scale that promotes regional and intercity comparisons.

Water treatment facility operations are shown to be the largest contributor for energy use and subsequent GHG emissions (5, 35). Pumping treated and raw water is shown to be the most energy-intensive operation at a drinking water treatment facility (35). Research for energy consumption and savings focused on the treatment of water include assessments on air emissions (18) and energy intensities (40) on water treatment alternatives. For example, Stokes et al. (19) developed the Water-Energy Sustainability Tool (WEST) to aid in analyzing air emissions from water supply, treatment, and distribution (19). Additionally, studies have been conducted investigated the energy recovery available using anaerobic digestion for wastewater treatment (39, 48). Other studies have integrated bi-level decision-making models in energy-water nexus management (49) and quantified energy use and intensity through a time-based water-energy profiling framework (37). However, these studies only looked at the energy needed to treat water and three studies consider the generation of operational GHG emissions within water utilities (5, 10, 34). Understanding the operational GHG emissions produced at water treatment plants is vital for determining future energy, water, and carbon goals.

Chapter Summary

LCA and I-O are common methods to account for carbon footprints. Hybrid models utilizing elements from both methods are commonplace when accounting for carbon footprints when data is unavailable or where a a full LCA is unwarranted.

The energy-water nexus is a highly explored topic which ranges from the use of water in energy production to the use of energy in water production to include accounting GHG emissions from electricity consumption. While there are many articles detailing GHG emissions of electricity consumption at water treatment plants, there is very little research done regarding the production of GHG emissions from the operation of the entirety of the water sector within the United States. Additionally, there is little research done detailing the behavior of GHG emissions within an intra-annual scale at drinking water and wastewater treatment plants.

III. Methodology

The purpose of this chapter is to outline the acquisition, processing, analysis, and visualization of the data as well as detail the software programs used to accomplish that goal. This chapter also outlines the challenges faced when conducting this research.

Data Collection

This analysis synthesized water and energy data from the Intergovernmental Panel on Climate Change (IPCC) (50), the U.S. Environmental Protection Agency (EPA) (51), and the U.S. National Renewable Energy Laboratory (NREL) (52). Additionally, the analysis relied heavily upon recent studies by Chini & Stillwell (1) and Siddik et al (53) to provide data on energy demand for water treatment at water utilities and locally-specific GHG emission factors for electricity, respectively. Figure 2 illustrates the process as a flowchart while Figure 3 details the types of data and their sources as well as how the data is combined for the annual and monthly temporal scopes.

Gomez et al. (50) provided data on standardized emission factors. The EPA also provided U.S. specific GHG emission factors for fuel sources (51). Table 1 provides the common GHG emissions factors associated for natural gas, biogas, and fuel oil used for national analysis. GHG emission factors for each city were calculated using the IPCC (50) and EPA (51) GHG emission factors for each fuel source. Minimum, maximum, and average GHG emission factors were generated for each fuel source. GHG emission values were then determined by multiplying the GHG emission factor by the amount of fuel source consumed at each water treatment plant.

Table 1. GHG emission factors for natural gas, biogas, and fuel oil used for each city.

Tabulated GHG emission factors are calculated from the range of IPCC (50) and EPA (51) reported values.

	Emission Factors		
Fuel	Minimum	Average	Maximum
Natural Gas (kg/therm)	5.27	5.77	6.17
Biogas (kg/therm)	3.32	7.22	9.19
Fuel Oil (kg/gal)	6.09	8.07	10.25

Direct electricity GHG emissions for the three sample cities were determined by the use of hourly eGRID-specific GHG emission factors provided by the NREL (52), which could then be aggregated to monthly time steps for intra-annual assessments of GHG emissions. City-specific electricity, natural gas, biogas, and fuel oil consumption as well as associated GHG emissions used for this study can be found in the supporting documents (53).

The overlap between datasets was not complete. Therefore, to be included in this study, data must be available for energy consumption and have a corresponding GHG emission factor from Siddik et al. (53). Siddik et al. assessed multiple attribution methods to assign GHG emissions from electricity production to end consumers (53). From these attribution methods, a maximum, minimum, and average emission value were calculated across the various accounting methods.

The accounting methods produces a range of likely emissions, thereby allowing us to capture uncertainty in our estimates. Of the 114 number of cities (77 drinking water and 93 wastewater utilities) that were available within the Chini & Stillwell (1) dataset, only 76 wastewater utilities and 64 drinking water utilities had water volume and energy consumption data that matched with the city-level emission factors in the Siddik et al (53) dataset.

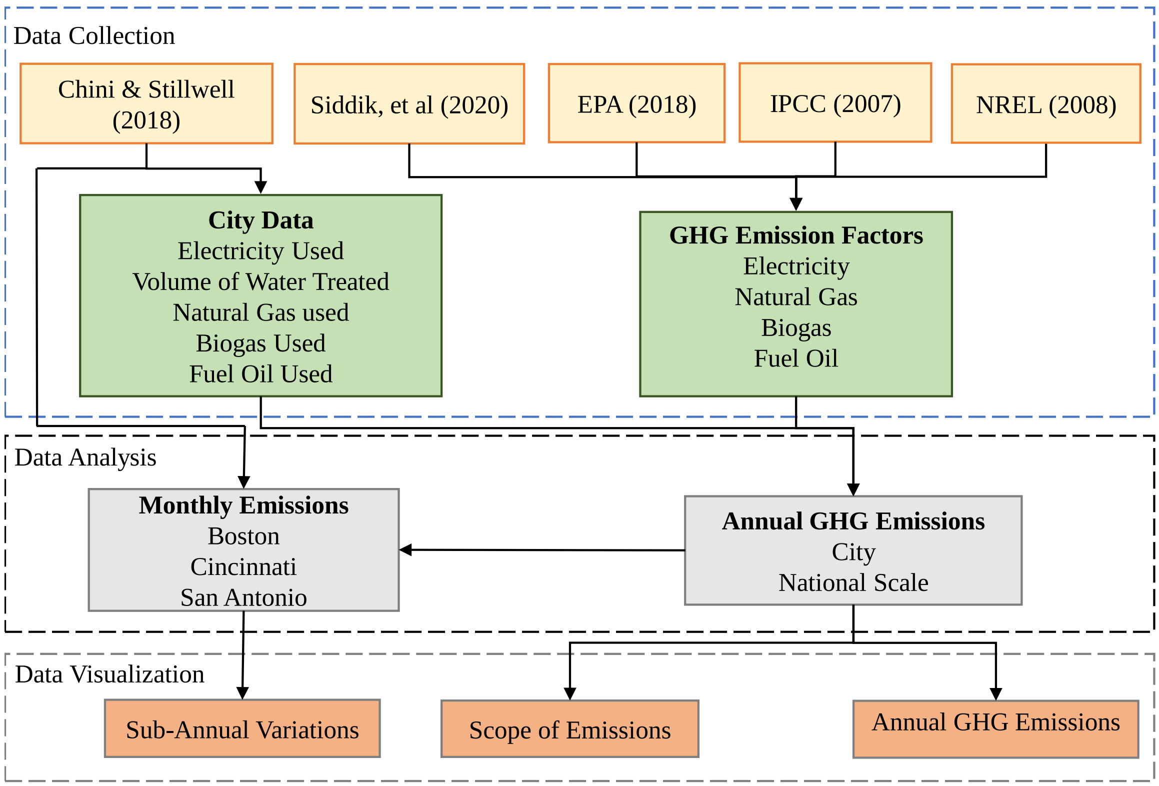

Figure 2. Process flowchart for conducted study.

Data is first complied into two separate dataframes before being analyzed at the annual and monthly temporal scales. Data is visualized into sub-annual variations, scope of emissions, and annual GHG emissions.

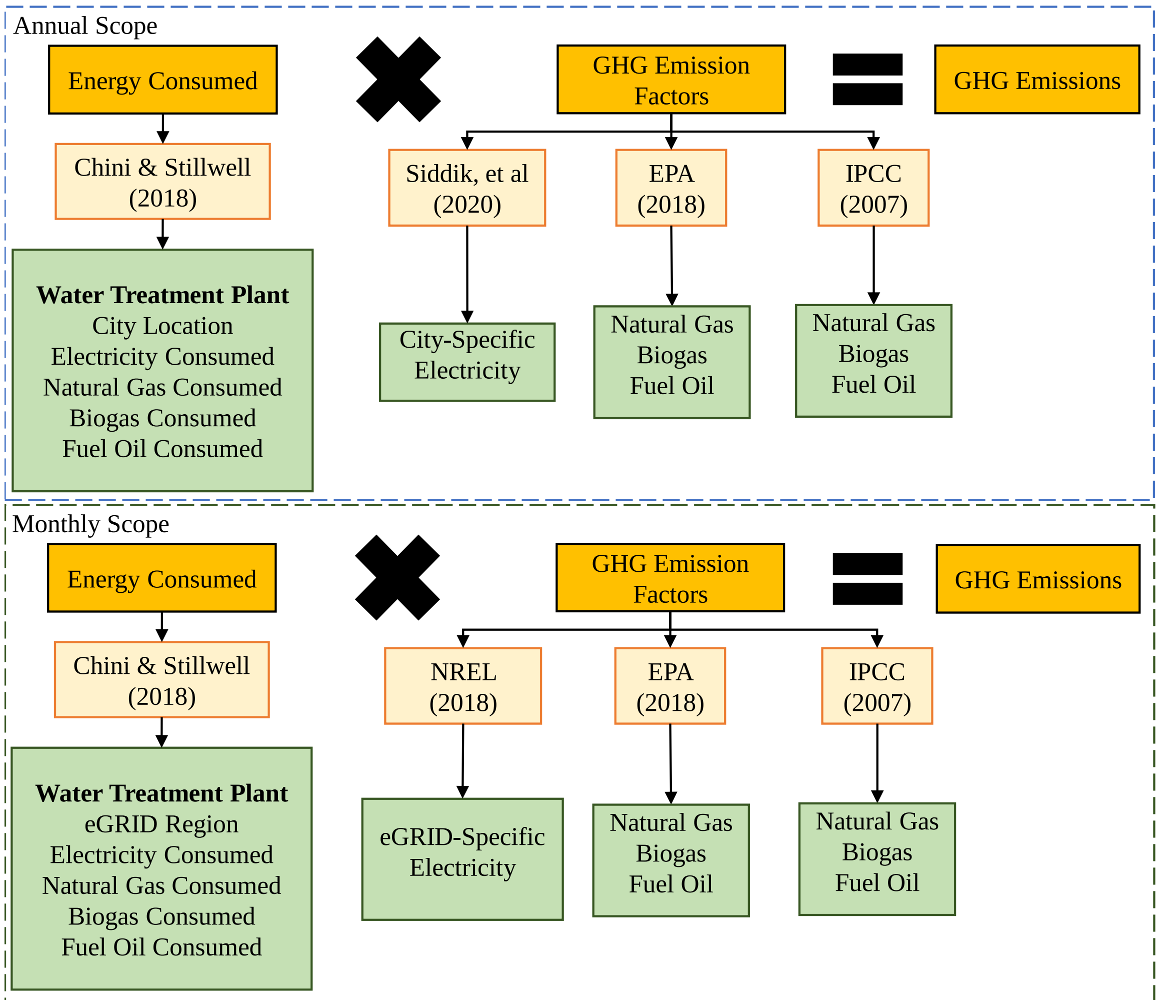

Figure 3. Data synthesis and calculation for operational GHG emissions for drinking water and wastewater treatment plants.

Data was first collected from several sources, including Environmental Protection Agency (EPA), Intergovernmental Panel on Climate Change (IPCC), United States National Renewable Energy Laboratory (NREL), before being analyzed at the annual and monthly level.

Data Analysis Overview

Input-output analysis relies on a top-down procedure to estimate GHG emissions (5) and is primarily based on IPCC guidelines (50). IPCC guidelines detail the process to normalize GHG emissions to a common unit: CO_{2e} (50). The guidelines cover direct and indirect CO_{2e} and non-CO_{2e} emissions of energy use from the treatment process. Top-down GHG compilation can be expressed as shown in Equation 1:

$$E^{GHG} = (EF_e * ET_e) + (EF_{ng} * ET_{ng}) + (EF_{fo} * ET_{fo}) + (EF_{bg} * ET_{bg}) \quad (1)$$

Where E^{GHG} is the GHG emission of energy, EF denotes the GHG emission factor for the type of energy, ET denotes the amount of energy consumed. EF can take on the minimum, mean, and maximum GHG emission factor value for its corresponding energy type, which enables us to assess uncertainty in our estimates. e references electricity consumption, ng refers to natural gas , fo is fuel oil, and bg is biogas consumption. Table 1 details the minimum, mean, and maximum of each GHG emission factor for natural gas, biogas, and fuel oil. Annual GHG emission factors for natural gas, biogas, and fuel oil were formed from the compilation of the EPA emission factors (51) and the IPCC emission factors (50) as seen in Table 1. The GHG emission factors were applied to each city, resulting in a mean emission value and an expected range. Electricity GHG emission factors were gathered from Siddik et. al. (53). On average, the emissions intensity of water due to electricity is 99×10^6 kg CO_{2e}/m^3 with a range between 0 and 8.6×10^9 kg CO_{2e}/m^3, depending on region.

Monthly GHG emission factors for electricity were formed from the NREL dataset (52). GHG emissions factors for the NREL dataset are tabulated based on

eGRID region at the hourly time scale. Using this information, monthly minimum, mean, and maximum values for the three representative cities were calculated. These representative cities were analyzed at the monthly temporal scale to identify and highlight the importance of intra-annual patterns of energy utilized by type. The cities were chosen for their diverse location, comparable size, and available data. The monthly electricity consumption at each city's treatment plant is available from (1). These values were then paired with the eGRID GHG emission factors compiled by NREL (52). These GHG emission factors were paired with monthly electricity consumption values for drinking water and wastewater utilities. Monthly GHG emission factors for natural gas, biogas, and fuel oil were taken from Table 1 due to the lack of intra-annual variability of these energy sources. The GHG emission factors were applied to each city, resulting in four emission values corresponding to each of the four potential energy sources. A minimum, maximum, and average GHG emission value are generated from the four GHG emission values.

Data Analysis

RStudio was the platform used for data compilation, wrangling, and analysis. The following packages were loaded into the RStudio library list: plyr, dplyr, readbulk, tidyr, gsubfn, mgsub, stringr, arcgisbinding, sf, data.table, openxlsx, anytime, lubridate, xts. (54–68)

Data Conditioning.

Data was first imported into RStudio from the Chini & Stillwell dataset (1), Siddik et. al. dataset (53), IPCC table (50), EPA dataset (51), and NREL dataset (52) and converted into S.I. units for commonality. four dataframes were created in order to analyze the emissions produced at water treatment plants; two dataframes

for drinking water (annual water dataframe & monthly water dataframe) and two dataframes for wastewater (annual waste dataframe, & monthly waste dataframe). These dataframes contain the data associated with each city pulled from the Chini & Stillwell dataset (1). Cities that reported digester gas values were added to the biogas values. Cities that reported landfill gas values were added to the biogas values. The data and source associated with each dataframe and can be found in the supporting documents metadata tab.

Data Synthesis.

Once the data was imported into RStudio and converted into S.I. units, cities were cross-referenced with the Siddik et. al. dataset (53) to match city data with city-level electricity emission factors. All cities that did not have a corresponding city-level electricity emission factor were omitted from the dataframes. There where some cities that were co-located within the same city-level electricity emission factor as identified by Siddik et. al. (53). For these co-located cities, the same city-level electricity emission factor was used. Since the city-level electricity emission factors as created by Siddik et. al. (53) contained Metropolitan Statistical Areas (MSA) for the continental United States, Alaska and Hawaii were omitted for this study. All analysis for annual and monthly emissions were calculated with the finalized list of cities.

Annual Analysis.

Annual analysis used the tier-2 approach as described in the IPCC (50). The tier-2 approach designates the use of GHG emission data as published by the nation for carbon footprint analysis. The tier-2 approach also allows for the use of IPCC standardized GHG emissions data in the event that published GHG emission data

from the nation is not available or as an additional data point when accounting for uncertainty when analyzing the carbon footprint. The analysis for GHG emissions generated by electricity consumption relied on the Siddik et. al. (53) city-level electricity emission factors coupled with the electricity consumed as noted in the Chini & Stillwell dataset (1).

The produced GHG emissions from electricity when applying the electricity consumed to each city-specific attribution method emission factor seen in the Siddik et. al. dataset (53) were then analyzed as a group to determine the minimum, average, and maximum city-specific electricity emission value.

The analysis for GHG emissions generated by natural gas, fuel oil, and biogas relied on EPA (51) and IPCC (50) emission factors coupled with consumption of each energy source noted in the Chini & Stillwell dataset (1). Since the emission factors published by the EPA (51) are single values rather than ranges, IPCC's emission factors are also used to account for uncertainty as IPCC's emissions factors have ranges associated. The 4 values where grouped together and a minimum, average, and maximum emission factor value were found in order to develop Table 1 which denotes the range of emission factors associated with natural gas, biogas, and fuel oil consumption at drinking water and wastewater treatment plants. Applying the consumed natural gas, fuel oil, and biogas values to the minimum, average, and maximum emission factors for each energy source equates to the minimum, average, and maximum GHG emissions associated with each energy source.

GHG emissions associated with the consumption of energy sources were found to be CO_2, CH_4, N_2O, SO_2, and NO_x. For this study, SO_2 and NO_x were omitted as they do not have 100-Year GWP values (69) associated. The rest of the GHG emissions were converted into CO_{2e} using their unique 100-Year GWP values. Table 2 details the 100-Year GWP conversion values associated with CH_4 and N_2O.

The 100-Year GWP value for CO_2 to CO_{2e} is 1.

Converting the emissions to CO_{2e} allowed for the summation of CO_{2e} emissions generated by all energy sources for each city. Summating minimum, average, and maximum CO_{2e} emissions produced by electricity, natural gas, biogas, and fuel oil determines the city-specific minimum, average, and maximum carbon footprints associated with the operation of drinking water and wastewater treatment plants. These values were then aggregated to determine the operational carbon footprint for the sample group. Extrapolation was then used in order to determine the minimum, average, and maximum national operational carbon footprint for drinking water and wastewater treatment plants.

Table 2. 100-Year GWP for CH_4 and N_2O.

The 100-year GWP (69) for CO_2 is 1.

Gas	100-Year GWP
CH_4	25
N_2O	298

Monthly Analysis.

The Tier-2 approach as described by IPCC (50) was used to analyze monthly carbon footprints for Boston, Cincinnati, and San Antonio. Unlike the analysis used for the annual carbon footprints, the monthly electricity emission factors came from the NREL dataset (52). The NREL (52) electricity emission factors are based on the eGRID region for the city rather than city-specific. The use of eGRID-specific electricity emission factors is due to the lack of availability of monthly city-specific and state-specific electricity emission factors.

The same emission factors for natural gas, fuel oil, and biogas as described in Table 1 were used since the emissions associated with these energy sources are only

dependent on the amount consumed. The Chini & Stillwell dataset contained monthly values for electricity, natural gas, biogas, and fuel oil consumed and monthly values for treated water produced at the three cities.

The calculations for the monthly values relied on the same operations as seen in the annual analysis. Minimum, average, and maximum emission factors were established for each energy source. Applying the monthly value of energy consumed to the corresponding minimum, average, and maximum emission factor resulted in minimum, average, and maximum GHG emissions produced each month. Converting the emissions into CO_{2e} allowed for the monthly summation of minimum, average, and maximum produced CO_{2e} emissions associated with city's drinking water and wastewater treatment plant.

Total monthly CO_{2e} emissions for each drinking water and wastewater treatment plant were divided by their monthly production of water in order to determine the emission intensity for treating water at to each city. Minimum, average, and maximum mission intensity values are displayed on Figure 3 along with average electricity consumed and average natural gas consumed across the year for Boston, Cincinnati and San Antonio's drinking and wastewater treatment plants.

Data Visualizations

Visualizations were conducted using two different visualiazation programs: ArcGIS and Grapher. ArcGIS allows for the user to develop spatially dependent figures in order to quantify and illustrate relationships between different attributes. Grapher is a user-friendly program which allows the user to develop 2-D or 3-D graphs to display the relation between two or more variables.

ArcGIS.

ArcGIS was used in order to visualize the data spatially across the United States. The annual water and waste dataframes were imported from RStudios into ArcGIS using the package called arcgisbinding (62).

The annual water and wastewater dataframes needed to be converted to a recognizable spatial dataframe in order for ArcGIS to display the data accurately across the United States. Coordinates for each city utilized needed to be appended to the data for AcrGIS to accurately place them on the map. The coordinate data for each city was converted into a dataframe from Chini & Stillwell's shapefiles (1) and incorporated as a separate value for each city. Once the coordinate data was included, the arcgisbinding package (62) was used in order to convert the annual water and wastewater dataframes into spatial dataframes and exported to ArcGIS as shapefiles recognized by ArcGIS.

The shapefiles were uploaded into ArcGIS in order to create visualizations across the United States to detail the CO_{2e} emissions associated with each city along with the amount of water produced at each city for both the drinking water and wastewater treatment plants. The NAD 1983(2011) coordinate system is used to spatially organize the United States and resulting city locations. The United States shapefile was supplied by Chini & Stillwell (1) and two visualizations were generated: a pie chart detailing the breakout of aggregated drinking water and wastewater CO_{2e} emissions (Figure 4(A)) & the typical make-up of wastewater CO_{2e} emissions corresponding to each eGRID region across the United States (Figure 4(B)), and a national view of CO_{2e} emissions generated vs treated water produced at drinking water (Figure 5(A)) & wastewater treatment plants (Figure 5(B)).

Figure 4(A) was constructed by summating the average CO_{2e} emissions from each energy source within the drinking water and wastewater treatment plants

sampled in the study. The selection of cities to detail the make-up of wastewater CO_{2e} emissions for each eGRID region as seen in Figure 4(B) were determined by selecting the water-treatment plant that most closely represented the make-up of the overall wastewater treatment plant CO_{2e} emissions within the eGRID region.

Figure 5 was constructed by categorizing the water production volume into 5 bins and constructing a emissions intensity scale. The emissions intensity was calculated by taking each individual city's combined CO_{2e} emissions for drinking water (Figure 5(A)) and wastewater (Figure 5(B)) and dividing the value by the respective volume of water treated at each city. The emissions intensity for each city was then analyzed through ArgGIS and correlated to a specific color as shown in Figure 5.

Grapher.

Grapher was used in order to construct Figures 6 & 7. The monthly water and wastewater dataframes from RStudio was first exported as a several .csv files as required by Grapher. A combined total of six .csv files were generated to be imported into Grapher. Each city was split into two .csv files: one .csv file for drinking water values and the other .csv file for wastewater values. The types of data found in each .csv file can be seen within the supporting document's metadata tab. Once the .csv files were imported into Grapher, the emissions intensity values were calculated by summating the monthly CO_{2e} emissions and dividing that value by the monthly amount of treated water produced. The monthly consumed electricity and natural gas values did not need any further processing within Grapher to be illustrated within the figures.

Challenges

Several challenges needed to be overcome in order to gather, condition, synthesize, and visualize the data. Due to the wide range of data formats that were collected for this study, a versatile and robust program was needed in order to compile the data. RStudio was chosen for it's versatility in third-party packages, its robust ability to process the data, and ability to condition the data for exportation to both ArgGIS and Grapher. Of the programs utilized, RStudio was the most difficult and time-consuming program. I ended up spending the most time with RStudio on this study conditioning the data for analysis.

Data Disparity.

All of the data gathered were disparate from each other. The Chini & Stillwell data were in the form of systematize folder trees full of .csv files and shapefiles, the Siddik et. al. dataset came in the form of Excel Spreadsheets, the monthly NREL electricity emission factors came in a .csv, and the IPCC and EPA emission factors for natural gas, fuel oil, and biogas were obtained in a .pdf format. The Chini & Stillwell data (1) and the NREL (52) & EPA (51) emission factor data were in imperial units while the IPCC (50) and Siddik et. al. (53) datasets were in S.I. units. Table 3 details the disparity of all obtained datasets.

Table 3. Data Disparity of all data collected for research.

Accepted data formats for RStudio are .csv and .xlsx. Conversion to S.I. units was necessary for commonality. Accepted data formats for ArcGIS is shapefiles. Accepted data formats for Grapher are .csv and .xlsx.

Data Disparity					
Source	Chini & Stillwell (1)	Siddik et. al. (53)	EPA (51)	IPCC (50)	NREL (52)
Data Format	.csv & shapefiles	.xlsx	.pdf	.pdf	.csv
Unit	Imperial	S.I.	Imperial	S.I.	Imperial

The data presented from Chini & Stillwell came in both a separate systematized folder tree for water and wastewater data in .csv files for each city as well as shapefiles for the cities and a shapefile for the United States. RStudio (54) and the package readbulk (57) allowed automation in importing the .csv files into RStudio with minimal coding. The ability to import the .csv files directly into RStudio saved considerable time by negating the need to create a complied .csv file for importation into RStudio.

The Siddik et. al. dataset (53) was in the form of an Excel Spreadsheet which contained location information as MSAs. Cross-referencing of the Siddik et. al. dataset (53) with the Chini & Stillwell dataset (1) was required in order to determine the correct emission factors were applied to each city. The Siddik et. al. dataset (53) was appended in order to account for cities in the Chini & Stillwell dataset (1) that inhibit the same MSA detailed in the Siddik et. al. dataset (53). For any city in the Chini & Stillewll dataset (1) that did not have a corresponding MSA, that city was omitted from the study.

IPCC (50) and EPA (51) emission factors for natural gas, fuel oil, and biogas were obtained in a .pdf format. The data was first manually entered into an Excel Spreadsheet before being imported into RStudio as a separate dataframe to be

incorporated into the annual and monthly water and wastewater dataframes.

Program Inexperience.

To accomplish this study, three different programs were utilized, one of which being a program language. While the author had experience in coding via Matlab, coding in R differs in that the developed R code was focused on data conditioning rather than computation. This led to the author researching about, and heavily rely on the packages and tools available in R for data manipulation and conditioning.

Once the data was conditioned and ready for exportation to Grapher and ArcGIS, the author ran into incompatibility issues between RStudio and ArcGIS. These issues stem from the programs running at different processing capacities: the current version of RStudio utilized for the study is available on a 64-bit platform while ArcGIS is only available in a 32-bit version. The eventual solution after much research was to re-run RStudio as a 32-bit platform. If unavailable, issues of processing overflow were possible resulting in re-writing R code. Other incompatibility issues arose from the different versions of RStudio that were installed on the author's personal laptop and personal desktop. Some coding script developed on the author's personal laptop would not execute correctly on the author's personal desktop. This incompatibility also extended to any desktop. The author speculates that the incompatibility is derived from the differing operating systems of the laptop (Linux) and desktops (Windows). To correct this issue, the finalized R code was developed on the author's personal desktop.

Utilizing ArcGIS to include the use of spatial data was also a challenge experince by the author. Data utilized for spatial purposes must include coordinates and a coordinate system in order to craft visualizations accurately. Incorporation of the coordinates and coordinate system within ArcGIS requires the imported data to

have recognizable coordinate data applied to the data being visualized within ArcGIS. Incompatible coordinate data for the desired coordinate system within ArcGIS was encountered. The solution was to determine the correct coordinate system represented by the coordinate data supplied by the Chini & Stillwell dataset (1) and transform the coordinate data for the desired coordinate system which, in turn, can then be visualized in ArcGIS.

Visualization of Data.

Presentation the data was a challenge experienced by the author. Presenting only single attributes on a national level without any normalizing characteristics would not show relationships found within the data nor would it detail why the data is important. For this study, presenting the CO_{2e} emissions normalized to water production as a color spectrum has no relational meaning if the visualization does not include the amount of water produced at each water treatment plant. Similarly, monthly CO_{2e} emissions normalized to water production has no relation if electricity and natural gas consumption is not present. The solution was to present related attributes that are visually distinct, but retains the interaction present between the attributes.

Chapter Summary

Data from Chini & Stillwell (1), Siddik et. al. (53), EPA (51), IPCC (50), and the NREL (52) were combined using RStudio and processed to generate annual and monthly drinking water and wastewater datasets that were visualized in ArcGIS and Grapher. GHG emissions were transformed to CO_{2e} in order to summate the total GHG emissions produced from electricity, natural gas, biogas, and fuel oil at each drinking water and wastewater treatment plant. Annual

electricity emission factors at drinking water and wastewater treatment plants were gathered from the Siddik et. al. (53) database. Monthly electricity emission factors at drinking water and wastewater treatment plants were gathered from the NREL (10) database. Emission factors for natural gas, biogas, and fuel oil were calculated from the IPCC (50) and EPA (51) emission factors. These respective emission factors were applied to the consumption data provided by Chini & Stillwell (1) in order to calculate the GHG emissions produced at each drinking water and wastewater treatment plant. Challenges were encountered in data disparity, program inexperience, and visualizing the relationships found within the annual and monthly drinking water and wastewater datasets.

IV. Results

The purpose of this chapter is to communicate the results of the methods taken in Chapter III, to include the results of the annual and monthly analysis as well as visualize the annual and monthly data. Additionally, this chapter examines the future impact that this research may have on the energy-water nexus and discusses current policy which may benefit from this research.

Regional Trends of GHG Emissions

Indirect emissions of electricity were the largest contributor of water-related energy emissions in 94% (132) of the investigated drinking water and wastewater utilities. Notably, there are few exceptions to this trend. Biogas was the primary contributor of water-related energy emissions for 3% (5) of the evaluated utilities, while 2% (3) of the utilities had natural gas as the primary contributor of water-related energy emissions. On average, the indirect emissions from electricity dominated the tabulated GHG emissions for both drinking water and wastewater (Figure 4(A)). However, wastewater treatment facilities exhibit greater spatial heterogeneity in utilized energy sources and associated emissions. Wastewater utilities had larger contributions to emissions from natural gas than drinking water utilities and some wastewater utilities have additional impacts from fuel oil and biogas consumption. On the bottom panel of Figure 4(B), average emissions portfolios by energy source are shown for select cities in each of the eGRID regions.

Figure 5 details the spatial variability of the GHG emissions of water (A) and wastewater (B) utilities across the country. While the maps show high heterogeneity across the country, there are some evident regional clustering. While these regional trends are visually apparent, these are not necessarily statistically significant

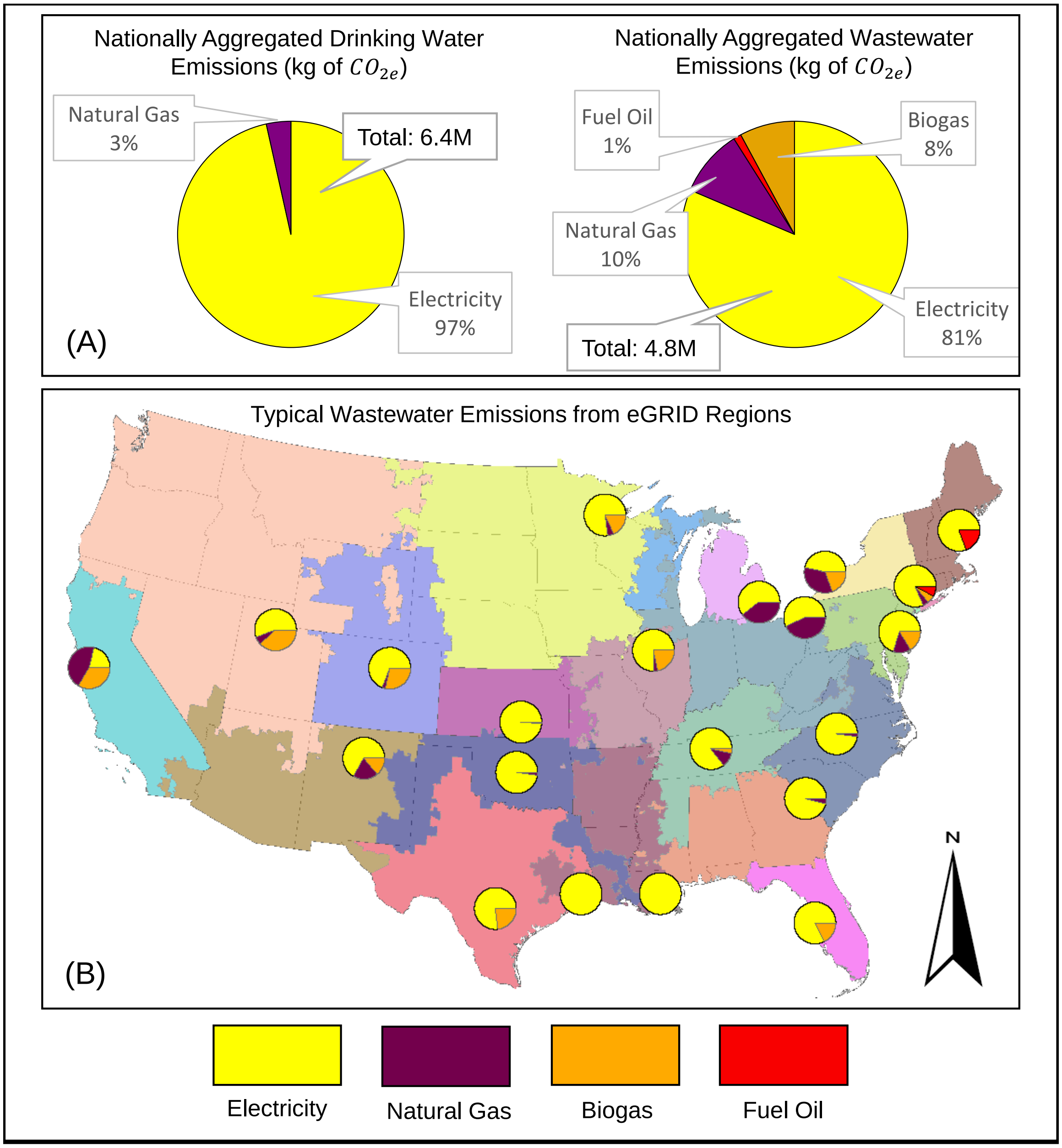

Figure 4. (A) Pie charts detailing nationally aggregated water (left) and wastewater (right) emissions by source. (B) Wastewater emissions with an eGRID region overlay.

Natural gas is abundantly used in the Mid-West, North East, and West Coast. Biogas is abundantly used in the North West, Mid-West, and Mid-Atlantic regions. Fuel oil is utilized in the North East region.

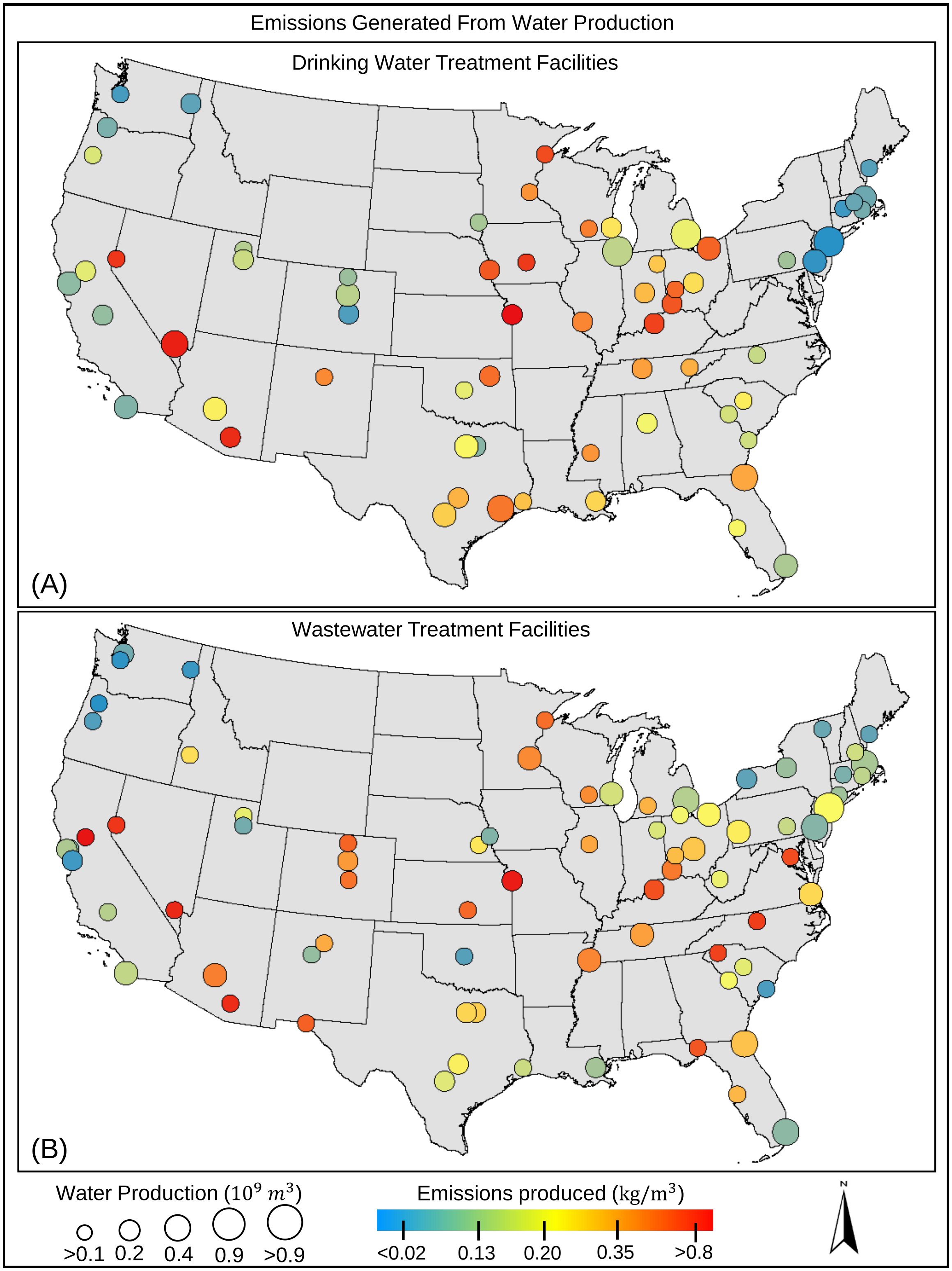

Figure 5. (A) Emissions generated from water treatment and (B) wastewater treatment.

The Mid-West region produces greater emissions at both water and wastewater treatment plants compared to other regions of the country.

clusters. First, the Midwest region sees a high intensity of GHG emissions per volume of treated drinking water relative to the rest of the sample group. The Midwest relies on an aggregated fuel mix where the major contributor is electricity produced by coal (65.5%) (70). The high mix of fossil fuel sources to produce electricity correlates to high GHG emission intensities for the treatment of water.

Second, the Northwest and Northeast regions see low GHG emissions for the treatment of their drinking water and wastewater systems. The Northwest relies on a fuel mix where the major contributor is hydroelectric power (47.7%) (70). The Northeast relies upon an aggregate fuel mix where the major contributor is natural gas (49.7%) (70), while also having relatively low energy intensities for water treatment (1). Since electrical emissions are the largest contributor for both regions, the low emissions produced from hydroelectricity and natural gas normalized by water volume is evident in these regions.

Finally, the Southwest region sees high GHG emissions per volume of drinking water and wastewater treated. The Southwest relies on an aggregated fuel mix where the major contributor is natural gas (43.1%) (70). The difference with the Southwest region and the Northeast region is the major contributors to emissions for the typical cities within those regions. Cities in California typically see the majority of their emissions from natural gas and biogas rather than from electricity from the grid. Cities in Arizona, New Mexico, and Nevada, however, have the majority of their emissions from grid electricity. In these cities, however, there are higher energy intensities for water treatment (1). Energy intensity of water resources also varies based on source of water (41), size of facility, and treatment technology (71). For example, Las Vegas, NV, utilizes ozonation in their treatment system for treating surface water, which has a high energy intensity relative to other treatment practices.

Extrapolating the Carbon Footprint of Water & Wastewater Utilities

On average, electricity production attributed to drinking water treatment emits 0.447 kg of CO_{2e} per m^3 of water, totaling 0.463 kg of CO_{2e} per m^3 of water including other energy sources. Using the same procedure for treated wastewater, we find that electricity used to treat one m^3 of wastewater emits 0.35 kg of CO_{2e}. When all forms of energy are considered when treating wastewater, the total emission intensity is 0.42 kg of CO_{2e} per m^3 of wastewater.

Total electricity-related water emissions from the 64 water utilities assessed in this study was estimated at 6.23 billion kg of CO_{2e} (1.91 $\times 10^9$ kg of CO_{2e} minimum, 19.93 $\times 10^9$ kg of CO_{2e} maximum). When adding in emissions from natural gas and fuel oil, the total average goes up to 6.45 billion kg of CO_{2e} (2.11 $\times 10^9$ kg of CO_{2e} minimum, 20.17 $\times 10^9$ kg of CO_{2e} maximum). The data in this study represents a service population of 65.8 million people across 64 utilities. Total drinking water emissions are therefore 98 kg of CO_{2e} per person per year (32.1 kg of CO_{2e} per person per year minimum, 306.5 kg of CO_{2e} per person per year maximum) when averaged across all sampled utilities. The United States' population serviced by public utilities for 2012 is 270 million people (1), assuming that approximately 86% of the population was serviced by a centralized drinking water system (72). Our current study, therefore, accounts for a large portion of the population serviced by a public drinking water utility (24.7%). Extrapolating the emissions generated per person to include the 2012 population serviced by a centralized drinking water system yields an average total emissions amount of 26.5 $\times 10^9$ kg of CO_{2e} for the United States.

Similarly, wastewater emissions equate to 4.67 billion kg of CO_{2e} (2.29 $\times 10^9$ kg of CO_{2e} minimum, 11.8 $\times 10^9$ kg of CO_{2e} maximum) for a service population of 62.6 million people across 76 wastewater utilities. Of that total, an average 0.76

billion kg of CO_{2e} (0.71 $\times 10^9$ kg of CO_{2e} minimum, 1.05 $\times 10^9$ kg of CO_{2e} maximum) are attributed to non-electric energy. Therefore the total emissions for wastewater treatment equals 74.6 kg of CO_{2e} per person per year (36.6 kg of CO_{2e} per person per year minimum, 188.3 kg of CO_{2e} per person per year maximum) when averaged across all study sites. Estimates put 74% of the total U.S. population for 2012 that is serviced by a centralized wastewater system (73). Extrapolating the emissions generated per person to this population yields an average total emissions estimate of 20.1 $\times 10^9$ kg of CO_{2e} for centralized wastewater systems.

Combining the total amount of emissions of national drinking water and wastewater utilities results in 46.6 $\times 10^9$ kg of CO_{2e} (18.5 $\times 10^9$ kg of CO_{2e} minimum, 133.6 $\times 10^9$ kg of CO_{2e} maximum). For perspective, total emissions in 2012 from the electricity generation sector in the United States equaled 2.07×10^{12} kg of CO_{2e} (74). Therefore, we find that the operational, energy-related GHG emissions of the water sector is equivalent to 2.25% (0.89% minimum, 6.45% maximum) of the total emissions generated by the electricity generation sector.

Sub-Annual Variations in GHG Emissions

We analyzed intra-annual GHG emissions associated with the operation of water and wastewater treatment facilities for three cities: Boston, MA; Cincinnati, OH; and San Antonio, TX. The results show differing behaviors and trends in GHG emissions between the cities. Figure 6 and Figure 7 detail the results of emissions produced at the water and wastewater treatment plants for each of the three cities. Energy consumption and emissions for each city's water and wastewater utility are normalized to the volume of water treated at each city for comparison and pattern behavior.

First, it is evident from Figures 6 and 7 that all three city's electricity

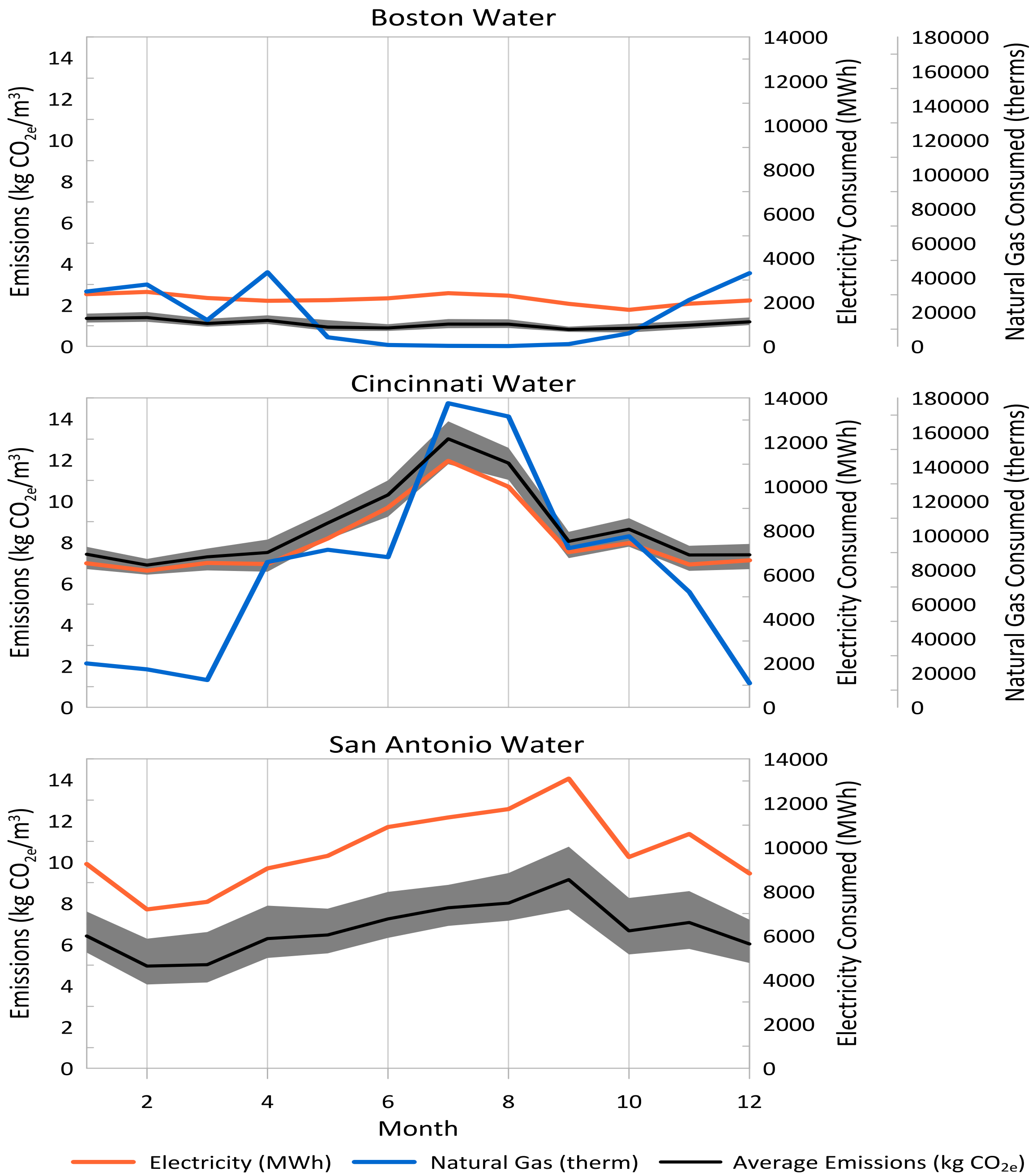

Figure 6. Sample cities showing intra-annual fluctuations in emissions per m^3 of water to electricity and natural gas consumed.

Electricity seems to be the overall factor in determining the emissions shape throughout the months. Uncertainty of the emissions can be seen as the shaded area bound by the maximum and minimum emissions. The uncertainty is bound by the maximum, average, and minimum values associated with the emission factors used.

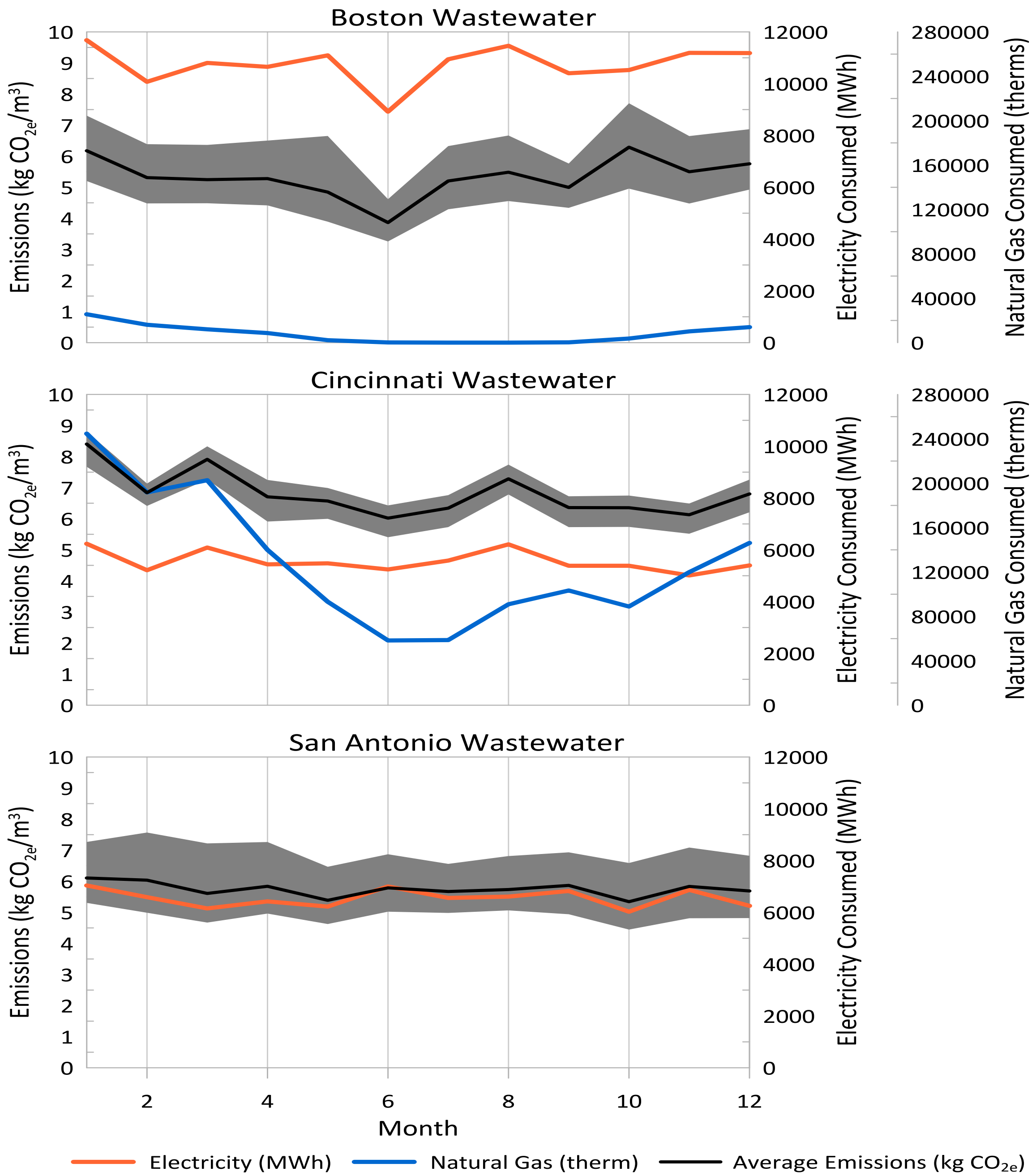

Figure 7. Sample cities showing intra-annual fluctuations in emissions attributed to electricity and natural gas consumed per m^3 of treated wastewater.

Electricity consumption plays a mediating role in the temporal patterns of emissions. Uncertainty of the emissions can be seen as the shaded area bound by the maximum and minimum emissions. The uncertainty is bound by the maximum, average, and minimum values associated with the emission factors used.

demand dictates the shape of GHG emissions per m^3 across the year. While natural gas is shown to have an effect, the overall contributor for emissions intensity of water is most certainly the electricity demand.

Second, with the exception of Cincinnati's drinking water treatment plant, water and wastewater utilities tend to have reduced direct natural gas consumption during the summer months. This may be in part to reduced heating loads required at the water utility plants. Cincinnati's water and wastewater treatment plants have non-zero direct natural gas consumption during the summer months, indicating that natural gas is used in some other capacity than purely for heating the treatment plants. Cincinnati's drinking water treatment plant sees a large increase in direct natural gas consumption during the summer months. However, this only minimally influences per unit volume of GHG emissions.

Finally, the peak of emissions per volume of water seen for Cincinnati's wastewater treatment in the summer months suggests that the GHG emissions are more dependent on carbon intensity of electricity, and, therefore, generation mixes. Cincinnati is treating less wastewater for the summer months when compared to the rest of the year. With energy (and emissions being produced) remaining relatively static throughout the year, Cincinnati sees an increase in the emissions generated per m^3 of water for the summer months due to increased energy intensity and the combined sewer system present in the city. This behavior is juxtaposed with Boston's wastewater treatment plant which is also a combined wastewater sewer system. We see that Boston's emissions per m^3 do not increase in the summer months, yet continues to follow the trend set by electricity consumption. Wastewater treatment remained consistent throughout the year with minor variations.

Intra-annual variation between the cities can be linked to the climate of each city. San Antonio is classified as having a humid subtropical climate with hot

summers (111 days over 32.2° C) (75). It's possible that the increase in water treatment (and GHG emissions) seen in San Antonio's drinking water plant during the summer is due to increases in lawn irrigation from lack of rainfall as the rainiest months of the year tend to be May, June, and December (75). Technology demands may also explain intra-annual variations. Natural gas consumption within Boston's treatment plants may be explained by solely using natural gas as a heating element for the winter months which would explain the lack of natural gas consumption during the summer months. In contrast, Cincinnati's drinking water treatment plants might be consuming natural gas both for building heating and as a fuel source for their drinking water treatment process which may require more natural gas as the demand for drinking water increases during the summer (76).

Investigative Questions Answered

1. *What are the GHG emissions associated with the operation of drinking water and wastewater treatment plants across the United States?*

   GHG emissions associated with the operation of drinking water and wastewater treatment plants across the United States is found to emit on average 0.463 kg of CO_{2e} per m^3 of water for drinking water treatment while wastewater treatment is found to emit on average 0.42 kg of CO_{2e} per m^3 of wastewater.

2. *Do the make-up of GHG emissions for water and wastewater differ across different regions?*

   The make-up of GHG emissions for water and wastewater are found to differ across different eGRID regions.

3. *How do GHG emissions change within the year at drinking water and*

wastewater treatment plants?

GHG emissions change intra-annually at drinking water and wastewater treatment plants. Peak emission intensities are observed during the summer across all but Cincinnati's wastewater treatment plant.

Chapter Summary

Regional trends in GHG emissions were apparent across the sampled drinking water and wastewater treatment plants. Indirect emissions of electricity were found to be the largest contributor of water-related energy emissions for the 94% of the investigated drinking water and wastewater utilities. Wastewater utilities had larger contributions to emissions from natural gas than drinking water utilities. Evident regional clustering of were apparent from the research conducted. The Midwest region sees a high intensity of GHG emissions per volume of treated drinking water relative to the rest of the sample group. The Northwest and Northeast regions see low GHG emissions for the treatment of their drinking water and wastewater systems. The Southwest region sees high GHG emissions per volume of drinking water and wastewater treated. Emission intensities per volume of treated water varied spatially and may be accounted by the emissions produced by grid electricity.

Extrapolation to the national scale for the water sector was achieved. Drinking water emissions were calculated to be 98 kg of CO_{2e} per person per year and wastewater emissions were calculated to be 74.6 kg of CO_{2e} per person per year. The total average drinking water emissions equates to 26.5 $\times 10^9$ kg of CO_{2e} and the average wastewater emissions equates to 4.67 $\times 10^9$ kg of CO_{2e} for the United States. The combined average water emissions equals 46.6 $\times 10^9$ kg of CO_{2e} for the United States. With total emissions in 2012 from the electricity generation sector equaling 2.07 $\times 10^{12}$ kg of CO_{2e}, the average operational energy-related GHG

emissions of the water sector is equivalent to 2.25% of the total emissions generated by the electricity generation sector.

Three cities: Boston, MA; Cincinnati, OH; and San Antonio, TX were analyzed for intra-annual GHG emission variance. First, all three city's electricity demand dictates the shape of GHG emissions per m^3 of water across the year. While natural gas is shown to have an effect, the overall contributor for emissions intensity of water is the electricity demand. Second, with the exception of Cincinnati's drinking water treatment plant, water and wastewater utilities tend to have reduced direct natural gas consumption during the summer months. Finally, the peak of emissinos per volume of water seen for Cincinnati's wastewater treatment in the summer months suggests that the GHG emissions are more dependent on the carbon intensity of electricity, and, by extension, generation mixes.

V. Discussion

The purpose of this chapter is to contextualize the results taken in Chapter IV. Additionally, this chapter outlines opportunities to reducing the operational GHG emissions of drinking water and wastewater treatment plants within the United States.

Contextualizing GHG Emissions

For comparison, an average car emits 0.251 kg of CO_{2e} per kilometer (77). Therefore, the total amount of GHG emissions produced for every m^3 of water treated in our dataset takes on the following: 6.6 km total per m^3 of water for treated drinking water and 10 km total per m^3 of water for treated wastewater. On average, a typical household consumes approximately 380 liters of water per person per day (78). Assuming a standard household size of four people, this equates to a monthly water demand of approximately 45 m^3 of drinking water with similar wastewater demands. Therefore, a household's monthly water delivers and wastewater production is the equivalent of driving nearly 1,494 km in a standard car. While this amount might not seem like a large amount of emissions, scaled nationally, it can be significant. For example, the EPA estimates that a standard vehicle emits nearly 4,600 kg of CO_{2e} per year based on driving 18,507 km (77). The average energy demand of water utilities is the equivalent of 10.13 million cars (4.02×10^6 cars minimum, 29.04×10^6 cars maximum) on the road each year. From this contextualization, it is evident that water utilities offer some opportunities for reducing total GHG emissions.

Renewable Energy and Water Efficiency

The relationship identified in this study between fuel-mix of electricity production and GHG emissions for water utilities suggest the opportunities for the integration of renewable energy technologies. The utilities in the Northeast that rely on fuel oil to provide a portion of their energy needs could invest in either biogas reclamation or renewable energy technology to reduce the GHG emissions that it produces for its wastewater treatment plants. Future work could investigate scenario analyses associated with integrating low carbon energy technologies within the water and wastewater treatment process. Renewable energy can also be used as a direct energy source within the water treatment plant in order to reduce the emissions associated with heating and cooling loads. Liu et al (38) suggest that adoption of a heat pump cycle integrating wind and solar energy sources for water treatment systems has the potential to reduce heating-related GHG emissions by 52% for treatment plants that currently use natural gas as their primary energy to meet heating demand. Investing in a mix of renewable energy solutions combined with energy efficiency technologies to meet electricity energy demands at water treatment plants can lead to large water treatment plants saving 15-34% of their electricity demand with small plants achieving 2% (6).

In the three study areas, it appears that peak energy demand occurs in the summer. With the energy to treat water remaining the same throughout the year, the volume of water to treat lowers during the summer months. Integrating solar technology to generate the needed energy during the summer months could be advantageous for water treatment plants. Whether the integration of solar energy is produced on-site at the plant, or off-site as part of the electrical grid energy mix, water treatment plants would experience lower emission intensities during the summer months as well as benefit from the long summer daylight available. A more

common proposed solution is to integrate a mix of renewable energy more heavily into the electrical grid. Since water treatment plants see the majority of their emission portfolio being directly linked to indirect electricity, water treatment plants would see a net savings in GHG emissions per volume of treated water if their regional electricity providers incorporate more renewable energy into the grid portfolio. By swapping in wind power from coal, regions that rely on fossil fuel generation can see a potential savings of 79% of their lifecycle CO_2 emissions and potentially consume 83% less water (23). These tier 3 emissions (50) and their economic viability are further detailed by Lam et al. (79). Whereas the first proposed solution would benefit water treatment plants the most during peak summer months with less benefits outside of the summer months, the second solution would offer benefits to water treatment plants year-round in reducing emission intensities for treating water.

Diverse baseline water quality, treatment processes, water/wastewater requirements, and energy mix converge to determine the GHG associated with water utilities' GHG emissions. Reducing water/wastewater demands for a water utility would see a direct reduction in GHG emissions produced since the energy needed to treat water reduces as water demand lowers. The water savings potential in the agricultural sector amounts to 9.98 $\times 10^9 m^3$ per year which is half of the total water consumption amount in all other water sectors combined (80). If the full water savings is realized, this would correspond to a decrease in GHG emissions generated by drinking water utilities by 4.62 $\times 10^9$ kg of CO_{2e} or a reduction of 1 million (1 $\times 10^6$) cars on the road each year. Achieving these water savings can be realized by improving on water productivity, where water is used more efficiently by the end user (80).

An additional way that GHG emissions can be reduced when treating water

is to improve the water quality of raw water being treated. Improved raw water quality inherently reduces the energy needed (and GHG emissions produced) to treat water. This can occur when cities, such as New York City, protect their supplying watersheds from development (81). In contrast, Des Moines, IA and Decatur, IL have significant water treatment costs due to nitrate contamination from upstream farmers (82). If protection of the supplying watershed from development is not feasible, cities could partner with upstream land owners to install Best Management Practices in order to improve the water quality at the city's intake as seen in Wichita, KS (83). Reductions in water utilities' GHG emissions can be found in reducing the GHG emissions associated with indirect energy, improving on water productivity within sectors reliant on water, and by improving the water quality of raw water being treated.

Chapter Summary

For contextualization, the amount of GHG emissions produced by the operation drinking water and wastewater treatment plants is equivalent to 10.13 million cars on the road each year. Opportunities for the integration of renewable energy technologies are available to reduce the GHG emissions produced to operate drinking water and wastewater treatment plants in the United States. Wastewater treatment plants that rely on fuel oil as an energy source could invest in either biogas reclamation or other renewable energy technologies to reduce their GHG emissions. Renewable energy technologies at the plant location could reduce the electricity demand from grid electricity, reducing the GHG emissions related to electricity consumption. Heating-related GHG emissions can be reduced when utilizing solar and wind energy to operate a heat pump as suggested by Liu et. al (38). Investing in a mix of renewable energy solutions combined with energy

efficiency technologies can lead to water treatemnt plants saving 15-34% of their electricity demand with small plants achieving 2% as concluded by Strazzabosco et. al. (6).

Additions of renewable energy for grid electricity would also see a direct reduction of operational GHG emissions at drinking water and wastewater treatment plants. Since the major contributor of operational GHG emissions at drinking water and wastewater treatment plants is grid electricity consumption, reducing the GHG emissions emitted for producing grid electricity would reduce the GHG emissions associated for consuming grid electricity. Integrating solar technologies would allow for reduced operational GHG emissions during the summer months when emission intensities peak at drinking water and wastewater treatment plants. A mor common proposed solution is to integrate a mix of renewable energy more heavily into the electrical grid.

Reductions in water/wastewater demands for a water utility would see a direct reduction in GHG emissions produced since the energy needed to treat water reduces as water demand lowers. Full water savings within the agricultural sector would correspond to a decrease in GHG emissions generated by drinking water utilites by 4.62 $\times 10^9$ kg of CO_{2e} each year. Improving the water quality of raw water being treated would also lower the operational GHG emissions at drinking water and wastewater treatment plants. Improving raw water quality inherently reduces the energy needed (and GHG emissions produced) to treat water. Polices enacted in New York City, NY (81), and Wichita, KS (83) are achievable by decision and policy makers.

VI. Conclusion and Recommendations

The purpose of this chapter is to summarize the operational GHG emissions emitted by drinking water and wastewater treatment plants, recommend actions for policy makers, and recommend future research efforts.

Conclusions of Research

In this study, we show that intra-annual GHG emissions of electricity has an impact on the variability on GHG accounting. Since water usage fluctuates throughout the year, GHG emissions accounting must be more granular than the accepted annual scale. Intra-annual emissions peak in the summer and are relatively low in the winter months. Therefore, future input-output or LCA studies of water and wastewater utilities should account for inter-annual variability.

Additionally, we illustrate the large impact of indirect emissions on water and wastewater utilities. Therefore, there is a strong potential to integrate renewable energy technologies at water treatment facilities. Renewable energy integration either locally at the water treatment plant or regionally at the electrical grid have the possibility to reduce GHG emissions associated with the production of water. Integration of direct renewable energy for heating and cooling demands would reduce the reliance on natural gas at water treatment plants. Partnerships with local electric utilities to create indirect renewable energy would benefit both the local energy and water sectors.

Finally, the operational GHG emissions associated with the water sector constitute approximately 2% of the total electricity emissions produced in the United States. Contextualizing this value, removing GHG emissions associated with operational energy requirements of treatment facilities is the equivalent of removing

nearly 3.4 million cars off the road each year. Water utilities and their energy demands should be incorporated into city and regional efforts to reduce emissions for climate mitigation efforts.

Significance of Research

The research conducted is the first study to determine 2012 operational GHG emissions produced by drinking water and wastewater treatment plants in the United States. It is shown that spatial clustering is apparent when determining emission intensities for water treatment. The spatial clustering reflect the water treatment sector's heavy reliance on grid electricity for operating drinking water and wastewater treatment plants. This research can aid policy makers and decision makers in focusing efforts on reducing GHG emissions within the water sector by implementing on-site renewable energy generation, increasing renewable energy sources for grid electricity, and implementing policy to more efficiently use water in reliant sectors and ensure cleaner raw water for treatment.

Recommendations for Future Research

The ability for researchers to access emission data from drinking water and wastewater treatment plants is limited to cooperating water managers. The author recommends the creation of a centralized database for the water treatment sector similar to eGRID for the electricity generation sector. Future research could focus on the changes from the 2012 to current operational GHG emissions produced by drinking water and wastewater treatment plants within the United States. Additional research could detail intra-annual variations in operational GHG emissions across the United States. Finally, future research could also analyze differences between the United States operational GHG emissions produced by the

water treatment sector and other developed nation's operational GHG emissions produced by the water treatment sector.

Chapter Summary

Operational GFHG emissions is found to vary both intra-annually as well as spatially across the United States. The total operational GHG emissions associated with the water sector constitutes approximately 2% of the total electricity emissions produced in the United States. This research can aid policy makers and decision makers in focusing efforts on reducing GHG emissions within the water treatment sector. Creation of a centralized database for the water sector similar to eGRID for the electricity sector would allow future researchers the ability to explore current spatial clustering, intra-annual variations, and comparisons to other nations on operational GHG emissions produced in the drinking water and wastewater treatment plants in the United States.

Appendix A. RStudio Code

[language = R]

Thesis1.R

LPclNeros

2021-01-09

```
###Thesis Script
##Louis Zib III
#
####Pre-Coding Organization####
#Downloaded the database from Chini's cloud from that one online database.
#Used bulkread to read the data into a single dataset.
#Cities either sent data as either monthly for 12 months or as annual.
#N/A in Month means annual. Annual in Month #means annual.
#Washington DC water data was altered to have commas removed.
#Wichita water data was altered to have commas removed.
#Different units are used depending on if the data was collected monthly
#or over the whole year. The intent of this script is to convert the data
#into a 2 dataframes: a wastewater and water dataframe at the year view.
####End Pre-Coding Organization####

####Project Note####
#While not needed in order to run code, I set up an R project in order
#to isolate files used for this Thesis Project.
####End Note####
```

```
####Use of Script####
#Script is organized by octothorpe use. 1 signals additional information or thought
#process. 2 signals code block. 3 signals major coding block. 2 and 3 blocks will
#always have ending lines in order to troubleshoot and run code in isolated
#environment.
####End Script####

####Version of R####
#Due to 32-bit version of ArcGIS that is used in parallel for this project, R
#version must be in 32-bit as well. This is due to the package arcgisbinding
#which allows for computations to come to and from arcgis into the Rstudio
#Environment.
####End Version Control####

####Assumptions####

#Fuel Oil data received is assumed to be Distilled No. 2 for emissions calculations.

####End Assumptions####

####The Set-up#####

##library Set-up##
library(plyr)
library(dplyr)
```

```
library(readbulk)
library(tidyr)
library(gsubfn)
library(mgsub)
library(stringr)
library(arcgisbinding)
library(sf)
library(data.table)
library(openxlsx)
library(anytime)
library(lubridate)
library(xts)
arc.check_product()

## product: ArcGIS Desktop ( 10.8.0.12790 )
## license: Advanced
## version: 1.0.1.232

##End Initial Set-up##

##Setting up Directory##
#Directory was set into the outer folder that the data comes in. No need to alter
#folders or files held within.

setwd("O:/MyStuff/Thesis/Data")
```

```
#This following code is used to check files to ensure that correct directory was
#located.
#list.files()
##End Setting Directory##

####End the Set-up####

###Compile csv data files into 1 dataframe####
#Used read_bulk package to read all .csv files held in each folder. Useful tool.
#NOTE: Wastewater_IndianapolisIN.csv originally had a merged cell for Volume and
#Electricity. I editted the csv file to ensure that the values would show up as
#seperate columns. Following code will not run fully unless user edits the csv
#file as noted here.

raw.df<-read_bulk(directory = ".", subdirectories = TRUE, extension = ".csv")
###End Compile####

###Create Wastewater dataframe####
#Wastewater dataframe was built by using dplyr to filter all rows that had 'Waste'
#in the "File" Column.
waste.df<-dplyr::filter(raw.df, grepl('Waste',File))

##Cleannig df of columns that are all N/A##
waste.df <- waste.df[,colSums(is.na(waste.df))<nrow(waste.df)]
##End Cleaning df of N/A##
```

```
##Remove byte order mark from column headers
colnames(waste.df) [1] <- gsubfn('^...','', colnames(waste.df)[1])
colnames(waste.df) [9] <- gsubfn('^...','', colnames(waste.df)[9])
##End remove BOM

##Add in Amarillo's data to right column
waste.df[26,7] <- waste.df[26,9]

##Merge values into consolidated columns##

#Prep columns into num in order to use next block of code#
waste.df<-transform(waste.df, Electricity..kWh..= as.numeric(Electricity..kWh..))
waste.df<-transform(waste.df, Electric.Consumption..kWh. =
                      as.numeric(Electric.Consumption..kWh.))
waste.df<-transform(waste.df, Fuel.Oil..gal. = as.numeric(Fuel.Oil..gal.))
waste.df<-transform(waste.df, Landfill.Gas..CF. = as.numeric(Landfill.Gas..CF.))

#The next block of code consolidates relevant columns into a consolidated column.
#Mutate from dyplr was used in order to consolidate the columns together.
#MGD is 1000000 Gal/Day, MG is 1000000 gals MG is typically associated with the
#yearly data.

#waste.df<-waste.df %>% mutate(Volume.MGD = coalesce(Volume..MGD.,Volume..MG.))

waste.df<-waste.df %>% mutate(Electricity.kWh =
                                coalesce(Electric.Consumption..kWh.,
```

```
                                Electricity..kWh.,
                                Electricity..kWh..))
waste.df<-waste.df %>% mutate(Natural.Gas.therm =
                                coalesce(Natural.Gas..therm.,
                                Natural.Gas..therms.))
waste.df<-waste.df %>% mutate(Biogas.therm =
                                coalesce(Biogas..therms.,Biogas..therm.,
                                Biogas..Therm.))
waste.df<-waste.df %>% mutate(Fuel.Oil.gal =
                                coalesce(Fuel.Oil..gal.,Fuel.Oil..Gal.))

#Tidying up Column names
waste.df<-plyr::rename(waste.df, c("Subdirectory"="City",
                                   "File" = "Type",
                                   "Landfill.Gas..CF." = "Landfill.Gas.CF",
                                   "Digester.Gas..therm." = "Digester.Gas.therm",
                                   "Volume..MGD." = "Volume.MGD",
                                   "Volume..MG." = "Volume.MG"))

##Keep consolidated columns##
keep<- c("Volume.MGD","Volume.MG", "Electricity.kWh", "Natural.Gas.therm",
         "Month", "Biogas.therm", "Fuel.Oil.gal", "City", "Type",
         "Landfill.Gas.CF", "Digester.Gas.therm")
waste.df<-waste.df[,keep]
##End Keep columns##
```

```
##End Merge consolidated columns##

##Converting Monthly data into aggregated year data##
#While the data is cleaned up into 2 dataframes: wastewater and water, Data in both
#dataframes are in two temporal frames: Month summing to a year and year data.

##Aggregate all values based on City column##

#Waste should be all cities with aggregated monthly data for each category that t
#applies to.
waste.df <- waste.df[,!names(waste.df) %in% "Type"]
#These pull out Month and Type columns since they are not needed in aggregate.

waste.df[is.na(waste.df)]<-0
#replaces all NAs as 0.

#Add in Albany's Volume.MGD as year amount.
waste.df[1,2] <- waste.df[1,1]*365

#Pull out Volume.MGD column
waste.df <-waste.df[,!(names(waste.df) %in% "Volume.MGD")]

#Convert Million Gals to M^3 and rename
waste.df$Volume.MG <- waste.df$Volume.MG* 3785.4118
waste.df <- waste.df %>% rename(Volume.M3 = Volume.MG)
```

```
#Convert landfill gas to therms
waste.df$Landfill.Gas.CF <- waste.df$Landfill.Gas.CF/96.7

#Digester and landfill data can go into Biogas data
waste.df <-transform(waste.df, Biogas.therm = Biogas.therm + Digester.Gas.therm +
                       Landfill.Gas.CF)

#Delete Landfill column
waste.df <-waste.df[,!(names(waste.df) %in% c("Landfill.Gas.CF",
            "Digester.Gas.therm"))]

Awaste.df <- aggregate(.~City, waste.df, FUN = sum)
#Aggregates all columns based on City.

##End Aggregate##

#Awaste does not need month column
Awaste.df <- Awaste.df[, !(names(Awaste.df) %in% "Month")]

##Continued data prep##
Awaste.df<- separate(Awaste.df, City, c("City", "State"), sep = -2, convert = TRUE)
waste.df <- separate(waste.df, City, c("City", "State"), sep = -2, convert = TRUE)
#Separates City into City and State for matching later on.

##End Monthly Convert##
###End Wastwater Dataframe####
```

```
###Create Water Dataframe####
#Water dataframe was built by using dplyr to filter all rows that had 'Water' in the
#"File" Column. NOTE: filter is case-sensitive so it didn't pull Wastewater due to
#c ap.
water.df<-dplyr::filter(raw.df, grepl('Water',File))

#Note Tucson reclaimed water was added into this side since I treat it as production
#potable water.

##Cleaning df of columns that are all N/A##
water.df <- water.df[,colSums(is.na(water.df))<nrow(water.df)]
##End Cleaning N/A##

##Remove BOM from column header
colnames(water.df)[8] <- gsubfn('^...','', colnames(water.df)[8])
##End Remove BOM

##Move Amarillo data to correct MG column##
water.df[2,7] <- water.df[2,8]

##Merge values into a consolidated columns##

#Need to prep columns for merge by transforming into numerical#
water.df<-transform(water.df, Electricity..kWh..= as.numeric(Electricity..kWh..))
water.df<-transform(water.df, Electric.Consumption..kWh. =
```

```
                      as.numeric(Electric.Consumption..kWh.))

#The next block of code merges all other relevant columns into consolidate columns#
#water.df<-water.df %>% mutate(Volume.MGD = coalesce(Volume..MGD.,Volume..MG.))
water.df<-water.df %>% mutate(Electricity.kWh =
                                coalesce(Electric.Consumption..kWh.,
                                         Electricity..kWh.,Electricity..kWh..))
water.df<-water.df %>% mutate(Natural.Gas.therm =
                                coalesce(Natural.Gas..therm.,Natural.Gas..therms.))

#The next block of code just tidies the column names#
water.df<-plyr::rename(water.df, c("Fuel.Oil..gal." = "Fuel.Oil.gal",
                                   "Subdirectory" = "City",
                                   "File" = "Type",
                                   "Volume..MGD." = "Volume.MGD",
                                   "Volume..MG." = "Volume.MG"))

##Delete the other columns by keeping all relevant columns##
keeps<- c("Volume.MGD","Volume.MG","Type","City","Month","Electricity.kWh",
          "Natural.Gas.therm","Fuel.Oil.gal")
water.df<-water.df[,keeps]
##End Relevant columns##

##End Merge into consolidated columns##

##Converting Monthly data into aggregated year data##
```

```
##Converting Monthly data into aggregated year data##
#While the data is cleaned up into 2 dataframes: wastewater and water, Data in both
#dataframes are in two temporal frames: Month summing to a year and year data.

##Aggregate all values based on City column##

#water should be all cities with aggregated monthly data for each category that t
#applies to.
water.df <-water.df[,!names(water.df) %in% "Type"]
#These pull out Month and Type columns since they are not needed in aggregate.



water.df[is.na(water.df)]<-0#replaces all NAs as 0. The only NAs not replaced are in

#Add in Albany's Volume.MGD as year amount.
water.df[1,2] <- water.df[1,1]*365

water.df <- water.df[,!(names(water.df) %in% "Volume.MGD")]
#Pull out Volume.MGD column


#Change Vol water from Mgal to M^3 and rename.
water.df$Volume.MG <- water.df$Volume.MG* 3785.4118
```

```
water.df <- water.df %>% rename(Volume.M3 = Volume.MG)


Awater.df <- aggregate(.~City, water.df, FUN = sum)
#Aggregates all columns based on City.


##End Aggregate##


##Continued data prep##
#Awater does not need Month column.
Awater.df <- Awater.df[, !(names(Awater.df) %in% "Month")]


#Seperate City from State
Awater.df<- separate(Awater.df, City, c("City", "State"), sep = -2, convert = TRUE)
water.df <- separate(water.df, City, c("City", "State"), sep = -2, convert = TRUE)
#Separates City into City and State for matching later on.


###End Monthly Convert for AWater.df###
####End Water Dataframe####


####Create Carbon Emission Dataframe####


##READ-ME##
#
#The GHG Emissions.csv needed to be preprocessed in order to match up the statistical
#areas to the Chini Database. If the Statistical area was tagged by several cities,
#an additional row was created for each city referenced in the Chini Database for
```

```
#the statistical area.

#Names of the folders containing the Chini Database were also altered in order to
#line up the database order for names and states was given to Chini except for the
#following cities and States NorthTex was reformatted to be NorthTexasTX
#SaltLakeCityCA was reformatted to be SaltLakeCityUT



##Set WD##
#WD is moved since the Carbon Emissions Dataframe is in a csv file outside of the
#Data folder.
setwd("O:/MyStuff/Thesis")

##Read in Data##
emissions.df <- read.csv("GHG Emission Intensity.csv")
IPCC.df <- read.csv("IPCC Emissions.csv")
EPA.df <- read.csv("EPA Emissions.csv")

#EPA and IPCC emissions factors are to be applied to the different fuel sources
#other than electricity. EPA emissions factors are Tier 2 country specific while
#IPCC emisions are Tier 1 calcs with default, min and max


##The raw1.df database is the carbon emissions related to each city based on the
#geographical region that the data is capturing. The city areas are based are
```

```
#sometimes based on groupings of cities...
#Maybe due to proximity?

##Convert Factor into Character##
emissions.df$MSA_NAME <- as.character(emissions.df$MSA_NAME)
EPA.df$Fuel <- as.character(EPA.df$Fuel)
IPCC.df$Fuel <- as.character(IPCC.df$Fuel)

emissions.df$MSA_NAME <- mgsub(emissions.df$MSA_NAME,"Metro Area", "")
#This deletes out the Metro Area from the end of each city.

emissions.df <- separate(emissions.df, MSA_NAME, c("City", "State"), sep = ",")
#This separates the MSA_NAME into a City and State variable.

#Clean column header names with units
colnames(EPA.df) <- c("Fuel", "CO2 kg/unit", "CH4 g/unit", " N2O g/unit")
colnames(IPCC.df) <- c("Fuel", "CO2 Default (kg/TJ", "CO2 min (kg/TJ)",
                       "CO2 Max (kg/TJ)", "CH4 Default (kg/TJ)", "CH4 min (kg/TJ)",
                       "CH4 max (kg/TJ)", "N2O default (kg/TJ)", "N2O min (kg/TJ)",
                       "N2O max (kg/TJ")

##Convert EPA and IPCC units to match current units used.

###EPA conversion###

##Match EPA units##
```

```
EPA.df[,3:4] <- EPA.df[,3:4]/1000
#made columns 2 and 3 into kg from g


EPA.df[1:2,2:4] <- EPA.df[1:2,2:4]*96.7
#converted scf to therms


#Updated names and column headers
EPA.df$Fuel <- c("Natural.Gas.therm", "Biogas.therm", "Fuel.Oil.gal")
colnames(EPA.df) <- c("Fuel", "EPA CO2 kg/unit", "EPA CH4 kg/unit",
                        "EPA N2O kg/unit)")
###End EPA Conversion###


###IPCC Conversion###


##Match IPCC units##
IPCC.df[c(1,3),2:10] <- IPCC.df[c(1,3),2:10]/9480.43
#Convert from TJ to therms


IPCC.df[2,2:10] <- IPCC.df[2,2:10]/6825.00682500679
#Converted from TJ to gal


#Update names and column headres
IPCC.df$Fuel <- c("Natural.Gas.therm", "Fuel.Oil.gal", "Biogas.therm")
colnames(IPCC.df) <- c("Fuel", "IPCC CO2 Default (kg/unit", "IPCC CO2 min (kg/unit)",
                       "IPCC CO2 Max (kg/unit)", "IPCC CH4 Default (kg/unit)",
                       "IPCC CH4 min (kg/unit)", "IPCC CH4 max (kg/unit)",
```

```
                        "IPCC N2O default (kg/unit)", "IPCC N2O min (kg/unit)",
                       "IPCC N2O max (kg/unit")

###End IPCC Conversion###

###Ready for Merge###
#IPCC row swap
IPCC.df <- IPCC.df[c(1,3,2),]



Factor.df <- bind_cols(IPCC.df,EPA.df)
Factor.df <- Factor.df[,c(1:10,12:14)]
Factor.df <- Factor.df[,c(1:4,11,5:7,12,8:10,13)]

#Factors.df holds the emissions factors for CO2, CH4, and N2O. Convert to CO2e and
#summate for each category.

###Convert CH4 and N2O into CO2 equiv.
Factor.df[,6:9] <- 25*Factor.df[,6:9]
#Converts CH4 into CO2e by mulitplying it by the EPA table using 25 as the factor

Factor.df[,10:13] <- 298*Factor.df[,10:13]
#Converts N2O into CO2e by multiplying it by the EPA table using 298 as the factor.

#Sum up the corresponding categories
Factors.df <- data.table( Fuel = c("Natural.Gas.therm", "Biogas.therm",
```

```
                          "Fuel.Oil.gal"),
                            IPCC.CO2e.Default = Factor.df[,2] + Factor.df[,6] +
                              Factor.df[,10],
                            IPCC.CO2e.min = Factor.df[,3] + Factor.df[,7] +
                            Factor.df[,11],
                            IPCC.CO2e.max = Factor.df[,4] + Factor.df[,8] +
                            Factor.df[,12],
                            EPA.CO2e = Factor.df[,5] + Factor.df[,9] + Factor.df[,13])
#Factors is now in CO2e for the respective emissions factors.

###End Merge###

####End Carbon Emissions Dataframe####

####Combine Dataframes for Annual Analysis####

#delete whitespace from State Column
emissions.df$State <- trimws(emissions.df$State)

##Merge Water dataframe##
filteredwater.df <- merge(Awater.df, emissions.df, by.x= c("City", "State"),
                          all.x = TRUE)
#merges the emissions.df and water.df for all cities and states in the water.df
#Alaska and Hawaii will be omitted for the rest of the analysis since Continental US
#is the focus
```

```
#RemeberAlaska

filteredwater.df <- filteredwater.df[-c(1,31),]
#Removed Alaska and Hawaii data

##Remove columns##
#
##This step is specifically to remove columns from the emission side for ease of use
#purposes.
#columns <-names(filteredwater.df)
##makes vector that contains names of the columns to cherry pick location based on
#column header

filteredwater.df <- filteredwater.df[,c(1:6, 13:28)]
#filtered out Rad columns.
##End Remove Columns##

##Remove cities that have no Electricity generation data##

#Since I'm interested in the GHG emissions associated with the generation of
#electrcity, all cities that did not have eletcrical data are not useful.

filteredwater.df <- filteredwater.df[!filteredwater.df$Electricity.kWh == 0,]
#This removes all the cities that do not have electrical data.

##End Water Dataframe##
```

```
##Merge Waste Dataframe##

filteredwaste.df <- merge(Awaste.df, emissions.df, by.x= c("City", "State"),
all.x = TRUE)
#Merges emissions.df data to waste.df data.

#Remove Alaska and Hawaii#
filteredwaste.df <- filteredwaste.df[-c(3,38),]

##Remove columns##
#
##This step is specifically to remove columns from the emission side for ease of use
#purposes.
#columns <-names(filteredwater.df)
##makes vector that contains names of the columns to cherry pick location based on
#column header

filteredwaste.df <- filteredwaste.df[,c(1:7, 14:29)]
#filtered out Rad columns.
##End Remove Columns##

#Since I'm interested in the GHG emissions associated with the generation of
#electrcity, all cities that did not have eletcrical data are not useful.

filteredwaste.df <- filteredwaste.df[!filteredwaste.df$Electricity.kWh == 0,]
```

```
#This removes all the cities that do not have electrical data.

###End Dataframes for Annual Analysis####

####Analysis of Annual CO2####

###Water CO2 Calcs###
#Since the values for the electricity usage is in kwh and the intensity dataframe is
#in CO2/MWh, I convert the kWh to MWh in the electricity usage.

filteredwater.df$Electricity.kWh <- filteredwater.df$Electricity.kWh/1000
colnames(filteredwater.df)[4] <- "Electricity.MWh"
#convert kWh to MWh

##Multiply across the different methods for each city
CO2 <- apply(filteredwater.df[7:22], 2, function(x) filteredwater.df[4]*x)
AEwaterCO2.df <- as.data.frame(matrix(unlist(CO2),
                                      nrow=length(unlist(CO2[1]))))

##Multiply across the different emisison factors for Natural Gal
NatGasCO2 <- apply(Factors.df[1,2:5],2, function(x) filteredwater.df[5]*x)
NatGasCO2.df <- as.data.frame(matrix(unlist(NatGasCO2),
                                     nrow=length(unlist(NatGasCO2[1]))))



##Multiply across the different emission factors for Fuel Oil
```

```
FuelOilCO2 <- apply(Factors.df[3,2:5], 2, function(x) filteredwater.df[6]*x)
FuelOilCO2.df <- as.data.frame(matrix(unlist(FuelOilCO2),
                                      nrow=length(unlist(FuelOilCO2[1]))))


#Add Column Names
colnames(NatGasCO2.df) <- c("Nat.Gas.IPCC.CO2e.Default", "Nat.Gas.IPCC.CO2e.Min",
                            "Nat.Gas.IPCC.CO2e.Max",
                            "Nat.Gas.EPA.CO2e")
colnames(FuelOilCO2.df) <- c("Fuel.Oil.IPCC.CO2e.Default", "Fuel.Oil.IPCC.CO2e.Min",
                             "Fuel.Oil.IPCC.CO2e.Max",
                             "Fuel.Oil.EPA.CO2e")



#Looks good#

#create new dataframe that holds city, state, water generated, electricity generated,
#and the CO2 calculated at
#each accounting level (kg of CO2/MWh)
AwaterCO2.df <- filteredwater.df
AwaterCO2.df[7:22] <- AEwaterCO2.df
AwaterCO2.df <- cbind(AwaterCO2.df, NatGasCO2.df,FuelOilCO2.df)

#WaterCO2.df holds all the information related to each city with the water generated,
#electricity used, and the CO2 created at each accounting level. based on their
#specefic fuel makeup as defined by the carbon intensity CO2 levels per MWh. CO2 is
```

```
#in kg.

#Since the water production is in annual, the kg of CO2 equivelant is in a per year
#basis.

###End Water CO2 Calcs###

###Waste CO2 Calcs###

filteredwaste.df$Electricity.kWh <- filteredwaste.df$Electricity.kWh/1000
colnames(filteredwaste.df)[4] <- "Electricity.MWh"
#convert kWh to MWh

##Multiply across the different methods for each city
CO2 <- apply(filteredwaste.df[8:23], 2, function(x) filteredwaste.df[4]*x)
AEwasteCO2.df <- as.data.frame(matrix(unlist(CO2), nrow=length(unlist(CO2[1]))))

##Multiply across the different emisison factors for Natural Gal
NatGasCO2 <- apply(Factors.df[1,2:5],2, function(x) filteredwaste.df[5]*x)
NatGasCO2.df <- as.data.frame(matrix(unlist(NatGasCO2),
                                     nrow=length(unlist(NatGasCO2[1]))))

##Multiply across the different emission factors for Biogas
BioGasCO2 <- apply(Factors.df[2,2:5], 2, function(x) filteredwaste.df[6]*x)
BioGasCO2.df <- as.data.frame(matrix(unlist(BioGasCO2),
                                     nrow=length(unlist(BioGasCO2[1]))))
```

```
##Multiply across the different emission factors for Fuel Oil
FuelOilCO2 <- apply(Factors.df[3,2:5], 2, function(x) filteredwaste.df[7]*x)
FuelOilCO2.df <- as.data.frame(matrix(unlist(FuelOilCO2),
                                      nrow=length(unlist(FuelOilCO2[1]))))


#Add Column Names
colnames(NatGasCO2.df) <- c("Nat.Gas.IPCC.CO2e.Default", "Nat.Gas.IPCC.CO2e.Min",
                            "Nat.Gas.IPCC.CO2e.Max",
                            "Nat.Gas.EPA.CO2e")
colnames(BioGasCO2.df) <- c("BioGas.IPCC.CO2e.Default", "BioGas.IPCC.CO2e.Min",
                            "BioGas.IPCC.CO2e.Max",
                            "BioGas.EPA.CO2e")
colnames(FuelOilCO2.df) <- c("Fuel.Oil.IPCC.CO2e.Default", "Fuel.Oil.IPCC.CO2e.Min",
                             "Fuel.Oil.IPCC.CO2e.Max",
                             "Fuel.Oil.EPA.CO2e")


#create new dataframe that holds city, state, water generated, electricity generated,
#and the CO2 calculated at each accounting level (kg of CO2/MWh)
AwasteCO2.df <- filteredwaste.df
AwasteCO2.df[8:23] <- AEwasteCO2.df
AwasteCO2.df <- cbind(AwasteCO2.df, NatGasCO2.df, BioGasCO2.df, FuelOilCO2.df)

###End Waste CO2 Calcs###
```

```
####End Analysis of Annual CO2####

####Combine Dataframes for Monthly Analysis####
#Used water.df and waste.df for monthly dataframes since they hold both the monthly
#and annual data for all cities.

###Combine Water.df and CE dataframe###

##Scrub water.df of all non-monthly city data##
water.df <- na.omit(water.df)
#deletes all rows that contain N/A; all cities that did not have monthly data

#removes all cities that do not contain Electricity.kWh data
water.df <- filter(water.df, Electricity.kWh != 0)

#remove all cities that contain "Annual" in the month column
water.df <- filter(water.df, Month != "Annual")

Mwater.df <- merge(water.df, emissions.df, by.x= c("City", "State"), all.x = TRUE)
#merges the emissions.df and water.df for all cities and states in the water.df
#Alaska and Hawaii will be omitted for the rest of the analysis since Continental US
#is the focus

#RemeberAlaska
```

```
Mwater.df <- na.omit(Mwater.df)
#removes Alaska and Hawaii

###End Water.df and CE dataframe merge###

###Merge waste.df and CE dataframe###

##Scrub water.df of all non-monthly city data##
waste.df <- na.omit(waste.df)
#deletes all rows that contain N/A; all cities that did not have monthly data

#removes all cities that do not contain Electricity.kWh data
waste.df <- filter(waste.df, Electricity.kWh != 0)

#remove all cities that contain "Annual" in the month column
waste.df <- filter(waste.df, Month != "Annual")

Mwaste.df <- merge(waste.df, emissions.df, by.x= c("City", "State"), all.x = TRUE)
#merges the emissions.df and water.df for all cities and states in the water.df
#Alaska and Hawaii will be omitted for the rest of the analysis since Continental US
#is the focus

#RemeberAlaska

Mwaste.df <- na.omit(Mwaste.df)
#removes Alaska and Hawaii
```

```
###End waste.df and CE dataframe merge###

####End Dataframe Combiniation for Monthly Scale####

####Analysis of Monthly CO2####
#Monthly CO2 analysis is similar to annual except I only take all cities that gave
#monthly data. Used Mwater.df and Mwaste.df for monthly analysis

##Build new specific Monthly Emissions Table using Daniel Studer EIA Data.

setwd("O:/MyStuff/Thesis/Data1")

MEmissionsRFCW <- read.xlsx("Monthly Factors.xlsx", sheet =1)
MEmissionsNEWE <- read.xlsx("Monthly Factors.xlsx", sheet =2)
MEmissionsERCT <- read.xlsx("Monthly Factors.xlsx", sheet =3)

MEmissionsRFCW$City <- "Columbus"
MEmissionsNEWE$City <- "Boston"
MEmissionsERCT$City <- "SanAntonio"


MonthlyE.df <- rbind(MEmissionsNEWE,MEmissionsRFCW,MEmissionsERCT)
```

```
MonthlyE.df <- MonthlyE.df %>% select(City,everything())

setwd("O:/MyStuff/Thesis")

###Mwater Calcs###

Mwater.df[5] <- Mwater.df[5]/1000
colnames(Mwater.df)[5] <- "Electricity.MWh"
#convert kWh to MWh

#Pull out Radius attribution methods
Mwater.df <- Mwater.df[,c(1:7, 14:29)]

##Multiply across the different methods for each city
CO2 <- apply(Mwater.df[8:23], 2, function(x) Mwater.df[5]*x)
MEwaterCO2.df <- as.data.frame(matrix(unlist(CO2), nrow=length(unlist(CO2[1]))))

#create new dataframe that holds city, state, water generated, electricity generated,
#and the CO2 calculated at each accounting level (kg of CO2/MWh)
MwaterCO2.df <- Mwater.df
MwaterCO2.df[8:23] <- MEwaterCO2.df

#MWaterCO2.df holds all the information related to each city with the water
#generated, electricity used, and the CO2 created at each accounting level.
#based on their specefic fuel makeup as defined by the carbon intensity CO2 levels pe
#MWh. CO2 is in kg.
```

```
Mwater1.df <- filter(Mwater.df, City %in% c("Cincinnati", "Boston", "SanAntonio"))
Mwater1.df <- Mwater1.df[,1:7]

##Rearrange rows to be for each city from Jan to Dec##

#Convert Month from Factor to Date
addFormats(c("%b-%Y","%b-%y"))
Mwater1.df <- Mwater1.df
Mwater1.df$Month <- anydate(Mwater1.df$Month)

Mwater1.df <- Mwater1.df %>% arrange(City,Month)
Mwater1.df$Month <- month(Mwater1.df$Month)

##End Rearrange Rows for Dates##

##Calculate Emmissions for Electricity, Nat Gas, and Fuel Oil##

#Calc for Elect
Swater.df <- cbind(Mwater1.df,MonthlyE.df)
Swater.df <- Swater.df[,-c(8:9)]
Swater.df[8:19] <- apply(Swater.df[8:19], 2, function(x) Swater.df$Electricity.MWh*x)

#Convert to kg of emissions.
```

```
Swater.df[8:19] <- apply(Swater.df[8:19], 2, function(x) x*0.45359237)

##Convert into CO2e 100-year GWP ##

Swater.df <- Swater.df %>% rename(CO2.Min.Kg = CO2.Min, CO2.Average.Kg = CO2.Average,
                                  CO2.Max.Kg = CO2.Max,
                                  CO2.Standard.Dev.Kg = CO2.Standard.Dev,
                                  SO2.Min.Kg = SO2.Min,
                                  SO2.Average.Kg = SO2.Average,
                                  SO2.Max.Kg = SO2.Max,
                                  SO2.Standard.Dev.Kg = SO2.Standard.Dev,
                                  NOX.Min.Kg = NOX.Min,
                                  NOX.Average.Kg = NOX.Average,
                                  NOX.Max.Kg = NOX.Max,
                                  NOX.Standard.Dev.Kg = NOX.Standard.Dev)

#NOTE: CO2e is in kgs of emissions.
#At this point, ignore SOx GWP CO2e factor cuz not treated the same as CO2e and NOx.


#NOx = 298

Swater.df[16:19] <- apply(Swater.df[16:19], 2, function(x) x*298)


#Combine data into CO2e min, avg, max, and standard dev
```

```
Swater.df$CO2e.Min.Kg <- Swater.df$CO2.Min.Kg+Swater.df$NOX.Min.Kg
Swater.df$CO2e.Average.Kg <- Swater.df$CO2.Average.Kg + Swater.df$NOX.Average.Kg
Swater.df$CO2e.Max.Kg <- Swater.df$CO2.Max.Kg + Swater.df$NOX.Max.Kg
Swater.df$CO2e.Standard.Dev.Kg <- Swater.df$CO2.Standard.Dev.Kg +
  Swater.df$NOX.Standard.Dev.Kg

#Delete columns
Swater.df <- Swater.df[, -c(8:11, 16:19)]

##Multiply across the different emisison factors for Natural Gal
NatGasCO2 <- apply(Factors.df[1,2:5],2, function(x) Swater.df[6]*x)
NatGasCO2.df <- as.data.frame(matrix(unlist(NatGasCO2),
                                     nrow=length(unlist(NatGasCO2[1]))))

##Multiply across the different emission factors for Fuel Oil
FuelOilCO2 <- apply(Factors.df[3,2:5], 2, function(x) Swater.df[7]*x)
FuelOilCO2.df <- as.data.frame(matrix(unlist(FuelOilCO2),
                                      nrow=length(unlist(FuelOilCO2[1]))))


#Add Column Names
colnames(NatGasCO2.df) <- c("Nat.Gas.IPCC.CO2e.Default.Kg",
                            "Nat.Gas.IPCC.CO2e.Min.Kg",
                            "Nat.Gas.IPCC.CO2e.Max.Kg",
                            "Nat.Gas.EPA.CO2e.Kg")
colnames(FuelOilCO2.df) <- c("Fuel.Oil.IPCC.CO2e.Default.Kg",
```

```
                                 "Fuel.Oil.IPCC.CO2e.Min.Kg",
                                  "Fuel.Oil.IPCC.CO2e.Max.Kg",
                                  "Fuel.Oil.EPA.CO2e.Kg")

#Add emission factors to Swater.df
Swater.df <- cbind(Swater.df, NatGasCO2.df, FuelOilCO2.df)

#At this point, Swater emissions factors has eGRID CO2e equiv for min, max, avg, and
#standard dev from the monthly emissions factors along with IPCC and EPA emission
#factors for the Nat Gas and Fuel Oil. I’m not sure if I want to combine the emission
#together to find an overall emissions min, max and calculate avg and standard dev fr
#those datapoints.



###End MWater Calcs###



###MWaste Calcs###

Mwaste.df[4] <- Mwaste.df[4]/1000
colnames(Mwaste.df)[4] <- "Electricity.MWh"
#convert kWh to MWh



#Pull out Radius attribution method
```

```
Mwaste.df <- Mwaste.df[,c(1:8, 15:30)]

##Multiply across the different methods for each city
CO2 <- apply(Mwaste.df[9:24], 2, function(x) Mwaste.df[4]*x)
MEwasteCO2.df <- as.data.frame(matrix(unlist(CO2), nrow=length(unlist(CO2[1]))))

#create new dataframe that holds city, state, water generated, electricity generated,
#and the CO2 calculated at each accounting level (kg of CO2/MWh)
MwasteCO2.df <- Mwaste.df
MwasteCO2.df[9:24] <- MEwasteCO2.df

#Build monthly to only have Boston, Cincinnati and San Antonio data

Mwaste1.df <- filter(Mwaste.df, City %in% c("Boston", "Cincinnati", "SanAntonio"))
Mwaste1.df <- Mwaste1.df[,1:8]



##Rearrange rows to be for each city from Jan to Dec##

#Convert Month from Factor to Date
addFormats(c("%b-%Y","%b-%y"))
Mwaste1.df <- Mwaste1.df
Mwaste1.df$Month <- anydate(Mwaste1.df$Month)

Mwaste1.df <- Mwaste1.df %>% arrange(City,Month)
Mwaste1.df$Month <- month(Mwaste1.df$Month)
```

```
##End Rearrange Rows for Dates##

##Calculate Emmissions for Electricity, Nat Gas, and Fuel Oil##

#Calc for Elect
Swaste.df <- cbind(Mwaste1.df,MonthlyE.df)
Swaste.df <- Swaste.df[,-c(9:10)]
Swaste.df[9:20] <- apply(Swaste.df[9:20], 2, function(x)
                            Swaste.df$Electricity.MWh*x)

Swaste.df[9:20] <- apply(Swaste.df[9:20], 2, function(x) x*0.45359237)

##Convert into CO2e 100-year GWP ##

Swaste.df <- Swaste.df %>% rename(CO2.Min.Kg = CO2.Min, CO2.Average.Kg = CO2.Average,
                                  CO2.Max.Kg = CO2.Max,
                                  CO2.Standard.Dev.Kg = CO2.Standard.Dev,
                                  SO2.Min.Kg = SO2.Min,
                                  SO2.Average.Kg = SO2.Average,
                                  SO2.Max.Kg = SO2.Max,
                                  SO2.Standard.Dev.Kg = SO2.Standard.Dev,
                                  NOX.Min.Kg = NOX.Min,
                                  NOX.Average.Kg = NOX.Average,
                                  NOX.Max.Kg = NOX.Max,
                                  NOX.Standard.Dev.Kg = NOX.Standard.Dev)
```

```
##Convert into CO2e 100-year GWP ##
#NOTE: CO2e is in lbs of emissions.
#At this point, ignore SOx GWP CO2e factor cuz not treated the same as CO2e and NOx.


#NOx = 298
Swaste.df[17:20] <- apply(Swaste.df[17:20], 2, function(x) x*298)


#Combine data into CO2e min, avg, max, and standard dev
Swaste.df$CO2e.Min.Kg <- Swaste.df$CO2.Min.Kg+Swaste.df$NOX.Min.Kg
Swaste.df$CO2e.Average.Kg <- Swaste.df$CO2.Average.Kg + Swaste.df$NOX.Average.Kg
Swaste.df$CO2e.Max.Kg <- Swaste.df$CO2.Max.Kg + Swaste.df$NOX.Max.Kg
Swaste.df$CO2e.Standard.Dev.Kg <- Swaste.df$CO2.Standard.Dev.Kg +
  Swaste.df$NOX.Standard.Dev.Kg

#Delete columns
Swaste.df <- Swaste.df[, -c(9:12, 17:20)]

##Multiply across the different emisison factors for Natural Gal
NatGasCO2 <- apply(Factors.df[1,2:5],2, function(x) Swaste.df[5]*x)
NatGasCO2.df <- as.data.frame(matrix(unlist(NatGasCO2),
                                     nrow=length(unlist(NatGasCO2[1]))))

##Multiply across the different emission factors for Biogas
```

```
BioGasCO2 <- apply(Factors.df[2,2:5], 2, function(x) Swaste.df[7]*x)
BioGasCO2.df <- as.data.frame(matrix(unlist(BioGasCO2),
                                     nrow=length(unlist(BioGasCO2[1]))))

##Multiply across the different emission factors for Fuel Oil
FuelOilCO2 <- apply(Factors.df[3,2:5], 2, function(x) Swaste.df[8]*x)
FuelOilCO2.df <- as.data.frame(matrix(unlist(FuelOilCO2),
                                      nrow=length(unlist(FuelOilCO2[1]))))



#Add Column Names
colnames(NatGasCO2.df) <- c("Nat.Gas.IPCC.CO2e.Default", "Nat.Gas.IPCC.CO2e.Min",
                            "Nat.Gas.IPCC.CO2e.Max",
                            "Nat.Gas.EPA.CO2e")
colnames(BioGasCO2.df) <- c("BioGas.IPCC.CO2e.Default", "BioGas.IPCC.CO2e.Min",
                            "BioGas.IPCC.CO2e.Max",
                            "BioGas.EPA.CO2e")
colnames(FuelOilCO2.df) <- c("Fuel.Oil.IPCC.CO2e.Default", "Fuel.Oil.IPCC.CO2e.Min",
                             "Fuel.Oil.IPCC.CO2e.Max",
                             "Fuel.Oil.EPA.CO2e")

#Add emission factors to Swater.df
Swaste.df <- cbind(Swaste.df, NatGasCO2.df, BioGasCO2.df, FuelOilCO2.df)

###End MWaste Calcs###
```

```
###Noramlize datapoints###

##Build Normalized by Population##
#Look at normalizing CO2e by Population served at each city

#Boston Pop from database = 2498777 (water), 2176445 (waste)
#Cincinnati Pop from database = 1004179 (water), 504000 (waste)
#SanAntonio Pop from database = 1431086(water), 1645749 (waste)

Swater1.df <- Swater.df
Swaste1.df <- Swaste.df

Swater.df[1:12,8:23] <- apply(Swater.df[1:12,8:23], 2, function(x) x/2498777)
Swater.df[13:24, 8:23] <- apply(Swater.df[13:24, 8:23], 2, function(x) x/1004179)
Swater.df[25:36, 8:23] <- apply(Swater.df[25:36, 8:23], 2, function(x) x/1431086)

Swaste.df[1:12, 9:28] <- apply(Swaste.df[1:12, 9:28], 2, function(x) x/2176445)
Swaste.df[13:24, 9:28] <- apply(Swaste.df[13:24, 9:28], 2, function(x) x/504000)
Swaste.df[25:36, 9:28] <- apply(Swaste.df[25:36, 9:28], 2, function(x) x/1645749)


##Build Normalized by Treated Volume##

Swater1.df[8:23] <- apply(Swater1.df[8:23], 2, function(x) x/Swater1.df$Volume.M3)
Swaste1.df[9:28] <- apply(Swaste1.df[9:28], 2, function(x) x/Swaste1.df$Volume.M3)
```

```
###End Normalized Datapoints###

####End Monthly CO2 analysis####

####Build Pretty Monthly Figures####



##Building CO2e emissions from eletcrical side only##
#Does not include IPCC or EPA amounts due to kg.



##End CO2e emissions from eletcrical side##

####End Monthly Figures####



####Annual Impact calcs####
##Average for columns for each city and sum down cities##

###Water Impact###

##Convert Energy sources to common unit for comparison.

#Conversion for therm: 34.1296 therm = 1 Mwh
#Conversion for gal: 22.779 gal  = 1 Mwh
```

```
AwaterCO2.df$Natural.Gas.Mwh <- AwaterCO2.df$Natural.Gas.therm/34.1296
AwaterCO2.df$Fuel.Oil.Mwh <- AwaterCO2.df$Fuel.Oil.gal/22.779

#Add water Electricity mean, mix, min as column to water dataframe
AwaterCO2.df$Elec.Mean.Emissons <- apply(AEwaterCO2.df,1,mean)
AwaterCO2.df$Elec.Max.Emissions <- apply(AEwaterCO2.df,1,max)
AwaterCO2.df$Elec.Min.Emissions <- apply(AEwaterCO2.df,1,min)

#Add mean, max, min Nat Gas as column to water dataframe
AwaterCO2.df$Nat.Gas.Mean.Emissions <-apply(AwaterCO2.df[23:26],1,mean)
AwaterCO2.df$Nat.Gas.Max.Emissions <-apply(AwaterCO2.df[23:26],1,max)
AwaterCO2.df$Nat.Gas.Min.Emissions <-apply(AwaterCO2.df[23:26],1,min)

#Add mean, max, min Fuel Oil as column to water dataframe
AwaterCO2.df$Fuel.Oil.Mean.Emissions <- apply(AwaterCO2.df[27:30],1,mean)
AwaterCO2.df$Fuel.Oil.Max.Emissions <- apply(AwaterCO2.df[27:30],1,max)
AwaterCO2.df$Fuel.Oil.Min.Emissions <- apply(AwaterCO2.df[27:30],1,min)



#Find Electric only emissions and all emissions
water.elec <- sum(AwaterCO2.df$Elec.Mean.Emissons)
water.all <- sum(c(AwaterCO2.df$Elec.Mean.Emissons,
                   AwaterCO2.df$Nat.Gas.Mean.Emissions,
                   AwaterCO2.df$Fuel.Oil.Mean.Emissions))

#Find water total population serviced through data analysis
```

```
water.pop <- 65813553

#Summates total mean CO2 emissions from all cities

water.elec.pop <- water.elec/water.pop
water.all.pop <- water.all/water.pop
#divides CO2 emissions across population serviced by central water system

#value found is CO2 just electricity generation only for drinking water consumption
water.elec.per<- water.elec/(1.87*(10^12))*100
water.all.per <- water.all/(1.87*(10^12))*100
##find what 1.87 number is for Estimated total electrical emissions across the
#states in 1 year##

##water.elec is the fraction of electricty emissions related to the water sector for
#water production##
##water.all is the fraction of all emissions related to the water sector for water
#production##

##Find emmissions of water per m^3 of water

#Find water volume
water.vol <- sum(AwaterCO2.df$Volume.M3)



water.elec.vol <- water.elec/water.vol
```

```
water.all.vol <- water.all/water.vol

###End Water Impact###

###Waste Impact###

##Convert Energy sources to common unit for comparison.

#Conversion for therm: 34.1296 therm = 1 Mwh
#Conversion for gal: 22.779 gal  = 1 Mwh

AwasteCO2.df$Natural.Gas.Mwh <- AwasteCO2.df$Natural.Gas.therm/34.1296
AwasteCO2.df$Fuel.Oil.Mwh <- AwasteCO2.df$Fuel.Oil.gal/22.779
AwasteCO2.df$Biogas.Mwh <- AwasteCO2.df$Biogas.therm/34.1296

#Add waste Electrical mean, max, min to waste dataframe
AwasteCO2.df$Elec.Mean.Emissons <- apply(AEwasteCO2.df,1,mean)
AwasteCO2.df$Elec.Max.Emissions <- apply(AEwasteCO2.df,1,max)
AwasteCO2.df$Elec.Min.Emissions <- apply(AEwasteCO2.df,1,min)

#Add mean, max, min Nat Gas as column to waste dataframe
AwasteCO2.df$Nat.Gas.Mean.Emissions <-apply(AwasteCO2.df[24:27],1,mean)
AwasteCO2.df$Nat.Gas.Max.Emissions <-apply(AwasteCO2.df[24:27],1,max)
AwasteCO2.df$Nat.Gas.Min.Emissions <-apply(AwasteCO2.df[24:27],1,min)

#Add mean, max, min BioGas as column to waste dataframe
```

```
AwasteCO2.df$Biogas.Mean.Emissions <-apply(AwasteCO2.df[28:31],1,mean)
AwasteCO2.df$Biogas.Max.Emissions <-apply(AwasteCO2.df[28:31],1,max)
AwasteCO2.df$Biogas.Min.Emissions <-apply(AwasteCO2.df[28:31],1,min)

#Add mean, max, min Fuel Oil as column to waste dataframe
AwasteCO2.df$Fuel.Oil.Mean.Emissions <- apply(AwasteCO2.df[32:35],1,mean)
AwasteCO2.df$Fuel.Oil.Max.Emissions <- apply(AwasteCO2.df[32:35],1,max)
AwasteCO2.df$Fuel.Oil.Min.Emissions <- apply(AwasteCO2.df[32:35],1,min)



waste.elec <- sum(AwasteCO2.df$Elec.Mean.Emissons)
waste.all <- sum(c(AwasteCO2.df$Elec.Mean.Emissons,
                   AwasteCO2.df$Nat.Gas.Mean.Emissions,
                   AwasteCO2.df$Biogas.Mean.Emissions,
                   AwasteCO2.df$Fuel.Oil.Mean.Emissions))
#Summates total CO2 emissions from all cities

#Find population serviced by wastewater utilities
waste.pop <- 62567735



waste.elec.pop <- waste.elec/waste.pop
waste.all.pop <- waste.all/waste.pop
#divides CO2 emissions across population serviced by central waste system

##value found is CO2 on electrical generation only on waste water consumption
```

```
waste.elec.per <- waste.elec/(1.87*(10^12))*100
waste.all.per <- waste.all/(1.87*(10^12))*100


waste.vol <- sum(AwasteCO2.df$Volume.M3)

waste.elec.vol <- waste.elec/waste.vol
waste.all.vol <- waste.all/waste.vol



###End waste Impact###

####End Annual Impact####



##Section 3.4 of Chini and Stillwell paper shows how to extrapolate to estimate the
#total impact of electricity

##Do same thing to numbers as in paper. Play around with what numbers to use
#(electricity and total carbon footprint). Electricity is the largest producer of
#carbon emissions.



#figure 3/4 color is emissions per m^3:emissions for natural gas, biogas, fuel oil
#all annalayzed and given individual factors circle size is embedded energy.
```

```
#The idea is that kwH per m^3. Small circle, but red color: higher intensity due to
#burning "dirty" fuel.

##Look at figures: mean emissions values, category view: balancing authority with
#transfers (most applicable to real-wold conditions)
#make one and change the input for the emissions intensity will look like.
#For information in order to understand the big picture#

#frame our numbers, but also show where uncertainty would be at. "How certain are
#the findings?"
#Allows us to bound our uncertainty to the numbers and show that, while a number was
#found, it can be described as a range.

##2 figures opposed/complementary: Show how emissions for water change over the
#country. (how does the emissions shift based on fuel make-up)
# We want to include variablity based on different accounting mechanisims.

##Figure out a scale that makes sense for monthly data Electricity data: Portfolio
#or eGrid  data at State level. Energy makeup is not statci throughout the year.

#E = Factor * electricity used where Factor varies due to energy make-up changes
#througout the months. Most likely not using Siddick data for this portion.



#####STUFFS####
#summate emissions associated with nat gas, fuel oil, and electricity into one
```

```
#emissions value for each city#
#Find three more estimates for the nat gas, fuel oil, etc in order to generate min,
#max, and mean values to factor for
# Found IPCC doc. Incorporate emissions factors as a new dataframe: build first as
#spreadsheet and convert to csv file.
#overall emissions when plotting in ArcGIS.

#LCA papers using SIMA-PRO may have factors that I'm looking for.
#Switch size of bubble and color: color is intensity, size is x factor.
####End Stuffs####

####Merge Data to ArcGIS####

##Open ArcGIS Table##
Shape <- arc.open("O:/MyStuff/ArcGIS/Shapefiles/WaterandWastewater_Cities/WaterandWas
shapes <- arc.data2sp(arc.select(Shape))
#This creates a formal class SpatialPointsDataFrame with cities in "City, State(2L)".
#Will need to transform the city
#state columns back into a single to smash my data back into the dataframe before
#saving the results to be transported back into ArcGIS.
shapes <- st_as_sf(shapes)

###Annual Water Merge###
#Combine State and City in AwaterCO2.df into 1 column for merge
AwaterCO2.df <- unite(AwaterCO2.df, Snippet, c(City, State), remove = TRUE)
```

```
#Format column to match ARCGIS data for join
AwaterCO2.df$Snippet <- str_replace(AwaterCO2.df$Snippet, "[:punct:]", ", ")
AwaterCO2.df$Snippet <- gsub("([[:lower:]])([[:upper:]])", "\\1 \\2",
                             AwaterCO2.df$Snippet)

#Perform right join for shapes and AWater.df
Ausawater.df <- right_join(shapes,AwaterCO2.df)
#Delete all rows with N/A
Ausawater.df <- na.omit(Ausawater.df)
###End Annual Water Merge###

###Annual Waste Merge###
#Combine state and city in AwasteCO2.df into 1 column for merge
AwasteCO2.df <- unite(AwasteCO2.df, Snippet, c(City, State), remove = TRUE)

#Format column to match ARCGIS data for join
AwasteCO2.df$Snippet <- str_replace(AwasteCO2.df$Snippet, "[:punct:]", ", ")
AwasteCO2.df$Snippet <- gsub("([[:lower:]])([[:upper:]])", "\\1 \\2",
                             AwasteCO2.df$Snippet)

#Perform right join for shapes and AWater.df
Ausawaste.df <- right_join(shapes,AwasteCO2.df)
#Delete all rows with N/A
Ausawaste.df <- na.omit(Ausawaste.df)
###End Annual Waste Merge###
```

```
####End Merge Data for ArcGIS####

####Reform data back into ArcGIS####

#Transform dataframe into spatialdataframe
Ausawater.sf <- as_Spatial(Ausawater.df)
Ausawaste.sf <- as_Spatial(Ausawaste.df)

#convert into arcgisbinding ready dataframe
arc.delete("O:/MyStuff/ArcGIS/Shapefiles/Water/Water_Cities.dbf")
arc.delete("O:/MyStuff/ArcGIS/Shapefiles/Waste/Waste_Cities.dbf")
arc.write("O:/MyStuff/ArcGIS/Shapefiles/Water/Water_Cities.dbf", Ausawater.sf)
arc.write("O:/MyStuff/ArcGIS/Shapefiles/Waste/Waste_Cities.dbf", Ausawaste.sf)

#Need to Normalize to population or water treated <-preferred.

####End data to ArcGIS####

####Build Annual Water Table####

#The purpose of this section is to create the water volume treated for water and
#wastewater of each city.


setwd("O:/MyStuff/Thesis/Data1")
```

```
#Create dataframe for arcgis total emissions table

Emissions.water <- c(sum(Ausawater.df$Elec.Mean.Emissons),
                     sum(Ausawater.df$Nat.Gas.Mean.Emissions),
                     sum(Ausawater.df$Fuel.Oil.Mean.Emissions), 0)
Emissions.waste <- c(sum(Ausawaste.df$Elec.Mean.Emissons),
                     sum(Ausawaste.df$Nat.Gas.Mean.Emissions),
                     sum(Ausawaste.df$Fuel.Oil.Mean.Emissions),
                     sum(Ausawaste.df$Biogas.Mean.Emissions))

Total.Emissions.df <- matrix(c(Emissions.water, Emissions.waste), nrow = 4, ncol = 2)

Total.Emissions.df <- as.data.frame(matrix(c(Emissions.water, Emissions.waste),
                                           nrow = 4, ncol = 2),
                                    row.names = c("Electricity", "Natural Gas",
                                                  "Fuel Oil", "Biogas"))

Total.Emissions.df <- rename(Total.Emissions.df, "Total Water Power Emissions (kg)"
                             = "V1", "Total Waste Power Emissions (kg)" = "V2")





write.xlsx(Total.Emissions.df, row.names = TRUE, file = "Total_Emissions.xlsx")
```

```
write.xlsx(list("Annual Water" = Awater.df, "Annual Wastewater" = Awaste.df),
           file = "Annual_Water.xlsx")
write.xlsx(list("Annual water" = Awater.df, "Annual Wastewater" = Awaste.df),
           file = "Annual_Water.xlsx", asTable = TRUE)

####End Annual Water Table####

####Build Monthly Water Tables####

#This exports the monthly dataframes as csvs for use in Grapher
write.csv(Swater.df[1:12,],
          "O://MyStuff/Thesis/Grapher\\Monthly Pop Water Data Boston.csv")
write.csv(Swater.df[13:24,],
          "O://MyStuff/Thesis/Grapher\\Monthly Pop Water Data Cincinnati.csv")
write.csv(Swater.df[25:36,],
          "O://MyStuff/Thesis/Grapher\\Monthly Pop Water Data San Antonio.csv")

write.csv(Swater1.df[1:12,],
          "O://MyStuff/Thesis/Grapher\\Monthly Vol Water Data Boston.csv")
write.csv(Swater1.df[13:24,],
"O://MyStuff/Thesis/Grapher\\Monthly Vol Water Data Cincinnati.csv")
write.csv(Swater1.df[25:36,],
          "O://MyStuff/Thesis/Grapher\\Monthly Vol Water Data San Antonio.csv")

write.csv(Swaste.df[1:12,],
          "O://MyStuff/Thesis/Grapher\\Monthly Pop Waste Data Boston.csv")
```

```
write.csv(Swaste.df[13:24,],
          "O://MyStuff/Thesis/Grapher\\Monthly Pop Waste Data Cincinnati.csv")
write.csv(Swaste.df[25:36,],
          "O://MyStuff/Thesis/Grapher\\Monthly Pop Waste Data San Antonio.csv")


write.csv(Swaste1.df[1:12,],
          "O://MyStuff/Thesis/Grapher\\Monthly Vol Waste Data Boston.csv")
write.csv(Swaste1.df[13:24,],
          "O://MyStuff/Thesis/Grapher\\Monthly Vol Waste Data Cincinnati.csv")
write.csv(Swaste1.df[25:36,],
"O://MyStuff/Thesis/Grapher\\Monthly Vol Waste Data San Antonio.csv")
```

Appendix B. Supporting Document

Operational Carbon Footprint of the U.S. Water Sector Related to Energy
Prepared by: Louis J. Zib III, Christopher M. Chini
Created on: 12/18/2020
Last date of modification:

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Publication of Record

General Comments

The emission factors table details the emission factors used from the IPCC and the EPA to calculate the emissions using each emission factor

Aside from the City data element, all data elements are calculated, source column details sources where original values can be located.

All data used is reflected on the Operational use of water treatment plants within 1 year; majority of water treatment plants responding with 2012 data See Source 1 for more details.

All data elements with Source 2 are calculations using Source 2 city specific emission factor values with source 1 consumed electricity values for each city

Table A. 1. Annual Drinking Water Metadata

Data Elements	Source	Unit	Description
City	1	-	Location for water treatment plant
Volume_M3	1	m$\hat{3}$	Volume of treated water at water treatment plant
Electricity_MWh	1	MWh	Electricity consumed at water treatment plant
Natural_Gas_therms	1	therms	Natural gas consumed at water treatment plant
Fuel_Oil_gal	1	gal	Fuel oil consumed at water treatment plant
HUC4_2014	2	kg CO_2	Hydrologic Unit Code-4 Boundaries
HUC4_2016	2	kg CO_2	Hydrologic Unit Code-4 Boundaries
PCA_NT_2014	2	kg CO_2	Power Control Areas (Balancing Authorities)
PCA_NT_2016	2	kg CO_2	Power Control Areas (Balancing Authorities)
State_2014	2	kg CO_2	State Boundaries
State_2016	2	kg CO_2	State Boundaries
PCA_T_2014	2	kg CO_2	Power Control Areas (Balancing Authorities) with Transfers
PCA_T_2016	2	kg CO_2	Power Control Areas (Balancing Authorities) with Transfers
HUC4_Bal_2014	2	kg CO_2	Hydrologic Unit Code-4 Boundaries with Transfers
HUC4_Bal_2016	2	kg CO_2	Hydrologic Unit Code-4 Boundaries with Transfers
State_Bal_2014	2	kg CO_2	State Boundaries with Transfers
State_Bal_2016	2	kg CO_2	State Boundaries with Transfers
Intercon_2014	2	kg CO_2	Interconnect boundaries
Intercon_2016	2	kg CO_2	Interconnect boundaries
eGrid_2014	2	kg CO_2	eGrid Boundaries
eGrid_2016	2	kg CO_2	eGrid Boundaries
Nat_Gas_IPCC_Avg	3	kg CO_2e	Calculated IPPC Emissions based on IPPC Average Emission Factor
Nat_Gas_IPCC_Min	3	kg CO_2e	Calculated IPPC Emissions based on IPPC Minimum Emission Factor

Data Elements	Source	Unit	Description
Nat_Gas_IPCC_Max	3	kg CO_2e	Calculated IPPC Emissions based on IPPC Maximum Emission Factor
Nat_Gas_EPA	4	kg CO_2e	Calculated EPA Emissions based on EPA Emission Factor
Fuel_Oil_IPCC_Avg	3	kg CO_2e	Calculated IPPC Emissions based on IPPC Average Emission Factor
Fuel_Oil_IPCC_Min	3	kg CO_2e	Calculated IPPC Emissions based on IPPC Minimum Emission Factor
Fuel_Oil_IPCC_Max	3	kg CO_2e	Calculated IPPC Emissions based on IPPC Maximum Emission Factor
Fuel_Oil_EPA	4	kg CO_2e	Calculated EPA Emissions based on EPA Emission Factor
Natural_Gas_MWh	-	MWh	Conversion from therms to MWh
Fuel_Oil_MWh	-	MWh	Conversion from gals to MWh
Elec_Mean_Emissions	-	kg CO_2e	Calculated Mean emissions based from average of IPCC and EPA values
Elec_Max_Emissions	-	kg CO_2e	Calculated Max emissions based from maximum of IPCC and EPA values
Elec_Min_Emissions	-	kg CO_2e	Calculated Min emissions based from min of IPCC and EPA values
Nat_Gas_Mean_Emissions	-	kg CO_2e	Calculated Mean emissions based from average of IPCC and EPA values
Nat_Gas_Max_Emissions	-	kg CO_2e	Calculated Max emissions based from maximum of IPCC and EPA values
Nat_Gas_Min_Emissions	-	kg CO_2e	Calculated Min emissions based from min of IPCC and EPA values
Fuel_Oil_Mean_Emissions	-	kg CO_2e	Calculated Mean emissions based from average of IPCC and EPA values
Fuel_Oil_Max_Emissions	-	kg CO_2e	Calculated Max emissions based from maximum of IPCC and EPA values
Fuel_Oil_Min_Emissions	-	kg CO_2e	Calculated Min emissions based from min of IPCC and EPA values

Table A. 2. Annual Wastewater Metadata

Data Elements	Source	Unit	Description
City	1	-	Location for water treatment plant
Volume_M3	1	m$\hat{3}$	Volume of treated water at water treatment plant
Electricity_MWh	1	MWh	Electricity consumed at water treatment plant
Natural_Gas_therms	1	therms	Natural gas consumed at water treatment plant
Biogas_therms	1	therms	Biogas consumed at water treatment plant
Fuel_Oil_gal	1	gal	Fuel oil consumed at water treatment plant
HUC4_2014	2	kg CO_2	Hydrologic Nuti Code-4 Boundaries
HUC4_2016	2	kg CO_2	Hydrologic Nuti Code-4 Boundaries
PCA_NT_2014	2	kg CO_2	Power Control Areas (Balancing Authorities)
PCA_NT_2016	2	kg CO_2	Power Control Areas (Balancing Authorities)
State_2014	2	kg CO_2	State Boundaries
State_2016	2	kg CO_2	State Boundaries
PCA_T_2014	2	kg CO_2	Power Control Areas (Balancing Authorities) with Transfers
PCA_T_2016	2	kg CO_2	Power Control Areas (Balancing Authorities) with Transfers
HUC4_Bal_2014	2	kg CO_2	Hydrologic Unit Code-4 Boundaries with Transfers
HUC4_Bal_2016	2	kg CO_2	Hydrologic Unit Code-4 Boundaries with Transfers
State_Bal_2014	2	kg CO_2	State Boundaries with Transfers
State_Bal_2016	2	kg CO_2	State Boundaries with Transfers
Intercon_2014	2	kg CO_2	Interconnect boundaries
Intercon_2016	2	kg CO_2	Interconnect boundaries
eGrid_2014	2	kg CO_2	eGrid Boundaries
eGrid_2016	2	kg CO_2	eGrid Boundaries
Nat_Gas_IPCC_Avg	3	kg CO_2e	Calculated IPPC Emissions based on IPPC Average Emission Factor

Data Elements	Source	Unit	Description
Nat_Gas_IPCC_Min	3	kg CO_2e	Calculated IPPC Emissions based on IPPC Minimum Emission Factor
Nat_Gas_IPCC_Max	3	kg CO_2e	Calculated IPPC Emissions based on IPPC Maximum Emission Factor
Nat_Gas_EPA	4	kg CO_2e	Calculated EPA Emissions based on EPA Emission Factor
BioGas_IPCC_Avg	3	kg CO_2e	Calculated IPPC Emissions based on IPPC Average Emission Factor
BioGas_IPCC_Min	3	kg CO_2e	Calculated IPPC Emissions based on IPPC Minimum Emission Factor
BioGas_IPCC_Max	3	kg CO_2e	Calculated IPPC Emissions based on IPPC Maximum Emission Factor
BioGas_EPA	4	kg CO_2e	Calculated EPA Emissions based on EPA Emission Factor
Fuel_Oil_IPCC_Avg	3	kg CO_2e	Calculated IPPC Emissions based on IPPC Average Emission Factor
Fuel_Oil_IPCC_Min	3	kg CO_2e	Calculated IPPC Emissions based on IPPC Minimum Emission Factor
Fuel_Oil_IPCC_Max	3	kg CO_2e	Calculated IPPC Emissions based on IPPC Maximum Emission Factor
Fuel_Oil_EPA	4	kg CO_2e	Calculated EPA Emissions based on EPA Emission Factor
Natural_Gas_Mwh	-	MWh	Conversion from therms to MWh
Fuel_Oil_Mwh	-	MWh	Conversion from gals to MWh
Biogas_Mwh	-	MWh	Conversion from gals to MWh
Elec_Mean_Emissions	-	kg CO_2e	Calculated Mean emissions based from average of IPCC and EPA values
Elec_Max_Emissions	-	kg CO_2e	Calculated Max emissions based from maximum of IPCC and EPA values
Elec_Min_Emissions	-	kg CO_2e	Calculated Min emissions based from min of IPCC and EPA values
Nat_Gas_Mean_Emissions	-	kg CO_2e	Calculated Mean emissions based from average of IPCC and EPA values
Nat_Gas_Max_Emissions	-	kg CO_2e	Calculated Max emissions based from maximum of IPCC and EPA values
Nat_Gas_Min_Emissions	-	kg CO_2e	Calculated Min emissions based from min of IPCC and EPA values
Biogas_Mean_Emissions	-	kg CO_2e	Calculated Mean emissions based from average of IPCC and EPA values

Data Elements	Source	Unit	Description
Biogas_Max_Emissions	-	kg CO_2e	Calculated Max emissions based from maximum of IPCC and EPA values
Biogas_Min_Emissions	-	kg CO_2e	Calculated Min emissions based from min of IPCC and EPA values
Fuel_Oil_Mean_Emissions	-	kg CO_2e	Calculated Mean emissions based from average of IPCC and EPA values
Fuel_Oil_Max_Emissions	-	kg CO_2e	Calculated Max emissions based from maximum of IPCC and EPA values
Fuel_Oil_Min_Emissions	-	kg CO_2e	Calculated Min emissions based from min of IPCC and EPA values

Table A. 3. Monthly Drinking Water Metadata

Data Elements	Source	Unit	Description
Month	1	-	Month for reported values
City	1	-	Location of Water Treatment Plant
State	1	-	Location of City
Volume.M3	1	$m\hat{3}$	Volume of treated water at water treatment plant
Electricity.MWh	1	MWh	Electricity consumed at water treatment plant
Natural.Gas.therm	1	therms	Natural gas consumed at water treatment plant
Fuel.Oil.gal	1	gal	Fuel oil consumed at water treatment plant
CO2e.Min.Kg	5	kg CO_2e	Calculated electricity minimum emissions based on NREL Emission Factor
CO2e.Average.Kg	5	kg CO_2e	Calculated electricity average emissions based on NREL Emission Factor
CO2e.Max.Kg	5	kg CO_2e	Calculated electricity maximum emissions based on NREL Emission Factor
Nat.Gas.IPCC.CO2e.Default.Kg	3	kg CO_2e	Calculated default emissions based on IPCC Emission Factor
Nat.Gas.IPCC.CO2e.Min.Kg	3	kg CO_2e	Calculated minimum emissions based on IPCC Emission Factor
Nat.Gas.IPCC.CO2e.Max.Kg	3	kg CO_2e	Calculated maximum emissions based on IPCC Emission Factor
Nat.Gas.EPA.CO2e.Kg	4	kg CO_2e	Calculated default emissions based on EPA Emission Factor
Fuel.Oil.IPCC.CO2e.Default.Kg	3	kg CO_2e	Calculated default emissions based on IPCC Emission Factor
Fuel.Oil.IPCC.CO2e.Min.Kg	3	kg CO_2e	Calculated minimum emissions based on IPCC Emission Factor
Fuel.Oil.IPCC.CO2e.Max.Kg	3	kg CO_2e	Calculated maximum emissions based on IPCC Emission Factor
Fuel.Oil.EPA.CO2e.Kg	4	kg CO_2e	Calculated default emissions based on EPA Emission Factor

Table A. 4. Monthly Wastewater Metadata

Data Elements	Source	Unit	Description
Month	1	-	Month for reported values
City	1	-	Location of Water Treatment Plant
State	1	-	Location of City
Volume.M3	1	m$\hat{3}$	Volume of treated water at water treatment plant
Electricity.MWh	1	MWh	Electricity consumed at water treatment plant
Natural.Gas.therm	1	therms	Natural gas consumed at water treatment plant
Biogas.therm	1	therms	Biogas consumed at water treatment plant
Fuel.Oil.gal	1	gal	Fuel oil consumed at water treatment plant
CO2e.Min.Kg	5	kg CO_2e	Calculated electricity minimum emissions based on NREL Emission Factor
CO2e.Average.Kg	5	kg CO_2e	Calculated electricity average emissions based on NREL Emission Factor
CO2e.Max.Kg	5	kg CO_2e	Calculated electricity maximum emissions based on NREL Emission Factor
Nat.Gas.IPCC.CO2e.Default	3	kg CO_2e	Calculated default emissions based on IPCC Emission Factor
Nat.Gas.IPCC.CO2e.Min	3	kg CO_2e	Calculated minimum emissions based on IPCC Emission Factor
Nat.Gas.IPCC.CO2e.Max	3	kg CO_2e	Calculated maximum emissions based on IPCC Emission Factor
Nat.Gas.EPA.CO2e	4	kg CO_2e	Calculated default emissions based on EPA Emission Factor
BioGas.IPCC.CO2e.Default	3	kg CO_2e	Calculated default emissions based on IPCC Emission Factor
BioGas.IPCC.CO2e.Min	3	kg CO_2e	Calculated minimum emissions based on IPCC Emission Factor
BioGas.IPCC.CO2e.Max	3	kg CO_2e	Calculated maximum emissions based on IPCC Emission Factor
BioGas.EPA.CO2e	4	kg CO_2e	Calculated default emissions based on EPA Emission Factor
Fuel.Oil.IPCC.CO2e.Default	3	kg CO_2e	Calculated default emissions based on IPCC Emission Factor

Data Elements	Source	Unit	Description
Fuel.Oil.IPCC.CO2e.Min	3	kg CO_2e	Calculated minimum emissions based on IPCC Emission Factor
Fuel.Oil.IPCC.CO2e.Max	3	kg CO_2e	Calculated maximum emissions based on IPCC Emission Factor
Fuel.Oil.EPA.CO2e	4	kg CO_2e	Calculated default emissions based on EPA Emission Factor

Table A. 5. Emission Factors

	IPCC (3)			EPA (4)
Range CO2_e	Default	Minimum	Maximum	Standard
Natural Gas (kg/therm)	5.92	5.73	6.17	5.27
Biogas (kg/therm)	9.19	7.97	8.4	3.32
Fuel Oil (kg/gal)	7.2	6.09	8.72	10.25

Table A. 6. Source Identifier

Source Identifier	Source Name	Citation Number
1	The State of U.S. Urban Water: Data and the Energy-Water Nexus.	(1)
2	Water and Carbon Footprints of Electricity Are Sensitive to Geographical Attribution Methods	(53)
3	IPCC Guidelines for National Greenhouse Gas Inventories: Chapter 2 (Table 2.4)	(50)
4	EPA Greenhous Gas Emission Factors (Table 1)	(51)
5	Hourly Energy Emission Factors for Electricity Generation in the United States (ERCT, NEWE, RFCW)	(52)

Table A. 7. Annual Drinking Water Data

City	Volume_M3	Electricity_MWh	Natural_Gas_therms	Fuel_Oil_gal
Augusta, GA	44682849.47	14008.662	0	0
Austin, TX	186470100.7	87351.2	0	0
Beaumont, TX	39519021.6	11770.4	0	0
Birmingham, AL	135055922.2	37917.399	0	0
Boston, MA	281108465.7	25607.345	211099	0
Chicago, IL	1095399754	164694.349	19793752	0
Cincinnati, OH	171702493.8	91085.781	946170	0
Cleveland, OH	309567017.2	205442.227	1472280	0
Colorado Springs, CO	111874060.3	3851.199	0	0
Columbia, SC	80859753.71	33134.07	29032	0
Columbus, OH	193820655	65943.982	654407	0
Dallas, TX	216646688.1	26561.106	0	0
Dayton, OH	77987178.82	51693.072	2260570	0
Denver, CO	272432301.8	41244.412	359017	0
Des Moines, IA	69924126.77	64442.96	178614.312	0
Detroit, MI	1538906172	371724.162	1299140	0
Duluth, MN	21266443.49	14052.502	0	0
Eugene, OR	32013227.59	15601.776	0	0
Fort Collins, CO	34336595.06	3921.35115	0	0
Fort Wayne, IN	42198597.27	14440.8	202910	0
Fort Worth, TX	268427222.6	74718.402	0	0
Fresno, CA	171039062.6	58270.036	70488	0
Greensboro, NC	47327902.81	13933.275	34921	0
Harrisburg, PA	10948887.24	3201.813	55506	8497
Houston, TX	619672585.5	277955.096	0	0
Indianapolis, IN	179156120.1	84688.0348	285349.409	0
Jackson, MS	42882924.01	22775.752	0	0
Jacksonville, FL	619672585.5	277955.096	0	0
Kansas City, MO	155608058.5	829580.66	0	0
Knoxville, TN	46864690.73	21862.148	0	0
Las Vegas, NV	892393103	953766.2984	0	0
Louisville, KY	178473350.1	93850.72079	0	0
Madison, WI	40346955.52	20321.466	51759	0
Miami, FL	412516008	104672.4	3127794.9	0
Milwaukee, WI	143542058.4	60901.979	667078	0
Minneapolis, MN	77892910.71	37989.727	754453	0
Nashville, TN	129817669.4	55064.848	130657	0
New Orleans, LA	197616930.9	70197.769	0	0
New York, NY	1394167166	7433.7	40394	0
Oakland, CA	254757678.6	74964.014	0	0
Ogden, UT	19523709.95	2935.44	0	0
Oklahoma City, OK	88108223	28227.5	7156.86	0

City	Volume_M3	Electricity_MWh	Natural_Gas_therms	Fuel_Oil_gal
Omaha, NE	143301116.9	85927.58438	0	0
Philadelphia, PA	336027220.1	10062.435	529190	0
Phoenix, AZ	352876422.2	71374.46	0	0
Portland, ME	30194867.18	4293.433	0	0
Portland, OR	136285206.2	17696.397	0	0
Providence, RI	84846485.06	7341.49205	33080.554	0
Reno, NV	93878969.34	49022.19393	49991	0
Sacramento, CA	117864462.4	18564.963	119119	0
Salt Lake City, UT	117864462.4	18564.963	119119	0
San Antonio, TX	252012962.3	118682.796	0	0
San Diego, CA	246269768.9	39914.22344	42624.76	0
Santa Fe, NM	12862007.86	10735.096	53730	0
Savannah, GA	73808754.21	27939.259	0	0
Sioux Falls, SD	68257905.84	18282.21824	0	0
Spokane, WA	146080937.9	38590.501	63514	0
Springfield, MA	36718305.19	1779.33	0	0
St Louis, MO	178739574.4	71959	370829.4	0
Tacoma, WA	82902032.58	7304.618	17378	0
Tampa, FL	103219602	33449.426	0	0
Tucson, AZ	147599568.1	123649.976	4635442.946	0
Tulsa, OK	159918052.7	79438.68867	294943.03	0
Worcester, MA	31737558.76	2608.421	0	0

City	HUC4_2014	HUC4_2016	PCA_NT_2014	PCA_NT_2016	State_2014
Augusta, GA	7442834.366	7299089.619	12784137.32	13422596	9673860
Austin, TX	161943063.9	159915490.4	41142829.01	41496277	42509963
Beaumont, TX	23854302.83	23170898.49	6893619.771	7261182	10301541
Birmingham, AL	54455721.49	60455060.63	18129408.54	19128787	15105357
Boston, MA	28777313.11	33830004.45	6247246.409	7077583	25326756
Chicago, IL	262073020.9	285916703.8	165260219	1.76E+08	3.07E+08
Cincinnati, OH	192167217.1	209473118.9	38052147.59	41407282	2.15E+08
Cleveland, OH	395468300.6	462958069.5	85825886.96	93393329	1.33E+08
Colorado Springs, CO	5616348.095	5985761.084	5552118.699	5981972	2577979
Columbia, SC	28382124.28	30147133.58	57317179.27	60243364	8823309
Columbus, OH	154183776	168290330.7	27548867.76	29977907	42849927
Dallas, TX	61138632.66	56437923.6	34854830.13	34978997	12926115
Dayton, OH	72892527.68	88497678.99	21595383.86	23499492	33589788
Denver, CO	62670358.7	65712923.92	82593630.09	90467088	27608862
Des Moines, IA	138320371.1	145903923	37742579.96	39754984	28060903
Detroit, MI	855530763.6	945266629.7	217709256.5	2.29E+08	1.85E+08
Duluth, MN	41788599.96	48579304.69	8230188.066	8669015	15601586
Eugene, OR	14215852.68	15294060.25	4160392.568	4951643	1970502
Fort Collins, CO	6345283.903	6473161.913	5653254.232	6090938	6253323
Fort Wayne, IN	20408835.47	21618459.95	8457604.192	8908557	21450146
Fort Worth, TX	171987602.2	158764151.8	98049275.85	98398566	36362139
Fresno, CA	30889115.07	46340066.89	9956825.245	13569842	10484329
Greensboro, NC	13465070.91	16257435.64	3930437.563	3944032	9544927
Harrisburg, PA	2836618.549	2715011.144	1337594.732	1455533	1194412
Houston, TX	760863642.4	762512597.2	293709299.5	3.04E+08	1.35E+08
Indianapolis, IN	69934134.68	70725190.28	84979012.73	90743097	70764648
Jackson, MS	37566533.38	41113992.96	13339170.66	14050404	9286830
Jacksonville, FL	445021203	515686278.6	202300276	2.16E+08	2.47E+08
Kansas City, MO	3332057589	3384079486	465296294.8	5.31E+08	1.02E+09
Knoxville, TN	30766588.48	30305538.67	8052482.988	9943253	35963422
Las Vegas, NV	649755822.3	8670663385	1029891812	6.23E+09	8.95E+08
Louisville, KY	257190093.8	262553046.4	137288621.7	1.47E+08	1.61E+08
Madison, WI	41411464.54	40742307.73	11901758.63	12536351	20880103
Miami, FL	30132388.64	30359674.82	188396216.5	1.81E+08	48552617
Milwaukee, WI	66197931.11	73326926.64	35668718.69	37570546	40544634
Minneapolis, MN	84945672.97	93139087.16	22249603.51	23435934	42177541
Nashville, TN	129326795.2	156286788.8	20282030.46	25044369	70048312
New Orleans, LA	82921010.04	100638785.8	41113023.2	43305136	55898651
New York, NY	8052787.397	9090648.418	6253796.404	7151535	9916643
Oakland, CA	57569492.22	79421625.7	12809389.5	17457511	13488019
Ogden, UT	1257721.725	1659443.656	2281356.529	2379397	3351468
Oklahoma City, OK	21147836.1	28182035.74	23021342.61	24008868	12315107

City	HUC4_2014	HUC4_2016	PCA_NT_2014	PCA_NT_2016	PCA_NT_2016
Omaha, NE	1.78E+08	2E+08	98520747	1.08E+08	88840301
Philadelphia, PA	6803078	9005790	4203700	4574348	15831652
Phoenix, AZ	2.71E+08	2.18E+08	1.84E+08	2.21E+08	30715498
Portland, ME	1226457	1339584	1047439	1186657	1056109
Portland, OR	18010123	19733120	8630354	9393909	3861008
Providence, RI	6608110	7387499	7729077	8107402	7050143
Reno, NV	62124346	61915702	17977598	2.78E+08	24896930
Sacramento, CA	16501078	21087367	16922404	1.2E+08	9428599
Salt Lake City, UT	19523782	23384606	17391644	18726384	19898039
San Antonio, TX	1.55E+08	1.65E+08	55900159	56380384	57757664
San Diego, CA	18145552	19098982	6820297	9295167	7181630
Santa Fe, NM	7534040	9311372	0	0	7446833
Savannah, GA	4206912	4162678	13358570	14094958	19293812
Sioux Falls, SD	2203341	7122759	10707424	11278335	19876062
Spokane, WA	2367541	2877930	3736510	4052775	6243956
Springfield, MA	833829.2	954793.3	434090.8	491786.9	1012241
St Louis, MO	2.34E+08	2.25E+08	42144531	44391643	82831792
Tacoma, WA	1809959	2171609	2264613	2442926	671152.4
Tampa, FL	19356532	19396042	40550051	40576387	15515620
Tucson, AZ	3.69E+08	2.61E+08	1.99E+08	2.11E+08	53211900
Tulsa, OK	1.17E+08	1.49E+08	1.05E+08	1.11E+08	69504312
Worcester, MA	3202138	3618268	636358.4	720938.4	2832304

City	State_2016	PCA_T_2014	PCA_T_2016	HUC4_Bal_2014	HUC4_Bal_2016
Augusta, GA	10549809.78	4119247.812	4451753.485	7055404	7581068
Austin, TX	43275061.59	48179657.82	46383153.84	41496359	45217839
Beaumont, TX	11069077.25	6472857.617	6525569.348	7260973	7713047
Birmingham, AL	16864344.62	16230876.27	17673705.57	19129062	20552999
Boston, MA	29596659.86	6903105.303	7819207.126	7076042	6732833
Chicago, IL	318139944.5	61933668.22	70039079.23	88201361	94980915
Cincinnati, OH	224196681.2	73649969.24	75418988.91	41408278	45466673
Cleveland, OH	138852228.6	128673596.7	136009297.2	93395574	1.03E+08
Colorado Springs, CO	2807063.991	2436889.703	2701467.668	3119667	3086075
Columbia, SC	9845829.178	11736850.54	12537532.91	9859911	11229735
Columbus, OH	44569556.1	46139195.38	47748830.2	29978628	32916812
Dallas, TX	13158760.25	16246762.99	15665946.28	12666237	13799517
Dayton, OH	34937794.21	39154343.47	40837429.82	23500057	25803281
Denver, CO	30062249.12	27230544.25	29545528.86	26753467	28266173
Des Moines, IA	35572168.39	32015849.89	36765214.98	39753839	42228945
Detroit, MI	212551842.9	179887903.3	210009405.8	2.29E+08	2.44E+08
Duluth, MN	16754899.82	7501475.809	8612351.935	8668765	9208490
Eugene, OR	2167960.074	766045.1057	1001051.86	1930442	1959706
Fort Collins, CO	6479353.468	2819542.489	3001300.349	3176493	3142290
Fort Wayne, IN	22043590.36	7159389.11	8131561.683	8908300	9462938
Fort Worth, TX	37016588.76	45703374.27	44069492.89	35631085	38819086
Fresno, CA	14132169.06	9551535.352	13645959.07	13572898	14269035
Greensboro, NC	10957405.39	4993692.091	5481924.014	3944576	4561727
Harrisburg, PA	1326277.297	1207509.993	1289016.149	1455568	1598227
Houston, TX	137703018.4	162155827.1	155274103.6	1.66E+08	1.77E+08
Indianapolis, IN	72036481.3	52431365.01	56668173.34	45354318	48840456
Jackson, MS	9586940.143	9416810.127	10292155.69	14050000	14924764
Jacksonville, FL	257762124.9	138935158.2	145058689.1	2.15E+08	2.27E+08
Kansas City, MO	1123929196	539042294.1	585348911.8	5.31E+08	5.64E+08
Knoxville, TN	39264423.67	8169135.925	8372066.998	9949494	10916075
Las Vegas, NV	5260031137	228306862.1	4017459845	2.91E+08	2.4E+08
Louisville, KY	167571365.1	80771520.08	83141587.2	57915383	61518128
Madison, WI	21969319.62	6223999.199	7085493.925	12535990	13316491
Miami, FL	49343720.97	40411477.03	40423453.81	33747875	33638424
Milwaukee, WI	40970604.87	19771700.44	22268711.05	37569464	39908569
Minneapolis, MN	45295426.4	16728411.47	18540122.04	23435259	24894358
Nashville, TN	76713433.03	33364280.97	37014664.71	25060089	27494647
New Orleans, LA	60786303.26	27903553.64	30084144.42	43303889	46000024
New York, NY	11338481.5	2003373.415	2343015.032	3208313	3503205
Oakland, CA	18180941.56	13380877.29	21372429.36	17461443	18357018
Ogden, UT	16749308.07	1940685.043	2057366.55	2378101	2364250
Oklahoma City, OK	15161312.86	11573122.98	14086296.14	18056353	19169775

City	State_2016	PCA_T_2014	PCA_T_2016	HUC4_Bal_2014	HUC4_Bal_2016
Omaha, NE	99776307	50803848	57177553	53247240	56558961
Philadelphia, PA	15571376	2938831	3236850	4574458	5022798
Phoenix, AZ	33275916	24030087	28286753	16921387	17784648
Portland, ME	1496282	1152271	1309075	1186398	1128855
Portland, OR	4208245	2714682	2860942	2201096	2230041
Providence, RI	7658281	2135108	2467829	2028664	1930268
Reno, NV	2.48E+08	7695275	12514091	2.76E+08	23912576
Sacramento, CA	93730683	3342262	5165380	5609520	4603985
Salt Lake City, UT	1.04E+08	13597548	14247698	14037295	13882247
San Antonio, TX	58797192	73478424	71640425	56380495	61436815
San Diego, CA	9680354	9466224	10866642	9297260	9774105
Santa Fe, NM	8127714	3867441	5257024	0	0
Savannah, GA	21040829	10071629	11272085	14095161	15144382
Sioux Falls, SD	23378417	4043154	5214187	11278010	11980188
Spokane, WA	7678988	700990.9	366650.3	3406374	2702056
Springfield, MA	1131153	523107.2	596825.3	491679.8	467831.9
St Louis, MO	83632591	60416065	59569374	44390365	47154145
Tacoma, WA	722035.1	871786.9	907005.9	873138.3	898173.4
Tampa, FL	15768427	15795502	15970582	19891305	21252847
Tucson, AZ	57647599	22471906	26894970	1.01E+08	1.03E+08
Tulsa, OK	90406068	31476595	38150859	50903488	54021286
Worcester, MA	3201380	751855.5	861573.7	720781.3	685821.3

City	State_Bal_2014	State_Bal_2016	Intercon_2014	Intercon_2016	eGrid_2014
Augusta, GA	2651993.132	2613086.466	6529912.396	7049461	11358957
Austin, TX	54320464.61	53725416.78	78890531.61	82561294	41099728
Beaumont, TX	5993296.885	5869663.173	10630341.81	11124970	16576743
Birmingham, AL	25147612.47	25796613.18	17674585.46	19080854	36884022
Boston, MA	8159055.666	9282688.956	11936451.86	12886169	6187532
Chicago, IL	44905351.38	55956644.54	76769620.9	82877754	3.5E+08
Cincinnati, OH	60347192.24	64360986.01	42458171.27	45836332	95252282
Cleveland, OH	68903635.62	85079701.74	95763588.61	1.03E+08	1.14E+08
Colorado Springs, CO	2927386.433	3122507.737	1354544.621	2474284	2367542
Columbia, SC	12508541.2	12367229.87	15444913.61	16673780	10945792
Columbus, OH	34023686.87	37426277.63	30738726.19	33184436	36499983
Dallas, TX	11126581.77	11750962.51	11607416.41	11738505	12497301
Dayton, OH	28599072.14	31315048.07	24095893.79	26013070	28612107
Denver, CO	26683289.7	31204269.75	14506494.32	26498342	25355184
Des Moines, IA	27372615.3	29945386.87	30039048.94	32429089	35239897
Detroit, MI	217794618.7	244899258.4	173273237.2	1.87E+08	2.2E+08
Duluth, MN	5648532.791	8265544.528	6550347.707	7071523	7684450
Eugene, OR	7253604.609	10791655.56	5487460.335	10023690	4470493
Fort Collins, CO	2628036.463	3018504.729	1379218.552	2519355	2410668
Fort Wayne, IN	10370317.54	11014561.03	6731346.572	7266922	7992980
Fort Worth, TX	31299916.87	33056347.16	32652541.1	33021302	35155854
Fresno, CA	13658292.31	21476737.11	20494750.81	37436813	12497833
Greensboro, NC	3187346.718	4132180.213	6494771.959	7011525	12314902
Harrisburg, PA	560408.2424	679634.3035	1492473.614	1611221	1127874
Houston, TX	126609365.6	132504844.3	251032902.7	2.63E+08	2.37E+08
Indianapolis, IN	67750159.7	69946120.41	39475964.82	42616848	46874813
Jackson, MS	8280573.443	9094834.93	10616550.34	11461250	30881489
Jacksonville, FL	156721811.2	166417879.2	129564295.8	1.4E+08	2.6E+08
Kansas City, MO	554283790	583383824.9	386695677	4.17E+08	1.09E+09
Knoxville, TN	12404768.02	12298629.65	10190688.53	11001505	10761484
Las Vegas, NV	275441779.7	5020823942	335458907.5	6.13E+08	9.36E+08
Louisville, KY	84479679.49	88320350.52	43747003.47	47227710	98143697
Madison, WI	7649533.647	7553143.36	9472524.41	10226201	27877489
Miami, FL	30043625.22	30276452.34	48791355.11	52673413	47779219
Milwaukee, WI	20566900.88	22943057.77	28388477.62	30647191	33709235
Minneapolis, MN	20681087.9	22617976.51	17708300	19117251	20774248
Nashville, TN	33517852.86	37877110.45	25667592.92	27709821	27105273
New Orleans, LA	21392610.46	26769663.53	32721560.56	35325034	99563885
New York, NY	2534562.971	2820668.293	3465099.649	3740798	11023241
Oakland, CA	26947850.92	35612119.3	26366360.69	48162211	16078379
Ogden, UT	1244804.523	1886431.339	1032453.649	1885935	841113.4
Oklahoma City, OK	7102781.375	9994329.417	13157794.95	14204688	15657329

City	State_Bal_2014	State_Bal_2016	Intercon_2014	Intercon_2016	eGrid_2014
Omaha, NE	49857288	55287448	40053761	43240616	46988519
Philadelphia, PA	2628400	3021734	4690442	5063635	3544604
Phoenix, AZ	21062074	31751458	25103842	45856026	34299980
Portland, ME	407796.9	652109.9	2001315	2160548	1037427
Portland, OR	5141477	7972603	6224181	11369423	5070680
Providence, RI	2578203	2863900	3422118	3694397	1773933
Reno, NV	24925867	31863027	17242098	31495342	24561037
Sacramento, CA	1978968	4604063	6529673	11927452	9301394
Salt Lake City, UT	8330675	12167301	6529673	11927452	5319557
San Antonio, TX	44337402	46631491	51865334	52451075	55841599
San Diego, CA	14575616	21342685	14038640	25643734	27742185
Santa Fe, NM	5213976	8403679	3775750	6896989	5158898
Savannah, GA	3986506	3944589	13023436	14059639	22654615
Sioux Falls, SD	960205.7	1335748	8521962	9200007	9997422
Spokane, WA	1357234	1652601	13573060	24793281	11057623
Springfield, MA	666532.4	754365.6	829406.1	895397.3	429941.5
St Louis, MO	59497466	59061757	33542530	36211323	54357491
Tacoma, WA	2819715	4687399	2569182	4693006	2093046
Tampa, FL	18907072	18945664	15591912	16832474	15268470
Tucson, AZ	52067335	82935036	43490199	79441533	59421700
Tulsa, OK	28065262	38601124	37029067	39975264	88786173
Worcester, MA	854969.2	952664.3	1215873	1312614	630275.7

City	eGrid_2016
Augusta, GA	12386270.18
Austin, TX	41586073.39
Beaumont, TX	17362184.83
Birmingham, AL	40921874.35
Boston, MA	7013548.3
Chicago, IL	349616995.2
Cincinnati, OH	105555159.8
Cleveland, OH	120517832.8
Colorado Springs, CO	2598557.357
Columbia, SC	12497414.78
Columbus, OH	38684480.36
Dallas, TX	12645185.22
Dayton, OH	30324520.42
Denver, CO	27829247.52
Des Moines, IA	40137008.47
Detroit, MI	246962192.7
Duluth, MN	8752319.755
Eugene, OR	5185226.709
Fort Collins, CO	2645891.807
Fort Wayne, IN	8471354.429
Fort Worth, TX	35571863.34
Fresno, CA	16563755.02
Greensboro, NC	13428940.11
Harrisburg, PA	1146841.616
Houston, TX	238595825.6
Indianapolis, IN	49680236.46
Jackson, MS	33288022.89
Jacksonville, FL	270065659
Kansas City, MO	1188459910
Knoxville, TN	12510133.77
Las Vegas, NV	2062408300
Louisville, KY	108759322.5
Madison, WI	28130924.36
Miami, FL	48631507.86
Milwaukee, WI	35726708.32
Minneapolis, MN	23661141.49
Nashville, TN	31509649.21
New Orleans, LA	105717988.5
New York, NY	12304553.22
Oakland, CA	21309160.74
Ogden, UT	975589.0541
Oklahoma City, OK	17407186.72

City	eGrid_2016
Omaha, NE	53518277
Philadelphia, PA	3604214
Phoenix, AZ	1.1E+08
Portland, ME	1175920
Portland, OR	5881371
Providence, RI	2010748
Reno, NV	30227429
Sacramento, CA	11447287
Salt Lake City, UT	6170037
San Antonio, TX	56502389
San Diego, CA	73044418
Santa Fe, NM	16594057
Savannah, GA	24703516
Sioux Falls, SD	11386714
Spokane, WA	12825495
Springfield, MA	487337.4
St Louis, MO	53143682
Tacoma, WA	2427679
Tampa, FL	15540830
Tucson, AZ	1.91E+08
Tulsa, OK	1.04E+08
Worcester, MA	714415.6

City	Nat_Gas_IPCC_Avg	Nat_Gas_IPCC_Min	Nat_Gas_IPCC_Max	Nat_Gas_EPA
Augusta, GA	0	0	0	0
Austin, TX	0	0	0	0
Beaumont, TX	0	0	0	0
Birmingham, AL	0	0	0	0
Boston, MA	1250388.656	1209454.23	1301816.096	1112433
Chicago, IL	117243013.7	113404786.8	122065120.9	1.04E+08
Cincinnati, OH	5604385.784	5420912.979	5834889.488	4986051
Cleveland, OH	8720658.129	8435166.789	9079331.51	7758503
Colorado Springs, CO	0	0	0	0
Columbia, SC	171963.3132	166333.688	179036.0206	152990.5
Columbus, OH	3876205.426	3749308.687	4035630.516	3448541
Dallas, TX	0	0	0	0
Dayton, OH	13389883.82	12951534.35	13940598.55	11912570
Denver, CO	2126541.5	2056924.142	2214004.375	1891919
Des Moines, IA	1057974.266	1023338.979	1101487.863	941247.4
Detroit, MI	7695109.491	7443191.908	8011602.914	6846104
Duluth, MN	0	0	0	0
Eugene, OR	0	0	0	0
Fort Collins, CO	0	0	0	0
Fort Wayne, IN	1201883.297	1162536.809	1251315.753	1069279
Fort Worth, TX	0	0	0	0
Fresno, CA	417516.8787	403848.4776	434688.999	371452
Greensboro, NC	206845.235	200073.6677	215352.6066	184023.9
Harrisburg, PA	328774.9953	318011.7694	342297.2361	292501.1
Houston, TX	0	0	0	0
Indianapolis, IN	1690191.161	1634858.762	1759707.312	1503711
Jackson, MS	0	0	0	0
Jacksonville, FL	0	0	0	0
Kansas City, MO	0	0	0	0
Knoxville, TN	0	0	0	0
Las Vegas, NV	0	0	0	0
Louisville, KY	0	0	0	0
Madison, WI	306580.6396	296543.9983	319190.0451	272755.4
Miami, FL	18526659.34	17920145.4	19288645.36	16482602
Milwaukee, WI	3951258.717	3821904.931	4113770.686	3515314
Minneapolis, MN	4468801.238	4322504.476	4652599.299	3975756
Nashville, TN	773911.9115	748576.0774	805742.2618	688525.8
New Orleans, LA	0	0	0	0
New York, NY	239263.0916	231430.2492	249103.7826	212865.1
Oakland, CA	0	0	0	0
Ogden, UT	0	0	0	0
Oklahoma City, OK	42391.75248	41003.95834	44135.28983	37714.65

City	Nat_Gas_IPCC_Avg	Nat_Gas_IPCC_Min	Nat_Gas_IPCC_Max	Nat_Gas_EPA
Omaha, NE	0	0	0	0
Philadelphia, PA	3134516	3031900	3263436	2788683
Phoenix, AZ	0	0	0	0
Portland, ME	0	0	0	0
Portland, OR	0	0	0	0
Providence, RI	195943.8	189529.2	204002.9	174325.2
Reno, NV	296108.4	286414.6	308287.1	263438.6
Sacramento, CA	705569.6	682471.2	734589.1	627723.7
Salt Lake City, UT	705569.6	682471.2	734589.1	627723.7
San Antonio, TX	0	0	0	0
San Diego, CA	252476.4	244211	262860.5	224620.5
Santa Fe, NM	318255.3	307836.5	331344.9	283142
Savannah, GA	0	0	0	0
Sioux Falls, SD	0	0	0	0
Spokane, WA	376208.2	363892.2	391681.4	334701
Springfield, MA	0	0	0	0
St Louis, MO	2196509	2124601	2286850	1954167
Tacoma, WA	102934	99564.16	107167.5	91577.19
Tampa, FL	0	0	0	0
Tucson, AZ	27456811	26557947	28586086	24427485
Tulsa, OK	1747016	1689824	1818870	1554267
Worcester, MA	0	0	0	0

City	Fuel_Oil_IPCC_Avg	Fuel_Oil_IPCC_Min	Fuel_Oil_IPCC_Max	Fuel_Oil_EPA
Augusta, GA	0	0	0	0
Austin, TX	0	0	0	0
Beaumont, TX	0	0	0	0
Birmingham, AL	0	0	0	0
Boston, MA	0	0	0	0
Chicago, IL	0	0	0	0
Cincinnati, OH	0	0	0	0
Cleveland, OH	0	0	0	0
Colorado Springs, CO	0	0	0	0
Columbia, SC	0	0	0	0
Columbus, OH	0	0	0	0
Dallas, TX	0	0	0	0
Dayton, OH	0	0	0	0
Denver, CO	0	0	0	0
Des Moines, IA	0	0	0	0
Detroit, MI	0	0	0	0
Duluth, MN	0	0	0	0
Eugene, OR	0	0	0	0
Fort Collins, CO	0	0	0	0
Fort Wayne, IN	0	0	0	0
Fort Worth, TX	0	0	0	0
Fresno, CA	0	0	0	0
Greensboro, NC	0	0	0	0
Harrisburg, PA	96677.46209	94101.34857	99157.71212	87044.03
Houston, TX	0	0	0	0
Indianapolis, IN	0	0	0	0
Jackson, MS	0	0	0	0
Jacksonville, FL	0	0	0	0
Kansas City, MO	0	0	0	0
Knoxville, TN	0	0	0	0
Las Vegas, NV	0	0	0	0
Louisville, KY	0	0	0	0
Madison, WI	0	0	0	0
Miami, FL	0	0	0	0
Milwaukee, WI	0	0	0	0
Minneapolis, MN	0	0	0	0
Nashville, TN	0	0	0	0
New Orleans, LA	0	0	0	0
New York, NY	0	0	0	0
Oakland, CA	0	0	0	0
Ogden, UT	0	0	0	0
Oklahoma City, OK	0	0	0	0

City	Fuel_Oil_IPCC_Avg	Fuel_Oil_IPCC_Min	Fuel_Oil_IPCC_Max	Fuel_Oil_EPA
Omaha, NE	0	0	0	0
Philadelphia, PA	0	0	0	0
Phoenix, AZ	0	0	0	0
Portland, ME	0	0	0	0
Portland, OR	0	0	0	0
Providence, RI	0	0	0	0
Reno, NV	0	0	0	0
Sacramento, CA	0	0	0	0
Salt Lake City, UT	0	0	0	0
San Antonio, TX	0	0	0	0
San Diego, CA	0	0	0	0
Santa Fe, NM	0	0	0	0
Savannah, GA	0	0	0	0
Sioux Falls, SD	0	0	0	0
Spokane, WA	0	0	0	0
Springfield, MA	0	0	0	0
St Louis, MO	0	0	0	0
Tacoma, WA	0	0	0	0
Tampa, FL	0	0	0	0
Tucson, AZ	0	0	0	0
Tulsa, OK	0	0	0	0
Worcester, MA	0	0	0	0

City	Natural_Gas_MWh	Fuel_Oil_MWh
Augusta, GA	0	0
Austin, TX	0	0
Beaumont, TX	0	0
Birmingham, AL	0	0
Boston, MA	6185.217524	0
Chicago, IL	579958.5111	0
Cincinnati, OH	27722.85641	0
Cleveland, OH	43137.92134	0
Colorado Springs, CO	0	0
Columbia, SC	850.6399137	0
Columbus, OH	19174.17725	0
Dallas, TX	0	0
Dayton, OH	66234.88116	0
Denver, CO	10519.22671	0
Des Moines, IA	5233.413576	0
Detroit, MI	38064.90554	0
Duluth, MN	0	0
Eugene, OR	0	0
Fort Collins, CO	0	0
Fort Wayne, IN	5945.279171	0
Fort Worth, TX	0	0
Fresno, CA	2065.304018	0
Greensboro, NC	1023.188083	0
Harrisburg, PA	1626.330224	373.0190087
Houston, TX	0	0
Indianapolis, IN	8360.760425	0
Jackson, MS	0	0
Jacksonville, FL	0	0
Kansas City, MO	0	0
Knoxville, TN	0	0
Las Vegas, NV	0	0
Louisville, KY	0	0
Madison, WI	1516.542825	0
Miami, FL	91644.63984	0
Milwaukee, WI	19545.43856	0
Minneapolis, MN	22105.53303	0
Nashville, TN	3828.260513	0
New Orleans, LA	0	0
New York, NY	1183.547419	0
Oakland, CA	0	0
Ogden, UT	0	0
Oklahoma City, OK	209.6965684	0

City	Natural_Gas_MWh	Fuel_Oil_MWh
Omaha, NE	0	0
Philadelphia, PA	15505.31	0
Phoenix, AZ	0	0
Portland, ME	0	0
Portland, OR	0	0
Providence, RI	969.2629	0
Reno, NV	1464.74	0
Sacramento, CA	3490.196	0
Salt Lake City, UT	3490.196	0
San Antonio, TX	0	0
San Diego, CA	1248.909	0
Santa Fe, NM	1574.293	0
Savannah, GA	0	0
Sioux Falls, SD	0	0
Spokane, WA	1860.965	0
Springfield, MA	0	0
St Louis, MO	10865.33	0
Tacoma, WA	509.1768	0
Tampa, FL	0	0
Tucson, AZ	135818.8	0
Tulsa, OK	8641.854	0
Worcester, MA	0	0

City	Elec_Mean_Emissions	Elec_Max_Emissions	Elec_Min_Emissions
Augusta, GA	7935592.591	13422596.01	2613086.466
Austin, TX	63983950.17	161943063.9	41099728.26
Beaumont, TX	11130016.67	23854302.83	5869663.173
Birmingham, AL	26451930.28	60455060.63	15105356.8
Boston, MA	13428262.27	33830004.45	6187531.768
Chicago, IL	174395076.2	350341117.4	44905351.38
Cincinnati, OH	98149608.64	224196681.2	38052147.59
Cleveland, OH	147373771.2	462958069.5	68903635.62
Colorado Springs, CO	3419385.216	5985761.084	1354544.621
Columbia, SC	20035040.04	60243364	8823309.409
Columbus, OH	52172588.72	168290330.7	27548867.76
Dallas, TX	21452479.57	61138632.66	11126581.77
Dayton, OH	35829218.02	88497678.99	21595383.86
Denver, CO	38936728.21	90467087.79	14506494.32
Des Moines, IA	48205114.01	145903923	27372615.3
Detroit, MI	299887302.4	945266629.7	173273237.2
Duluth, MN	13599212.11	48579304.69	5648532.791
Eugene, OR	5726861.58	15294060.25	766045.1057
Fort Collins, CO	4002288.435	6479353.468	1379218.552
Fort Wayne, IN	11774804.03	22043590.36	6731346.572
Fort Worth, TX	60347449.11	171987602.2	31299916.87
Fresno, CA	18658747.16	46340066.89	9551535.352
Greensboro, NC	7728180.876	16257435.64	3187346.718
Harrisburg, PA	1439638.866	2836618.549	560408.2424
Houston, TX	268958363.3	762512597.2	126609365.6
Indianapolis, IN	61176313.74	90743097.34	39475964.82
Jackson, MS	17328145.18	41113992.96	8280573.443
Jacksonville, FL	233327165.2	515686278.6	129564295.8
Kansas City, MO	1018635275	3384079486	386695677
Knoxville, TN	16304355.61	39264423.67	8052482.988
Las Vegas, NV	2297339333	8670663385	228306862.1
Louisville, KY	117879493	262553046.4	43747003.47
Madison, WI	17469568.36	41411464.54	6223999.199
Miami, FL	58386202.38	188396216.5	30043625.22
Milwaukee, WI	36611211.05	73326926.64	19771700.44
Minneapolis, MN	32462588.87	93139087.16	16728411.47
Nashville, TN	49001419.31	156286788.8	20282030.46
New Orleans, LA	53340328.88	105717988.5	21392610.46
New York, NY	6171920.037	12304553.22	2003373.415
Oakland, CA	27748426.78	79421625.7	12809389.5
Ogden, UT	2767839.032	16749308.07	841113.4365
Oklahoma City, OK	16515384.93	28182035.74	7102781.375

City	Elec_Mean_Emissions	Elec_Max_Emissions	Elec_Min_Emissions
Omaha, NE	79988567	2E+08	40053761
Philadelphia, PA	5894744	15831652	2628400
Phoenix, AZ	82127428	2.71E+08	16921387
Portland, ME	1222765	2160548	407796.9
Portland, OR	7218953	19733120	2201096
Providence, RI	4340355	8107402	1773933
Reno, NV	73256483	2.78E+08	7695275
Sacramento, CA	21400078	1.2E+08	1978968
Salt Lake City, UT	19325284	1.04E+08	5319557
San Antonio, TX	69958904	1.65E+08	44337402
San Diego, CA	17875843	73044418	6820297
Santa Fe, NM	5474236	16594057	0
Savannah, GA	13069582	24703516	3944589
Sioux Falls, SD	9280246	23378417	960205.7
Spokane, WA	6212067	24793281	366650.3
Springfield, MA	687519.9	1131153	429941.5
St Louis, MO	76178906	2.34E+08	33542530
Tacoma, WA	2057652	4693006	671152.4
Tampa, FL	20322482	40576387	15268470
Tucson, AZ	1.2E+08	3.69E+08	22471906
Tulsa, OK	72126888	1.49E+08	28065262
Worcester, MA	1432014	3618268	630275.7

City	Nat_Gas_Mean_Emissions	Nat_Gas_Max_Emissions	Nat_Gas_Min_Emissions
Augusta, GA	0	0	0
Austin, TX	0	0	0
Beaumont, TX	0	0	0
Birmingham, AL	0	0	0
Boston, MA	1218522.885	1301816.096	1112432.556
Chicago, IL	114255111.5	122065120.9	104307524.6
Cincinnati, OH	5461559.731	5834889.488	4986050.674
Cleveland, OH	8498414.832	9079331.51	7758502.898
Colorado Springs, CO	0	0	0
Columbia, SC	167580.8809	179036.0206	152990.5019
Columbus, OH	3777421.519	4035630.516	3448541.45
Dallas, TX	0	0	0
Dayton, OH	13048646.74	13940598.55	11912570.23
Denver, CO	2072347.242	2214004.375	1891918.952
Des Moines, IA	1031012.116	1101487.863	941247.3559
Detroit, MI	7499001.986	8011602.914	6846103.632
Duluth, MN	0	0	0
Eugene, OR	0	0	0
Fort Collins, CO	0	0	0
Fort Wayne, IN	1171253.67	1251315.753	1069278.821
Fort Worth, TX	0	0	0
Fresno, CA	406876.5891	434688.999	371452.0012
Greensboro, NC	201573.8476	215352.6066	184023.8811
Harrisburg, PA	320396.2654	342297.2361	292501.0608
Houston, TX	0	0	0
Indianapolis, IN	1647117.158	1759707.312	1503711.398
Jackson, MS	0	0	0
Jacksonville, FL	0	0	0
Kansas City, MO	0	0	0
Knoxville, TN	0	0	0
Las Vegas, NV	0	0	0
Louisville, KY	0	0	0
Madison, WI	298767.5261	319190.0451	272755.4212
Miami, FL	18054513.11	19288645.36	16482602.36
Milwaukee, WI	3850562.1	4113770.686	3515314.068
Minneapolis, MN	4354915.21	4652599.299	3975755.826
Nashville, TN	754189.0039	805742.2618	688525.7649
New Orleans, LA	0	0	0
New York, NY	233165.5451	249103.7826	212865.057
Oakland, CA	0	0	0
Ogden, UT	0	0	0
Oklahoma City, OK	41311.41167	44135.28983	37714.64602

City	Nat_Gas_Mean_Emissions	Nat_Gas_Max_Emissions	Nat_Gas_Min_Emissions
Omaha, NE	0	0	0
Philadelphia, PA	3054634	3263436	2788683
Phoenix, AZ	0	0	0
Portland, ME	0	0	0
Portland, OR	0	0	0
Providence, RI	190950.3	204002.9	174325.2
Reno, NV	288562.1	308287.1	263438.6
Sacramento, CA	687588.4	734589.1	627723.7
Salt Lake City, UT	687588.4	734589.1	627723.7
San Antonio, TX	0	0	0
San Diego, CA	246042.1	262860.5	224620.5
Santa Fe, NM	310144.7	331344.9	283142
Savannah, GA	0	0	0
Sioux Falls, SD	0	0	0
Spokane, WA	366620.7	391681.4	334701
Springfield, MA	0	0	0
St Louis, MO	2140532	2286850	1954167
Tacoma, WA	100310.7	107167.5	91577.19
Tampa, FL	0	0	0
Tucson, AZ	26757082	28586086	24427485
Tulsa, OK	1702494	1818870	1554267
Worcester, MA	0	0	0

City	Fuel_Oil_Mean_Emissions	Fuel_Oil_Max_Emissions	Fuel_Oil_Min_Emissions
Augusta, GA	0	0	0
Austin, TX	0	0	0
Beaumont, TX	0	0	0
Birmingham, AL	0	0	0
Boston, MA	0	0	0
Chicago, IL	0	0	0
Cincinnati, OH	0	0	0
Cleveland, OH	0	0	0
Colorado Springs, CO	0	0	0
Columbia, SC	0	0	0
Columbus, OH	0	0	0
Dallas, TX	0	0	0
Dayton, OH	0	0	0
Denver, CO	0	0	0
Des Moines, IA	0	0	0
Detroit, MI	0	0	0
Duluth, MN	0	0	0
Eugene, OR	0	0	0
Fort Collins, CO	0	0	0
Fort Wayne, IN	0	0	0
Fort Worth, TX	0	0	0
Fresno, CA	0	0	0
Greensboro, NC	0	0	0
Harrisburg, PA	94245.13888	99157.71212	87044.03273
Houston, TX	0	0	0
Indianapolis, IN	0	0	0
Jackson, MS	0	0	0
Jacksonville, FL	0	0	0
Kansas City, MO	0	0	0
Knoxville, TN	0	0	0
Las Vegas, NV	0	0	0
Louisville, KY	0	0	0
Madison, WI	0	0	0
Miami, FL	0	0	0
Milwaukee, WI	0	0	0
Minneapolis, MN	0	0	0
Nashville, TN	0	0	0
New Orleans, LA	0	0	0
New York, NY	0	0	0
Oakland, CA	0	0	0
Ogden, UT	0	0	0
Oklahoma City, OK	0	0	0

City	Fuel_Oil_Mean_Emissions	Fuel_Oil_Max_Emissions	Fuel_Oil_Min_Emissions
Omaha, NE	0	0	0
Philadelphia, PA	0	0	0
Phoenix, AZ	0	0	0
Portland, ME	0	0	0
Portland, OR	0	0	0
Providence, RI	0	0	0
Reno, NV	0	0	0
Sacramento, CA	0	0	0
Salt Lake City, UT	0	0	0
San Antonio, TX	0	0	0
San Diego, CA	0	0	0
Santa Fe, NM	0	0	0
Savannah, GA	0	0	0
Sioux Falls, SD	0	0	0
Spokane, WA	0	0	0
Springfield, MA	0	0	0
St Louis, MO	0	0	0
Tacoma, WA	0	0	0
Tampa, FL	0	0	0
Tucson, AZ	0	0	0
Tulsa, OK	0	0	0
Worcester, MA	0	0	0

Table A. 8. Annual Wastwater Data

City	Volume_M3	Electricity_MWh	Natural_Gas_therms	Biogas_therms
Augusta, GA	44750305.51	22970.693	95952	0
Beaumont, TX	29879201.69	6687.482	0	0
Buffalo, NY	156390503.1	56110.868	1692810	1062219
Cleveland, OH	299229232	135627.499	12632184	0
Denver, CO	172751052.9	83947.88345	495970	6171819
Detroit, MI	808484466.8	182551.487	16591555.44	0
Duluth, MN	49475332.23	28884.47692	296564	1258609
Greensboro, NC	27173275.77	44812.972	89713	0
Nashville, TN	205120230.3	105683.558	2058747	764700.2
New Orleans, LA	140933099.6	30842.145	0	0
New York, NY	1707183246	612015.78	4991379.701	7214910
Oklahoma City, OK	62796688.45	8490.709825	19633.06	0
Peoria, IL	24749022.35	16187.016	83010	613721
Philadelphia, PA	555179850.8	131883.405	2606060	3419000
Portland, ME	29918600.26	9115.3	3810	0
Salt Lake City, UT	42113349.8	4921.732	99036	666434.4
San Antonio, TX	173116017.8	78570.001	0	2648025
San Jose, CA	148516997.9	30376.622	3812303	3091256
Santa Fe, NM	8045212.401	6852	176113.3	138377.2
Tampa, FL	82590114.65	55471.081	0	1356869
Wichita, KS	40508940.86	32010.17536	51115	0
Albuquerque, NM	78190292.66	13181.6257	2544500	261605.9
Alexandria, VA	46107784.46	40340.30516	514570	841746.9
Austin, TX	142190984.3	63911.96	0	0
Bakersfield, CA	43119528.6	18126.712	166665	10681.1
Boise, ID	38156950.94	23922.641	89989	104602
Boston, MA	404259267.8	128932.724	93038	0
Bridgeport, CT	41494927.07	16821	108747	0
Burlington, VT	5201307.23	1631.128	0	0
Charleston, SC	84558528.79	12341.202	0	0
Charleston, WV	16737463.25	5585.04	32390	0
Cincinnati, OH	141453268.1	66671.047	1538810	0
Colorado Springs, CO	45640710.07	29033.697	0	0
Columbia, SC	44489225.66	19762.169	0	0
Columbus, OH	212475164.3	100545.852	1709125	0
Dallas, TX	115356639.2	53311.241	0	0
Dayton, OH	54809575.55	31584.108	41433	0
El Paso, TX	85334538.21	63293.347	815521	1401414
Eugene, OR	57542044.77	12116.739	0	971493
Fort Collins, CO	17713710.31	10147.2	121032	0
Fort Wayne, IN	56630510.04	18501.6	156646.7	0
Fort Worth, TX	149425315.2	66906.90245	128389.86	1738363

City	Volume_M3	Electricity_MWh	Natural_Gas_therms	Biogas_therms
Greenville, SC	25313694	31351.16	46939	483019
Harrisburg, PA	31029778	13780.32	31400.1	328366.8
Jacksonville, FL	6.2E+08	277955.1	0	0
Kalamazoo, MI	34265358	22816	12730	0
Kansas City, MO	1.47E+08	239355.3	0	0
Las Vegas, NV	54608729	35632.55	77811	1443986
Lincoln, NE	36643713	15419.75	118651.2	882437.6
Louisville, KY	1.84E+08	99792	111580	0
Madison, WI	50802033	27609.56	144841	2021323
Manchester, NH	25115450	13232.9	0	0
Memphis, TN	2.03E+08	120910.2	0	8685180
Miami, FL	4.6E+08	120707.6	0	0
Milwaukee, WI	2.17E+08	81131.92	15376699	1280093
Minneapolis, MN	3.21E+08	177054.8	2733935	0
Newark, NJ	3.09E+08	170894.8	41345.34	0
Norfolk, VA	2.04E+08	127245	1268658	0
Oakland, CA	96884378	39909.26	0	6540562
Ogden, UT	43949010	12647.4	0	0
Phoenix, AZ	2.36E+08	103376.3	0	0
Pittsburgh, PA	2.54E+08	84835.6	823900	0
Providence, RI	60124416	18991.97	151178.8	0
Reno, NV	38810464	30096.79	25863	0
Sacramento, CA	38810464	110911.1	11054	6429888
Salem, OR	62296976	3398.42	79961.63	0
San Diego, CA	2.38E+08	104857.6	2096324	2062782
San Francisco, CA	1.31E+08	63104.09	76638	817858.7
Seattle, WA	1.42E+08	52661.47	0	3208500
Spokane, WA	46757607	16688.34	93343	1377066
Springfield, MA	47450591	15707.81	205010	0
Syracuse, NY	1.04E+08	63628.12	687307	1281696
Tacoma, WA	30842463	2380	0	770492
Tallahassee, FL	22347538	20505.6	293396	0
Toledo, OH	79727208	33163.91	0	471778.5
Tucson, AZ	76962154	103724.3	1994269	581779.9

City	Fuel_Oil_gal
Augusta, GA	0
Beaumont, TX	0
Buffalo, NY	0
Cleveland, OH	0
Denver, CO	0
Detroit, MI	0
Duluth, MN	0
Greensboro, NC	0
Nashville, TN	0
New Orleans, LA	0
New York, NY	4411820.097
Oklahoma City, OK	0
Peoria, IL	0
Philadelphia, PA	0
Portland, ME	55951
Salt Lake City, UT	0
San Antonio, TX	0
San Jose, CA	0
Santa Fe, NM	0
Tampa, FL	0
Wichita, KS	0
Albuquerque, NM	0
Alexandria, VA	0
Austin, TX	0
Bakersfield, CA	0
Boise, ID	0
Boston, MA	365589
Bridgeport, CT	0
Burlington, VT	0
Charleston, SC	0
Charleston, WV	0
Cincinnati, OH	0
Colorado Springs, CO	0
Columbia, SC	0
Columbus, OH	0
Dallas, TX	0
Dayton, OH	0
El Paso, TX	0
Eugene, OR	0
Fort Collins, CO	0
Fort Wayne, IN	0
Fort Worth, TX	0

City	Fuel_Oil_gal
Greenville, SC	0
Harrisburg, PA	0
Jacksonville, FL	0
Kalamazoo, MI	0
Kansas City, MO	0
Las Vegas, NV	0
Lincoln, NE	0
Louisville, KY	0
Madison, WI	0
Manchester, NH	0
Memphis, TN	0
Miami, FL	0
Milwaukee, WI	0
Minneapolis, MN	0
Newark, NJ	0
Norfolk, VA	0
Oakland, CA	0
Ogden, UT	0
Phoenix, AZ	0
Pittsburgh, PA	0
Providence, RI	0
Reno, NV	0
Sacramento, CA	0
Salem, OR	0
San Diego, CA	0
San Francisco, CA	0
Seattle, WA	0
Spokane, WA	0
Springfield, MA	0
Syracuse, NY	0
Tacoma, WA	13660
Tallahassee, FL	0
Toledo, OH	0
Tucson, AZ	0

City	HUC4_2014	HUC4_2016	PCA_NT_2014	PCA_NT_2016	State_2014
Augusta, GA	12204382.06	11968676.72	20962779.57	22009692	15862705
Beaumont, TX	13553084.07	13164800.4	3916685.765	4125520	5852933
Buffalo, NY	20577739.96	28368659.02	10074800.16	12964813	9671723
Cleveland, OH	261077663.2	305632615.2	56659969.9	61655794	88129777
Denver, CO	127557739.7	133750503.7	168109086.7	1.84E+08	56194412
Detroit, MI	420145982	464214722.9	106915698.7	1.13E+08	90853413
Duluth, MN	85895155.96	99853236.46	16916893.32	17818888	32068570
Greensboro, NC	43307108.04	52288066.39	12641291.33	12685016	30698922
Nashville, TN	248211270	299954408.5	38926415.32	48066563	1.34E+08
New Orleans, LA	36432237.83	44216733.2	18063449.04	19026577	24559674
New York, NY	662985183.7	748432178.1	514874434.6	5.89E+08	8.16E+08
Oklahoma City, OK	6361177.566	8477034.372	6924720.216	7221764	3704331
Peoria, IL	10867666.23	10494255.58	16242632.64	17344362	5855720
Philadelphia, PA	89164606.21	118034479.1	55095830.95	59953742	2.07E+08
Portland, ME	2603866.307	2844044.283	2223796.539	2519367	2242203
Salt Lake City, UT	5175923.098	6199461.058	4610674.983	4964526	5275142
San Antonio, TX	102689886.8	109116829	37006842.68	37324759	38236542
San Jose, CA	23757046.85	31073049.29	5190570.275	7074064	5465562
Santa Fe, NM	4808828.972	5943264.752	0	0	4753166
Tampa, FL	32100035.59	32165556.79	67246449.62	67290124	25730433
Wichita, KS	26753589.97	44500485.93	17953909.38	20491741	28007074
Albuquerque, NM	22380315.75	24144952.15	11088989.49	11097274	9143967
Alexandria, VA	49213925.02	54655874.86	16852633.08	18338564	96422484
Austin, TX	118488339.2	117004831.4	30102835.93	30361442	31103122
Bakersfield, CA	13333820.63	16222906.88	15819440.45	19440903	3261477
Boise, ID	1895025.725	3365054.11	3642560.935	4892748	12539379
Boston, MA	144893481.5	170333731.5	31454822.71	35635561	1.28E+08
Bridgeport, CT	8973036.405	10075502.3	4103702.74	4649136	6553839
Burlington, VT	110350.0036	192473.1668	397934.9886	450825.5	323206.9
Charleston, SC	4698650.993	4591555.136	14716192.54	15028115	3286353
Charleston, WV	12214612.11	13281586.01	2333215.613	2538940	4999715
Cincinnati, OH	140658502.6	153325711.2	27852607.65	30308428	1.58E+08
Colorado Springs, CO	42340930.41	45125887.71	41856713.2	45097325	19435053
Columbia, SC	16927963.77	17980669.1	34185712.27	35930978	5262491
Columbus, OH	235086487.8	256594979.1	42004202.61	45707798	65333974
Dallas, TX	122712374.2	113277502.3	69957713.69	70206931	25944221
Dayton, OH	44536828.2	54071467.27	13194629.57	14358027	20523127
El Paso, TX	60142272.75	59451307.28	31744903.66	28497411	74708055
Eugene, OR	11040395.44	11877759.07	3231067.468	3845573	1530343
Fort Collins, CO	16419561.11	16750468.41	14628810.11	15761395	16181597
Fort Wayne, IN	26147866.48	27697641.31	10835910.04	11413672	27481997
Fort Worth, TX	154007010.5	142166017.1	87798630.04	88111403	32560628

City	HUC4_2014	HUC4_2016	PCA_NT_2014	PCA_NT_2016	State_2014
Greenville, SC	35740859	34033182	32607561	32828002	33340883
Harrisburg, PA	12208555	11685168	5756889	6264486	5140644
Jacksonville, FL	4.45E+08	5.16E+08	2.02E+08	2.16E+08	2.47E+08
Kalamazoo, MI	11748520	12905285	13362743	14075233	11355215
Kansas City, MO	9.61E+08	9.76E+08	1.34E+08	1.53E+08	2.94E+08
Las Vegas, NV	24274772	3.24E+08	38476590	2.33E+08	33430945
Lincoln, NE	34661378	36589344	8648648	9871157	9228094
Louisville, KY	2.73E+08	2.79E+08	1.46E+08	1.56E+08	1.71E+08
Madison, WI	56263275	55354132	16170206	17032388	28368545
Manchester, NH	8849627	10137719	3228338	3657424	6314083
Memphis, TN	2.25E+08	2.27E+08	44534860	54991904	1.63E+08
Miami, FL	34748494	35010600	2.17E+08	2.09E+08	55990595
Milwaukee, WI	88187042	97684092	47516875	50050436	54012433
Minneapolis, MN	3.96E+08	4.34E+08	1.04E+08	1.09E+08	1.97E+08
Newark, NJ	1.85E+08	2.09E+08	1.44E+08	1.64E+08	2.28E+08
Norfolk, VA	1.41E+08	1.7E+08	53158100	57845157	87168635
Oakland, CA	30648786	42282402	6819449	9294012	7180737
Ogden, UT	5418918	7149745	9829269	10251678	14439863
Phoenix, AZ	3.93E+08	3.16E+08	2.67E+08	3.2E+08	44487248
Pittsburgh, PA	2.09E+08	2.05E+08	35441062	38565971	1.63E+08
Providence, RI	17094762	19110992	19994633	20973334	18238272
Reno, NV	38140758	38012663	11037206	1.7E+08	15285276
Sacramento, CA	98580992	1.26E+08	1.01E+08	7.18E+08	56328477
Salem, OR	3096535	3331393	1114912	1130717	429220.1
San Diego, CA	47669714	50174445	17917427	24419094	18866675
San Francisco, CA	48461525	66856471	10782839	14695589	11354103
Seattle, WA	13048611	15655866	16326363	17611883	4838566
Spokane, WA	1023836	1244552	1615842	1752610	2700180
Springfield, MA	7360990	8428853	3832125	4341463	8935995
Syracuse, NY	35178615	41916974	11424535	14701727	10967457
Tacoma, WA	589723.2	707556.4	737859	795957.3	218675.7
Tallahassee, FL	24281709	28821168	8563424	9171520	18211530
Toledo, OH	19483489	21951665	13854612	15076201	38054905
Tucson, AZ	3.1E+08	2.19E+08	1.67E+08	1.77E+08	44637017

City	State_2016	PCA_T_2014	PCA_T_2016	HUC4_Bal_2014	HUC4_Bal_2016
Augusta, GA	17299042.66	6754533.508	7299759.436	11569093	12431051
Beaumont, TX	6289017.782	3677625.128	3707573.876	4125401	4382252
Buffalo, NY	12617927.97	5103778.681	6024324.77	12965054	13682743
Cleveland, OH	91666551.55	84946889.27	89789723.8	61657276	67700261
Denver, CO	61187978.27	55424394.33	60136258.29	54453363	57532288
Detroit, MI	104382924.1	88341861	103134348.6	1.13E+08	1.2E+08
Duluth, MN	34439170.84	15419048.14	17702419.16	17818375	18927762
Greensboro, NC	35241815.09	16060989.53	17631268.12	12686765	14671679
Nashville, TN	147232741.8	64034607.4	71040629.48	48096734	52769275
New Orleans, LA	26707116.28	12259726.48	13217792.5	19026030	20210606
New York, NY	933496051.3	164937533.6	192900194	2.64E+08	2.88E+08
Oklahoma City, OK	4560457.286	3481145.3	4237096.909	5431273	5766185
Peoria, IL	6610114.262	5963866.579	6831162.476	8668888	9335218
Philadelphia, PA	204086392.7	38517813.57	42423808.19	59955183	65831347
Portland, ME	3176725.517	2446364.01	2779270.914	2518818	2396648
Salt Lake City, UT	27590015.95	3604827.324	3777187.774	3721408	3680304
San Antonio, TX	38924727.22	48643949	47427162.92	37324833	40672202
San Jose, CA	7367209.409	4984161.8	7178859.274	7075657	7438558
Santa Fe, NM	5187759.592	2468510.979	3355454.449	0	0
Tampa, FL	26149677.88	26194577.76	26484922.41	32986880	35244802
Wichita, KS	36429529.87	13098255.06	18001899.15	20491403	21745750
Albuquerque, NM	9980021.185	11375569.57	12107513.12	11090263	11208500
Alexandria, VA	97135755.06	16130620.73	17237452.83	18339005	20136397
Austin, TX	31662919.4	35251448.9	33937006.85	30361502	33084385
Bakersfield, CA	4396251.933	3529974.293	4445467.361	4281346	4496431
Boise, ID	120698375.2	3314626.994	5367607.198	2800172	2833626
Boston, MA	149018884.1	34757065.63	39369629.08	35627800	33899746
Bridgeport, CT	7750146.686	5107304.366	5836236.947	4648123	4422676
Burlington, VT	424831.6587	252605.8779	328763.6344	450727.3	428865.7
Charleston, SC	3667203.176	2734653.718	3046590.384	6572264	7217786
Charleston, WV	4984710.53	4413702.074	4405550.091	2539001	2787847
Cincinnati, OH	164102753.5	53908749.61	55203599.28	30309157	33279736
Colorado Springs, CO	21162096.63	18371399.99	20366019.44	23518768	23265524
Columbia, SC	5872352.541	7000215.302	7477766.669	5880751	6697756
Columbus, OH	67955920.4	70349174.7	72803410.85	45708897	50188793
Dallas, TX	26411168.22	32609150.29	31443383.33	25422617	27697242
Dayton, OH	21346749.63	23923031.95	24951386.01	14358372	15765626
El Paso, TX	79276862.19	25695806.15	26566443.66	30439185	33795925
Eugene, OR	1683693.342	594930.2571	777442.5238	1499231	1521958
Fort Collins, CO	16766490.17	7296072.31	7766403.399	8219747	8131239
Fort Wayne, IN	28242319.78	9172632.649	10418183.32	11413343	12123947
Fort Worth, TX	33146657.68	40925275.73	39462209.88	31906002	34760711

City	State_2016	PCA_T_2014	PCA_T_2016	HUC4_Bal_2014	HUC4_Bal_2016
Greenville, SC	36240222	10949744	11052340	9008891	10411675
Harrisburg, PA	5708180	5197016	5547812	6264637	6878629
Jacksonville, FL	2.58E+08	1.39E+08	1.45E+08	2.15E+08	2.27E+08
Kalamazoo, MI	13046187	9776877	11471970	14074828	14951138
Kansas City, MO	3.24E+08	1.56E+08	1.69E+08	1.53E+08	1.63E+08
Las Vegas, NV	1.97E+08	8529507	1.5E+08	10862960	8954077
Lincoln, NE	9393289	10608970	11305237	9870994	10475230
Louisville, KY	1.78E+08	85884812	88404918	61581753	65412572
Madison, WI	29848398	8456175	9626636	17031898	18092318
Manchester, NH	7728348	3414303	3809117	3656628	3479270
Memphis, TN	1.65E+08	64623622	69580572	55026421	60372173
Miami, FL	56902891	46602279	46616091	38917852	38791634
Milwaukee, WI	54579900	26339309	29665757	50048995	53165085
Minneapolis, MN	2.11E+08	77964388	86408041	1.09E+08	1.16E+08
Newark, NJ	2.61E+08	46055935	53864021	73756511	80535841
Norfolk, VA	1E+08	48933983	54663553	57846547	63516046
Oakland, CA	9679151	7123697	11378232	9296105	9772890
Ogden, UT	72164718	8361479	8864204	10246095	10186416
Phoenix, AZ	48195668	34804333	40969540	24508343	25758659
Pittsburgh, PA	1.68E+08	56375038	59211987	38566899	42346813
Providence, RI	19811488	5523389	6384118	5248026	4993481
Reno, NV	1.52E+08	4724454	7682929	1.69E+08	14680940
Sacramento, CA	5.6E+08	19967393	30859089	33512477	27505195
Salem, OR	472230.8	730934	807298.9	408524.9	420791.1
San Diego, CA	25431008	24868475	28547476	24424593	25677299
San Francisco, CA	15304567	11263912	17991135	14698899	15452787
Seattle, WA	5205396	6285008	6538914	6294751	6475237
Spokane, WA	3320755	303141.3	158556.8	1473076	1168496
Springfield, MA	9985746	4617957	5268735	4340517	4129989
Syracuse, NY	14308370	7039347	8752608	14702001	15515840
Tacoma, WA	235254.4	284046.7	295521.8	284487.1	292644
Tallahassee, FL	19015903	7543812	8444177	9272422	9189793
Toledo, OH	41377615	14508486	17046500	15076563	16554206
Tucson, AZ	48357921	18850649	22560954	84680634	86763910

City	State_Bal_2014	State_Bal_2016	Intercon_2014	Intercon_2016	eGrid_2014
Augusta, GA	4348603.748	4284806.572	10707418.95	11559349	18625842
Beaumont, TX	3405157.432	3334913.581	6039745.42	6320774	9418258
Buffalo, NY	5491204.293	8936625.583	26155178.31	28236201	5944238
Cleveland, OH	45488349.24	56167358.25	63220576.45	68250687	75069798
Denver, CO	54310525.6	63512419.57	29526169.37	53934087	51607330
Detroit, MI	106957619.5	120268544.1	85093438.47	91863851	1.08E+08
Duluth, MN	11610381.91	16989567.42	13464034.17	14535293	15795146
Greensboro, NC	10251321.33	13290147.23	20888845.87	22550855	39607872
Nashville, TN	64329351.22	72695883.93	49262690.15	53182249	52021968
New Orleans, LA	9399073.548	11761539.66	14376569.65	15520434	43744464
New York, NY	208670316.8	232225339.4	285281308.7	3.08E+08	9.08E+08
Oklahoma City, OK	2136485.895	3006251.031	3957807.772	4272709	4709657
Peoria, IL	10867666.52	10494255.85	7545317.064	8145656	21187107
Philadelphia, PA	34449154.59	39604387.29	61475327.28	66366578	46457388
Portland, ME	865785.2774	1384481.169	4248950.433	4587016	2202540
Salt Lake City, UT	2208533.817	3225656.64	1731072.74	3162070	1410260
San Antonio, TX	29352103.35	30870828.67	34335720.76	34723491	36968075
San Jose, CA	5639618.41	8136513.534	10684072.66	19516101	6515217
Santa Fe, NM	3327977.757	5363902.836	2409987.056	4402212	3292823
Tampa, FL	31354669.45	31418669.25	25856951.9	27914246	25320571
Wichita, KS	7571977.756	13543224.76	14921028.21	16108212	35776786
Albuquerque, NM	6500752.518	10193693.42	4636244.501	8468813	10111641
Alexandria, VA	20088335.69	20356071.86	18803984.19	20300113	49865032
Austin, TX	39744472.44	39309095.79	57721571.09	60407346	30071301
Bakersfield, CA	4458604.705	6839506.455	6375531.421	11645888	3887841
Boise, ID	5175545.999	12669868.79	8414076.936	15369605	6854732
Boston, MA	41080763.05	46738245.34	60099914.8	64881732	31154160
Bridgeport, CT	3407169.927	3787511.523	7840838.505	8464691	10127778
Burlington, VT	607938.1059	698507.6493	760324.0728	820818.8	566928.7
Charleston, SC	4698650.854	4591555	5752652.746	6210359	4076898
Charleston, WV	4749793.934	4572020.876	2603376.534	2810513	3091319
Cincinnati, OH	44171663.74	47109595.77	31077635.84	33550311	69720754
Colorado Springs, CO	22069192.14	23540186.71	10211738.76	18653311	17848593
Columbia, SC	7460475.129	7376192.747	9211817.112	9944750	6528404
Columbus, OH	51876463.63	57064448.6	46867831.16	50596844	55652112
Dallas, TX	22332348.75	23585553.8	23297440.01	23560549	25083542
Dayton, OH	17473834.47	19133276.9	14722423.77	15893805	17481799
El Paso, TX	26431656.12	38500955.95	49921251.35	68636220	60196726
Eugene, OR	5633335.196	8381076.222	4261702.299	7784654	3471899
Fort Collins, CO	6800516.092	7810922.821	3568975.578	6519283	6238036
Fort Wayne, IN	13286484.61	14111891.47	8624223.155	9310405	10240633
Fort Worth, TX	28027640.17	29600442.93	29238853.13	29569062	31480455

City	State_Bal_2014	State_Bal_2016	Intercon_2014	Intercon_2016	eGrid_2014
Greenville, SC	9378496	9185234	14613840	15776582	25421166
Harrisburg, PA	2411948	2925086	6423474	6934555	4854270
Jacksonville, FL	1.57E+08	1.66E+08	1.3E+08	1.4E+08	2.6E+08
Kalamazoo, MI	11639081	12717023	10635311	11481504	26134093
Kansas City, MO	1.6E+08	1.68E+08	1.12E+08	1.2E+08	3.16E+08
Las Vegas, NV	10290460	1.88E+08	12532690	22892885	34976291
Lincoln, NE	10613697	11419342	7187667	7759550	8432112
Louisville, KY	89827719	93911526	46516435	50217490	1.04E+08
Madison, WI	10392963	10262003	12869751	13893726	37875474
Manchester, NH	5811807	6368768	6168302	6659079	3197480
Memphis, TN	65270191	66930440	56360366	60844648	1.06E+08
Miami, FL	34646133	34914628	56265906	60742672	55098716
Milwaukee, WI	27398653	30564103	37818340	40827336	44906505
Minneapolis, MN	96386221	1.05E+08	82531254	89097808	96820405
Newark, NJ	58267553	64844883	79659839	85997930	2.53E+08
Norfolk, VA	55354693	67920768	59313228	64032453	42035213
Oakland, CA	14346469	18959143	14036896	25640548	8559791
Ogden, UT	5363264	8127726	4448347	8125589	3623954
Phoenix, AZ	30505568	45987696	36359523	66416257	49678886
Pittsburgh, PA	69474859	68269480	39544750	42691106	76840769
Providence, RI	6669647	7408727	8852803	9557172	4589052
Reno, NV	15303042	19562057	10585651	19336320	15079058
Sacramento, CA	11822782	27505665	39009672	71257163	55568530
Salem, OR	1419092	2369183	1195293	2183387	973774.6
San Diego, CA	38291227	56068818	36880551	67367995	72880781
San Francisco, CA	22684479	29977989	22194985	40542553	13534647
Seattle, WA	20328281	33793053	18522106	33833473	15089483
Spokane, WA	586931.4	714662.1	5869628	10721778	4781835
Springfield, MA	5884105	6659490	7321943	7904509	3795496
Syracuse, NY	5101173	7117055	29659224	32019044	6740596
Tacoma, WA	918723	1527254	837094.2	1529081	681959.1
Tallahassee, FL	8689847	9589076	9558356	10318861	19213095
Toledo, OH	19379608	21834624	15458824	16688797	37986886
Tucson, AZ	43676894	69570389	36481929	66639851	49846133

City	eGrid_2016
Augusta, GA	20310377.23
Beaumont, TX	9864515.951
Buffalo, NY	8201181.328
Cleveland, OH	79562670.65
Denver, CO	56642980.57
Detroit, MI	121281638.7
Duluth, MN	17990118.62
Greensboro, NC	43190902.16
Nashville, TN	60475093.66
New Orleans, LA	46448335.57
New York, NY	1013032640
Oklahoma City, OK	5236006.424
Peoria, IL	21450283.22
Philadelphia, PA	47238666.76
Portland, ME	2496572.636
Salt Lake City, UT	1635730.203
San Antonio, TX	37405528.8
San Jose, CA	8634814.044
Santa Fe, NM	10591658.92
Tampa, FL	25772240.93
Wichita, KS	41957360.11
Albuquerque, NM	24756737.46
Alexandria, VA	53329425
Austin, TX	30427143.06
Bakersfield, CA	5152672.583
Boise, ID	7950653.635
Boston, MA	35313145.01
Bridgeport, CT	12371376.63
Burlington, VT	685152.7859
Charleston, SC	4654819.656
Charleston, WV	3276331.875
Cincinnati, OH	77262037.44
Colorado Springs, CO	19590191.77
Columbia, SC	7453838.994
Columbus, OH	58982850.58
Dallas, TX	25380363.18
Dayton, OH	18528071.38
El Paso, TX	127969987.4
Eugene, OR	4026979.921
Fort Collins, CO	6846719.999
Fort Wayne, IN	10853526.89
Fort Worth, TX	31852972.32

City	eGrid_2016
Greenville, SC	27720276
Harrisburg, PA	4935905
Jacksonville, FL	2.7E+08
Kalamazoo, MI	28542722
Kansas City, MO	3.43E+08
Las Vegas, NV	77051238
Lincoln, NE	9603881
Louisville, KY	1.16E+08
Madison, WI	38219801
Manchester, NH	3624333
Memphis, TN	1.15E+08
Miami, FL	56081571
Milwaukee, WI	47594127
Minneapolis, MN	1.1E+08
Newark, NJ	2.83E+08
Norfolk, VA	47993924
Oakland, CA	11344549
Ogden, UT	4203344
Phoenix, AZ	1.6E+08
Pittsburgh, PA	80153647
Providence, RI	5201677
Reno, NV	18557895
Sacramento, CA	68388553
Salem, OR	1129460
San Diego, CA	1.92E+08
San Francisco, CA	17937876
Seattle, WA	17501961
Spokane, WA	5546346
Springfield, MA	4302183
Syracuse, NY	9299905
Tacoma, WA	790989.4
Tallahassee, FL	19923572
Toledo, OH	41487919
Tucson, AZ	1.6E+08

City	Nat_Gas_IPCC_Avg	Nat_Gas_IPCC_Min	Nat_Gas_IPCC_Max	Nat_Gas_EPA
Augusta, GA	568346.095	549739.9433	591721.695	505640.1
Beaumont, TX	0	0	0	0
Buffalo, NY	10026908.8	9698654.259	10439307.18	8920634
Cleveland, OH	74823374.69	72373854.8	77900797.56	66568069
Denver, CO	2937746.089	2841572.033	3058573.131	2613623
Detroit, MI	98275655.98	95058370.28	102317651.6	87432846
Duluth, MN	1756617.802	1699110.769	1828866.024	1562809
Greensboro, NC	531391.0416	513994.7008	553246.7111	472762.4
Nashville, TN	12194439.07	11795225.31	12695986.16	10849020
New Orleans, LA	0	0	0	0
New York, NY	29565107.16	28597223.55	30781095.31	26303172
Oklahoma City, OK	116291.1975	112484.1305	121074.1573	103460.7
Peoria, IL	491687.6078	475591.0528	511910.3083	437439.4
Philadelphia, PA	15436301.74	14930957.94	16071183.93	13733206
Portland, ME	22567.51941	21828.71836	23495.70262	20077.63
Salt Lake City, UT	586613.3469	567409.1736	610740.2637	521892
San Antonio, TX	0	0	0	0
San Jose, CA	22581160.61	21841912.99	23509904.88	20089768
Santa Fe, NM	1043160.188	1009009.875	1086064.495	928067.7
Tampa, FL	0	0	0	0
Wichita, KS	302766.0773	292854.3147	315218.593	269361.7
Albuquerque, NM	15071667.49	14578260.86	15691552.58	13408802
Alexandria, VA	3047918.231	2948137.43	3173276.561	2711640
Austin, TX	0	0	0	0
Bakersfield, CA	987195.7013	954877.5185	1027798.236	878277.8
Boise, ID	533025.854	515575.9938	554948.762	474216.8
Boston, MA	551085.7928	533044.6978	573751.4909	490284.2
Bridgeport, CT	644133.8669	623046.6235	670626.5546	573066.2
Burlington, VT	0	0	0	0
Charleston, SC	0	0	0	0
Charleston, WV	191853.5311	185572.7527	199744.3065	170686.2
Cincinnati, OH	9114730.85	8816338.609	9489612.113	8109097
Colorado Springs, CO	0	0	0	0
Columbia, SC	0	0	0	0
Columbus, OH	10123546.35	9792128.154	10539919.35	9006610
Dallas, TX	0	0	0	0
Dayton, OH	245417.3311	237383.0152	255511.1409	218340.3
El Paso, TX	4830521.258	4672382.736	5029196.561	4297567
Eugene, OR	0	0	0	0
Fort Collins, CO	716900.7897	693431.3492	746386.3201	637804.7
Fort Wayne, IN	927854.9717	897479.4478	966016.8713	825484.2
Fort Worth, TX	760483.1121	735586.9014	791761.147	676578.6

City	Nat_Gas_IPCC_Avg	Nat_Gas_IPCC_Min	Nat_Gas_IPCC_Max	Nat_Gas_EPA
Greenville, SC	278030.7	268928.7	289465.8	247355.4
Harrisburg, PA	185990.1	179901.3	193639.7	165469.7
Jacksonville, FL	0	0	0	0
Kalamazoo, MI	75402.76	72934.27	78504.01	67083.53
Kansas City, MO	0	0	0	0
Las Vegas, NV	460892.7	445804.3	479848.8	410042.2
Lincoln, NE	702798.9	679791.2	731704.5	625258.7
Louisville, KY	660914.4	639277.8	688097.2	587995.3
Madison, WI	857927.1	829840.8	893212.9	763271.5
Manchester, NH	0	0	0	0
Memphis, TN	0	0	0	0
Miami, FL	0	0	0	0
Milwaukee, WI	91079778	88098066	94825813	81030893
Minneapolis, MN	16193735	15663595	16859770	14407071
Newark, NJ	244898.1	236880.8	254970.5	217878.3
Norfolk, VA	7514557	7268551	7823625	6685472
Oakland, CA	0	0	0	0
Ogden, UT	0	0	0	0
Phoenix, AZ	0	0	0	0
Pittsburgh, PA	4880152	4720389	5080869	4341722
Providence, RI	895467.5	866152.2	932297.3	796670
Reno, NV	153192.6	148177.5	159493.3	136290.8
Sacramento, CA	65475.42	63331.93	68168.37	58251.48
Salem, OR	473631.4	458126	493111.5	421375.4
San Diego, CA	12417016	12010516	12927718	11047040
San Francisco, CA	453944.8	439083.8	472615.1	403860.8
Seattle, WA	0	0	0	0
Spokane, WA	552892.4	534792.1	575632.4	491891.4
Springfield, MA	1214322	1174568	1264266	1080345
Syracuse, NY	4071080	3937803	4238520	3621915
Tacoma, WA	0	0	0	0
Tallahassee, FL	1737853	1680960	1809329	1546115
Toledo, OH	0	0	0	0
Tucson, AZ	11812522	11425811	12298361	10509240

City	BioGas_IPCC_Avg	BioGas_IPCC_Min	BioGas_IPCC_Max	BioGas_EPA
Augusta, GA	0	0	0	0
Beaumont, TX	0	0	0	0
Buffalo, NY	6123706.098	5178244.097	7413280.073	3521276
Cleveland, OH	0	0	0	0
Denver, CO	35580615.34	30087190.4	43073436.65	20459694
Detroit, MI	0	0	0	0
Duluth, MN	7255896.955	6135631.752	8783895.806	4172312
Greensboro, NC	0	0	0	0
Nashville, TN	4408506.37	3727860.501	5336881.278	2534995
New Orleans, LA	0	0	0	0
New York, NY	41594049.17	35172187.58	50353222.54	23917561
Oklahoma City, OK	0	0	0	0
Peoria, IL	3538109.401	2991847.392	4283189.869	2034496
Philadelphia, PA	19710578.66	16667388.33	23861373.76	11334048
Portland, ME	0	0	0	0
Salt Lake City, UT	3842003.107	3248821.807	4651079.693	2209243
San Antonio, TX	15265897.94	12908938.57	18480700.28	8778252
San Jose, CA	17821131.75	15069660.24	21574033.56	10247572
Santa Fe, NM	797746.4344	674579.3639	965741.6034	458723
Tampa, FL	7822369.361	6614644.354	9469660.037	4498047
Wichita, KS	0	0	0	0
Albuquerque, NM	1508161.08	1275310.422	1825760.463	867228.2
Alexandria, VA	4852681.799	4103458.017	5874594.357	2790407
Austin, TX	0	0	0	0
Bakersfield, CA	61576.67788	52069.62314	74543.9366	35408.04
Boise, ID	603031.8656	509927.5093	730022.6434	346757.6
Boston, MA	0	0	0	0
Bridgeport, CT	0	0	0	0
Burlington, VT	0	0	0	0
Charleston, SC	0	0	0	0
Charleston, WV	0	0	0	0
Cincinnati, OH	0	0	0	0
Colorado Springs, CO	0	0	0	0
Columbia, SC	0	0	0	0
Columbus, OH	0	0	0	0
Dallas, TX	0	0	0	0
Dayton, OH	0	0	0	0
El Paso, TX	8079169.604	6831796.242	9780539.117	4645713
Eugene, OR	5600669.549	4735961.127	6780098.735	3220517
Fort Collins, CO	0	0	0	0
Fort Wayne, IN	0	0	0	0
Fort Worth, TX	10021683.45	8474398.074	12132121.47	5762705

City	BioGas_IPCC_Avg	BioGas_IPCC_Min	BioGas_IPCC_Max	BioGas_EPA
Greenville, SC	2784611	2354684	3371014	1601217
Harrisburg, PA	1893039	1600766	2291689	1088542
Jacksonville, FL	0	0	0	0
Kalamazoo, MI	0	0	0	0
Kansas City, MO	0	0	0	0
Las Vegas, NV	8324596	7039330	10077649	4786839
Lincoln, NE	5087264	4301822	6158577	2925297
Louisville, KY	0	0	0	0
Madison, WI	11652951	9853808	14106914	6700722
Manchester, NH	0	0	0	0
Memphis, TN	50070174	42339651	60614310	28791533
Miami, FL	0	0	0	0
Milwaukee, WI	7379753	6240365	8933834	4243532
Minneapolis, MN	0	0	0	0
Newark, NJ	0	0	0	0
Norfolk, VA	0	0	0	0
Oakland, CA	37706425	31884788	45646915	21682085
Ogden, UT	0	0	0	0
Phoenix, AZ	0	0	0	0
Pittsburgh, PA	0	0	0	0
Providence, RI	0	0	0	0
Reno, NV	0	0	0	0
Sacramento, CA	37068386	31345259	44874513	21315198
Salem, OR	0	0	0	0
San Diego, CA	11891967	10055922	14396263	6838162
San Francisco, CA	4714966	3987005	5707877	2711217
Seattle, WA	18497041	15641213	22392280	10636235
Spokane, WA	7938801	6713100	9610611	4564998
Springfield, MA	0	0	0	0
Syracuse, NY	7388995	6248181	8945023	4248847
Tacoma, WA	4441896	3756095	5377303	2554195
Tallahassee, FL	0	0	0	0
Toledo, OH	2719809	2299888	3292566	1563955
Tucson, AZ	3353969	2836137	4060271	1928611

City	Fuel_Oil_IPCC_Avg	Fuel_Oil_IPCC_Min	Fuel_Oil_IPCC_Max	Fuel_Oil_EPA
Augusta, GA	0	0	0	0
Beaumont, TX	0	0	0	0
Buffalo, NY	0	0	0	0
Cleveland, OH	0	0	0	0
Denver, CO	0	0	0	0
Detroit, MI	0	0	0	0
Duluth, MN	0	0	0	0
Greensboro, NC	0	0	0	0
Nashville, TN	0	0	0	0
New Orleans, LA	0	0	0	0
New York, NY	50196960.12	48859388.11	51484757.81	45195082
Oklahoma City, OK	0	0	0	0
Peoria, IL	0	0	0	0
Philadelphia, PA	0	0	0	0
Portland, ME	636601.2336	619638.055	652933.1707	573167.1
Salt Lake City, UT	0	0	0	0
San Antonio, TX	0	0	0	0
San Jose, CA	0	0	0	0
Santa Fe, NM	0	0	0	0
Tampa, FL	0	0	0	0
Wichita, KS	0	0	0	0
Albuquerque, NM	0	0	0	0
Alexandria, VA	0	0	0	0
Austin, TX	0	0	0	0
Bakersfield, CA	0	0	0	0
Boise, ID	0	0	0	0
Boston, MA	4159611.238	4048772.263	4266325.623	3745127
Bridgeport, CT	0	0	0	0
Burlington, VT	0	0	0	0
Charleston, SC	0	0	0	0
Charleston, WV	0	0	0	0
Cincinnati, OH	0	0	0	0
Colorado Springs, CO	0	0	0	0
Columbia, SC	0	0	0	0
Columbus, OH	0	0	0	0
Dallas, TX	0	0	0	0
Dayton, OH	0	0	0	0
El Paso, TX	0	0	0	0
Eugene, OR	0	0	0	0
Fort Collins, CO	0	0	0	0
Fort Wayne, IN	0	0	0	0
Fort Worth, TX	0	0	0	0

City	Fuel_Oil_IPCC_Avg	Fuel_Oil_IPCC_Min	Fuel_Oil_IPCC_Max	Fuel_Oil_EPA
Greenville, SC	0	0	0	0
Harrisburg, PA	0	0	0	0
Jacksonville, FL	0	0	0	0
Kalamazoo, MI	0	0	0	0
Kansas City, MO	0	0	0	0
Las Vegas, NV	0	0	0	0
Lincoln, NE	0	0	0	0
Louisville, KY	0	0	0	0
Madison, WI	0	0	0	0
Manchester, NH	0	0	0	0
Memphis, TN	0	0	0	0
Miami, FL	0	0	0	0
Milwaukee, WI	0	0	0	0
Minneapolis, MN	0	0	0	0
Newark, NJ	0	0	0	0
Norfolk, VA	0	0	0	0
Oakland, CA	0	0	0	0
Ogden, UT	0	0	0	0
Phoenix, AZ	0	0	0	0
Pittsburgh, PA	0	0	0	0
Providence, RI	0	0	0	0
Reno, NV	0	0	0	0
Sacramento, CA	0	0	0	0
Salem, OR	0	0	0	0
San Diego, CA	0	0	0	0
San Francisco, CA	0	0	0	0
Seattle, WA	0	0	0	0
Spokane, WA	0	0	0	0
Springfield, MA	0	0	0	0
Syracuse, NY	0	0	0	0
Tacoma, WA	155421.2	151279.8	159408.5	139934.3
Tallahassee, FL	0	0	0	0
Toledo, OH	0	0	0	0
Tucson, AZ	0	0	0	0

City	Natural_Gas_Mwh	Fuel_Oil_Mwh	Biogas_Mwh
Augusta, GA	2811.401247	0	0
Beaumont, TX	0	0	0
Buffalo, NY	49599.46791	0	31123.10135
Cleveland, OH	370123.9979	0	0
Denver, CO	14531.96053	0	180834.7886
Detroit, MI	486133.8966	0	0
Duluth, MN	8689.348835	0	36877.34401
Greensboro, NC	2628.59805	0	0
Nashville, TN	60321.45117	0	22405.77656
New Orleans, LA	0	0	0
New York, NY	146247.823	193679.2702	211397.4426
Oklahoma City, OK	575.2502227	0	0
Peoria, IL	2432.199616	0	17982.07421
Philadelphia, PA	76357.76569	0	100176.9725
Portland, ME	111.6333036	2456.253567	0
Salt Lake City, UT	2901.762693	0	19526.58247
San Antonio, TX	0	0	77587.34354
San Jose, CA	111700.7817	0	90574.05449
Santa Fe, NM	5160.133726	0	4054.463545
Tampa, FL	0	0	39756.38128
Wichita, KS	1497.673574	0	0
Albuquerque, NM	74554.05279	0	7665.072326
Alexandria, VA	15076.94201	0	24663.25213
Austin, TX	0	0	0
Bakersfield, CA	4883.297783	0	312.9570812
Boise, ID	2636.684872	0	3064.846936
Boston, MA	2726.020815	16049.38759	0
Bridgeport, CT	3186.295767	0	0
Burlington, VT	0	0	0
Charleston, SC	0	0	0
Charleston, WV	949.0295814	0	0
Cincinnati, OH	45087.25564	0	0
Colorado Springs, CO	0	0	0
Columbia, SC	0	0	0
Columbus, OH	50077.49871	0	0
Dallas, TX	0	0	0
Dayton, OH	1213.990202	0	0
El Paso, TX	23894.83029	0	41061.54189
Eugene, OR	0	0	28464.82232
Fort Collins, CO	3546.247246	0	0
Fort Wayne, IN	4589.760794	0	0
Fort Worth, TX	3761.83313	0	50934.16712

City	Natural_Gas_Mwh	Fuel_Oil_Mwh	Biogas_Mwh
Greenville, SC	1375.316	0	14152.5
Harrisburg, PA	920.0254	0	9621.175
Jacksonville, FL	0	0	0
Kalamazoo, MI	372.99	0	0
Kansas City, MO	0	0	0
Las Vegas, NV	2279.869	0	42308.9
Lincoln, NE	3476.49	0	25855.49
Louisville, KY	3269.303	0	0
Madison, WI	4243.853	0	59224.92
Manchester, NH	0	0	0
Memphis, TN	0	0	254476.5
Miami, FL	0	0	0
Milwaukee, WI	450538.5	0	37506.83
Minneapolis, MN	80104.51	0	0
Newark, NJ	1211.422	0	0
Norfolk, VA	37171.78	0	0
Oakland, CA	0	0	191639
Ogden, UT	0	0	0
Phoenix, AZ	0	0	0
Pittsburgh, PA	24140.34	0	0
Providence, RI	4429.552	0	0
Reno, NV	757.788	0	0
Sacramento, CA	323.8831	0	188396.2
Salem, OR	2342.882	0	0
San Diego, CA	61422.46	0	60439.69
San Francisco, CA	2245.5	0	23963.33
Seattle, WA	0	0	94009.29
Spokane, WA	2734.957	0	40348.14
Springfield, MA	6006.809	0	0
Syracuse, NY	20138.15	0	37553.8
Tacoma, WA	0	599.6751	22575.48
Tallahassee, FL	8596.526	0	0
Toledo, OH	0	0	13823.15
Tucson, AZ	58432.25	0	17046.2

City	Elec_Mean_Emissions	Elec_Max_Emissions	Elec_Min_Emissions
Augusta, GA	13012381.99	22009691.73	4284806.572
Beaumont, TX	6323641.182	13553084.07	3334913.581
Buffalo, NY	13438512.04	28368659.02	5103778.681
Cleveland, OH	97292247.55	305632615.2	45488349.24
Denver, CO	79250879.4	184134533	29526169.37
Detroit, MI	147272839.9	464214722.9	85093438.47
Duluth, MN	27952753.78	99853236.46	11610381.91
Greensboro, NC	24855804.05	52288066.39	10251321.33
Nashville, TN	94046284.11	299954408.5	38926415.32
New Orleans, LA	23435647.33	46448335.57	9399073.548
New York, NY	508133561.4	1013032640	164937533.6
Oklahoma City, OK	4967756.304	8477034.372	2136485.895
Peoria, IL	11119010.66	21450283.22	5855719.523
Philadelphia, PA	77259525.31	207497701	34449154.59
Portland, ME	2596028.053	4587015.848	865785.2774
Salt Lake City, UT	5123299.636	27590015.95	1410260.443
San Antonio, TX	46313967.56	109116829	29352103.35
San Jose, CA	10358192.19	31073049.29	4984161.8
Santa Fe, NM	3494096.653	10591658.92	0
Tampa, FL	33701925.48	67290124	25320570.85
Wichita, KS	23584514.06	44500485.93	7571977.756
Albuquerque, NM	12392827.87	24756737.46	4636244.501
Alexandria, VA	36700354.51	97135755.06	16130620.73
Austin, TX	46814922.56	118488339.2	30071300.55
Bakersfield, CA	7974253.969	19440903.42	3261477.362
Boise, ID	13611478.66	120698375.2	1895025.725
Boston, MA	67611165.19	170333731.5	31154160.09
Bridgeport, CT	6757441.828	12371376.63	3407169.927
Burlington, VT	468765.9359	820818.8415	110350.0036
Charleston, SC	5971518.724	15028115.21	2734653.718
Charleston, WV	4725139.636	13281586.01	2333215.613
Cincinnati, OH	71841478.43	164102753.5	27852607.65
Colorado Springs, CO	25778308.08	45125887.71	10211738.76
Columbia, SC	11949508.38	35930978.01	5262490.593
Columbus, OH	79548386.75	256594979.1	42004202.61
Dallas, TX	43057631.28	122712374.2	22332348.75
Dayton, OH	21891403.39	54071467.27	13194629.57
El Paso, TX	51373435.52	127969987.4	25695806.15
Eugene, OR	4447627.44	11877759.07	594930.2571
Fort Collins, CO	10356639.75	16766490.17	3568975.578
Fort Wayne, IN	15085917.28	28242319.78	8624223.155
Fort Worth, TX	54038373.18	154007010.5	28027640.17

City	Elec_Mean_Emissions	Elec_Max_Emissions	Elec_Min_Emissions
Greenville, SC	21769310	36240222	9008891
Harrisburg, PA	6196078	12208555	2411948
Jacksonville, FL	2.33E+08	5.16E+08	1.3E+08
Kalamazoo, MI	14244858	28542722	9776877
Kansas City, MO	2.94E+08	9.76E+08	1.12E+08
Las Vegas, NV	85828223	3.24E+08	8529507
Lincoln, NE	12854287	36589344	7187667
Louisville, KY	1.25E+08	2.79E+08	46516435
Madison, WI	23734856	56263275	8456175
Manchester, NH	5381539	10137719	3197480
Memphis, TN	99992214	2.27E+08	44534860
Miami, FL	67330627	2.17E+08	34646133
Milwaukee, WI	48772437	97684092	26339309
Minneapolis, MN	1.51E+08	4.34E+08	77964388
Newark, NJ	1.42E+08	2.83E+08	46055935
Norfolk, VA	73179492	1.7E+08	42035213
Oakland, CA	14772679	42282402	6819449
Ogden, UT	11925288	72164718	3623954
Phoenix, AZ	1.19E+08	3.93E+08	24508343
Pittsburgh, PA	87008399	2.09E+08	35441062
Providence, RI	11228223	20973334	4589052
Reno, NV	44975247	1.7E+08	4724454
Sacramento, CA	1.28E+08	7.18E+08	11822782
Salem, OR	1325797	3331393	408524.9
San Diego, CA	46961168	1.92E+08	17917427
San Francisco, CA	23358397	66856471	10782839
Seattle, WA	14834310	33833473	4838566
Spokane, WA	2686389	10721778	158556.8
Springfield, MA	6069381	9985746	3795496
Syracuse, NY	16527779	41916974	5101173
Tacoma, WA	670426.7	1529081	218675.7
Tallahassee, FL	13738017	28821168	7543812
Toledo, OH	22863806	41487919	13854612
Tucson, AZ	1E+08	3.1E+08	18850649

City	Nat_Gas_Mean_Emissions	Nat_Gas_Max_Emissions	Nat_Gas_Min_Emissions
Augusta, GA	553861.9691	591721.695	505640.1432
Beaumont, TX	0	0	0
Buffalo, NY	9771376.104	10439307.18	8920634.18
Cleveland, OH	72916523.94	77900797.56	66568068.69
Denver, CO	2862878.531	3058573.131	2613622.872
Detroit, MI	95771131.04	102317651.6	87432846.29
Duluth, MN	1711850.936	1828866.024	1562809.149
Greensboro, NC	517848.7039	553246.7111	472762.3621
Nashville, TN	11883667.54	12695986.16	10849019.59
New Orleans, LA	0	0	0
New York, NY	28811649.47	30781095.31	26303171.87
Oklahoma City, OK	113327.552	121074.1573	103460.7228
Peoria, IL	479157.1	511910.3083	437439.4311
Philadelphia, PA	15042912.32	16071183.93	13733205.68
Portland, ME	21992.3931	23495.70262	20077.632
Salt Lake City, UT	571663.6858	610740.2637	521891.9587
San Antonio, TX	0	0	0
San Jose, CA	22005686.66	23509904.88	20089768.16
Santa Fe, NM	1016575.57	1086064.495	928067.7238
Tampa, FL	0	0	0
Wichita, KS	295050.1767	315218.593	269361.7217
Albuquerque, NM	14687570.67	15691552.58	13408801.74
Alexandria, VA	2970242.97	3173276.561	2711639.658
Austin, TX	0	0	0
Bakersfield, CA	962037.3216	1027798.236	878277.8313
Boise, ID	519441.8536	554948.762	474216.8047
Boston, MA	537041.5404	573751.4909	490284.1801
Bridgeport, CT	627718.3129	670626.5546	573066.2066
Burlington, VT	0	0	0
Charleston, SC	0	0	0
Charleston, WV	186964.2027	199744.3065	170686.2206
Cincinnati, OH	8882444.73	9489612.113	8109097.348
Colorado Springs, CO	0	0	0
Columbia, SC	0	0	0
Columbus, OH	9865550.88	10539919.35	9006609.657
Dallas, TX	0	0	0
Dayton, OH	239162.9457	255511.1409	218340.2957
El Paso, TX	4707416.906	5029196.561	4297567.067
Eugene, OR	0	0	0
Fort Collins, CO	698630.793	746386.3201	637804.7129
Fort Wayne, IN	904208.8724	966016.8713	825484.1986
Fort Worth, TX	741102.4333	791761.147	676578.5726

City	Nat_Gas_Mean_Emissions	Nat_Gas_Max_Emissions	Nat_Gas_Min_Emissions
Greenville, SC	270945.1	289465.8	247355.4
Harrisburg, PA	181250.2	193639.7	165469.7
Jacksonville, FL	0	0	0
Kalamazoo, MI	73481.15	78504.01	67083.53
Kansas City, MO	0	0	0
Las Vegas, NV	449147	479848.8	410042.2
Lincoln, NE	684888.3	731704.5	625258.7
Louisville, KY	644071.2	688097.2	587995.3
Madison, WI	836063	893212.9	763271.5
Manchester, NH	0	0	0
Memphis, TN	0	0	0
Miami, FL	0	0	0
Milwaukee, WI	88758638	94825813	81030893
Minneapolis, MN	15781043	16859770	14407071
Newark, NJ	238656.9	254970.5	217878.3
Norfolk, VA	7323051	7823625	6685472
Oakland, CA	0	0	0
Ogden, UT	0	0	0
Phoenix, AZ	0	0	0
Pittsburgh, PA	4755783	5080869	4341722
Providence, RI	872646.7	932297.3	796670
Reno, NV	149288.5	159493.3	136290.8
Sacramento, CA	63806.8	68168.37	58251.48
Salem, OR	461561.1	493111.5	421375.4
San Diego, CA	12100573	12927718	11047040
San Francisco, CA	442376.1	472615.1	403860.8
Seattle, WA	0	0	0
Spokane, WA	538802.1	575632.4	491891.4
Springfield, MA	1183375	1264266	1080345
Syracuse, NY	3967330	4238520	3621915
Tacoma, WA	0	0	0
Tallahassee, FL	1693564	1809329	1546115
Toledo, OH	0	0	0
Tucson, AZ	11511484	12298361	10509240

City	Biogas_Mean_Emissions	Biogas_Max_Emissions	Biogas_Min_Emissions
Augusta, GA	0	0	0
Beaumont, TX	0	0	0
Buffalo, NY	5559126.485	7413280.073	3521275.674
Cleveland, OH	0	0	0
Denver, CO	32300234.19	43073436.65	20459694.38
Detroit, MI	0	0	0
Duluth, MN	6586934.17	8783895.806	4172312.164
Greensboro, NC	0	0	0
Nashville, TN	4002060.865	5336881.278	2534995.31
New Orleans, LA	0	0	0
New York, NY	37759255.05	50353222.54	23917560.9
Oklahoma City, OK	0	0	0
Peoria, IL	3211910.788	4283189.869	2034496.491
Philadelphia, PA	17893347.28	23861373.76	11334048.37
Portland, ME	0	0	0
Salt Lake City, UT	3487786.789	4651079.693	2209242.551
San Antonio, TX	13858447.19	18480700.28	8778251.958
San Jose, CA	16178099.33	21574033.56	10247571.77
Santa Fe, NM	724197.6119	965741.6034	458723.0459
Tampa, FL	7101180.233	9469660.037	4498047.18
Wichita, KS	0	0	0
Albuquerque, NM	1369115.054	1825760.463	867228.2499
Alexandria, VA	4405285.212	5874594.357	2790406.675
Austin, TX	0	0	0
Bakersfield, CA	55899.57052	74543.9366	35408.04448
Boise, ID	547434.8968	730022.6434	346757.5689
Boston, MA	0	0	0
Bridgeport, CT	0	0	0
Burlington, VT	0	0	0
Charleston, SC	0	0	0
Charleston, WV	0	0	0
Cincinnati, OH	0	0	0
Colorado Springs, CO	0	0	0
Columbia, SC	0	0	0
Columbus, OH	0	0	0
Dallas, TX	0	0	0
Dayton, OH	0	0	0
El Paso, TX	7334304.587	9780539.117	4645713.386
Eugene, OR	5084311.678	6780098.735	3220517.302
Fort Collins, CO	0	0	0
Fort Wayne, IN	0	0	0
Fort Worth, TX	9097726.933	12132121.47	5762704.738

City	Biogas_Mean_Emissions	Biogas_Max_Emissions	Biogas_Min_Emissions
Greenville, SC	2527881	3371014	1601217
Harrisburg, PA	1718509	2291689	1088542
Jacksonville, FL	0	0	0
Kalamazoo, MI	0	0	0
Kansas City, MO	0	0	0
Las Vegas, NV	7557104	10077649	4786839
Lincoln, NE	4618240	6158577	2925297
Louisville, KY	0	0	0
Madison, WI	10578599	14106914	6700722
Manchester, NH	0	0	0
Memphis, TN	45453917	60614310	28791533
Miami, FL	0	0	0
Milwaukee, WI	6699371	8933834	4243532
Minneapolis, MN	0	0	0
Newark, NJ	0	0	0
Norfolk, VA	0	0	0
Oakland, CA	34230053	45646915	21682085
Ogden, UT	0	0	0
Phoenix, AZ	0	0	0
Pittsburgh, PA	0	0	0
Providence, RI	0	0	0
Reno, NV	0	0	0
Sacramento, CA	33650839	44874513	21315198
Salem, OR	0	0	0
San Diego, CA	10795578	14396263	6838162
San Francisco, CA	4280266	5707877	2711217
Seattle, WA	16791692	22392280	10636235
Spokane, WA	7206878	9610611	4564998
Springfield, MA	0	0	0
Syracuse, NY	6707761	8945023	4248847
Tacoma, WA	4032372	5377303	2554195
Tallahassee, FL	0	0	0
Toledo, OH	2469054	3292566	1563955
Tucson, AZ	3044747	4060271	1928611

City	Fuel_Oil_Mean_Emissions	Fuel_Oil_Max_Emissions	Fuel_Oil_Min_Emissions
Augusta, GA	0	0	0
Beaumont, TX	0	0	0
Buffalo, NY	0	0	0
Cleveland, OH	0	0	0
Denver, CO	0	0	0
Detroit, MI	0	0	0
Duluth, MN	0	0	0
Greensboro, NC	0	0	0
Nashville, TN	0	0	0
New Orleans, LA	0	0	0
New York, NY	48934047.04	51484757.81	45195082.14
Oklahoma City, OK	0	0	0
Peoria, IL	0	0	0
Philadelphia, PA	0	0	0
Portland, ME	620584.8847	652933.1707	573167.0796
Salt Lake City, UT	0	0	0
San Antonio, TX	0	0	0
San Jose, CA	0	0	0
Santa Fe, NM	0	0	0
Tampa, FL	0	0	0
Wichita, KS	0	0	0
Albuquerque, NM	0	0	0
Alexandria, VA	0	0	0
Austin, TX	0	0	0
Bakersfield, CA	0	0	0
Boise, ID	0	0	0
Boston, MA	4054958.936	4266325.623	3745126.619
Bridgeport, CT	0	0	0
Burlington, VT	0	0	0
Charleston, SC	0	0	0
Charleston, WV	0	0	0
Cincinnati, OH	0	0	0
Colorado Springs, CO	0	0	0
Columbia, SC	0	0	0
Columbus, OH	0	0	0
Dallas, TX	0	0	0
Dayton, OH	0	0	0
El Paso, TX	0	0	0
Eugene, OR	0	0	0
Fort Collins, CO	0	0	0
Fort Wayne, IN	0	0	0
Fort Worth, TX	0	0	0

City	Fuel_Oil_Mean_Emissions	Fuel_Oil_Max_Emissions	Fuel_Oil_Min_Emissions
Greenville, SC	0	0	0
Harrisburg, PA	0	0	0
Jacksonville, FL	0	0	0
Kalamazoo, MI	0	0	0
Kansas City, MO	0	0	0
Las Vegas, NV	0	0	0
Lincoln, NE	0	0	0
Louisville, KY	0	0	0
Madison, WI	0	0	0
Manchester, NH	0	0	0
Memphis, TN	0	0	0
Miami, FL	0	0	0
Milwaukee, WI	0	0	0
Minneapolis, MN	0	0	0
Newark, NJ	0	0	0
Norfolk, VA	0	0	0
Oakland, CA	0	0	0
Ogden, UT	0	0	0
Phoenix, AZ	0	0	0
Pittsburgh, PA	0	0	0
Providence, RI	0	0	0
Reno, NV	0	0	0
Sacramento, CA	0	0	0
Salem, OR	0	0	0
San Diego, CA	0	0	0
San Francisco, CA	0	0	0
Seattle, WA	0	0	0
Spokane, WA	0	0	0
Springfield, MA	0	0	0
Syracuse, NY	0	0	0
Tacoma, WA	151511	159408.5	139934.3
Tallahassee, FL	0	0	0
Toledo, OH	0	0	0
Tucson, AZ	0	0	0

Table A. 9. Monthly Drinking Water Data on Boston, Cincinnati, and San Antonio

Month	City	State	Volume.M3	Electricity.MWh	Natural.Gas.therm	Fuel.Oil.gal
1	Boston	MA	21152881.14	2359.913	31908	0
2	Boston	MA	19184467	2461.97	35960	0
3	Boston	MA	20634279.72	2186.868	15221	0
4	Boston	MA	21834255.26	2060.618	43078	0
5	Boston	MA	23147793.16	2088.644	5271	0
6	Boston	MA	24544610.11	2172.809	788	0
7	Boston	MA	29246091.57	2405.718	279	0
8	Boston	MA	28780485.92	2292.248	168	0
9	Boston	MA	26240474.6	1923.414	1311	0
10	Boston	MA	24340197.87	1651.347	7554	0
11	Boston	MA	20974966.78	1927.821	27007	0
12	Boston	MA	21027962.55	2075.975	42554	0
1	Cincinnati	OH	12522142.23	6516.269	25520	0
2	Cincinnati	OH	11481153.99	6182.923	22070	0
3	Cincinnati	OH	12503215.18	6532.537	15860	0
4	Cincinnati	OH	12253378	6482.429	84490	0
5	Cincinnati	OH	14770676.84	7637.587	91650	0
6	Cincinnati	OH	17655160.64	9035.78	87350	0
7	Cincinnati	OH	19854484.89	11150.24	176900	0
8	Cincinnati	OH	18756715.47	9979.883	169170	0
9	Cincinnati	OH	14233148.37	7022.815	92580	0
10	Cincinnati	OH	13267868.36	7432.619	99470	0
11	Cincinnati	OH	12037609.52	6461.528	67110	0
12	Cincinnati	OH	12366940.35	6651.169	14000	0
1	SanAntonio	TX	17919644.05	9242.167	0	0
2	SanAntonio	TX	16216579.85	7187.684	0	0
3	SanAntonio	TX	18488368.44	7528.872	0	0
4	SanAntonio	TX	21488537.29	9043.558	0	0
5	SanAntonio	TX	21218923.28	9611.259	0	0
6	SanAntonio	TX	24824765.3	10915.23	0	0
7	SanAntonio	TX	23971737.57	11349.56	0	0
8	SanAntonio	TX	26470685.93	11726.13	0	0
9	SanAntonio	TX	22304617.75	13105.63	0	0
10	SanAntonio	TX	20245576.28	9559.03	0	0
11	SanAntonio	TX	19671598.37	10600.95	0	0
12	SanAntonio	TX	19191928.2	8812.733	0	0

Month	City	State	CO2e.Min.Kg	CO2e.Average.Kg	CO2e.Max.Kg
1	Boston	MA	0.045841928	0.055037	0.065697
2	Boston	MA	0.051224937	0.061629	0.07517
3	Boston	MA	0.041923287	0.049314	0.060215
4	Boston	MA	0.038314008	0.045924	0.056739
5	Boston	MA	0.031148667	0.038875	0.053551
6	Boston	MA	0.030163044	0.036136	0.04355
7	Boston	MA	0.030003664	0.036785	0.045163
8	Boston	MA	0.0308501	0.037271	0.045461
9	Boston	MA	0.026333825	0.030848	0.036158
10	Boston	MA	0.025754525	0.034175	0.043116
11	Boston	MA	0.032973399	0.04126	0.050585
12	Boston	MA	0.037387388	0.044541	0.054197
1	Cincinnati	OH	0.52341931	0.580399	0.608649
2	Cincinnati	OH	0.548987104	0.58917	0.61475
3	Cincinnati	OH	0.523614973	0.575861	0.607532
4	Cincinnati	OH	0.496909667	0.571587	0.621139
5	Cincinnati	OH	0.51562288	0.568034	0.605467
6	Cincinnati	OH	0.495072862	0.553894	0.592565
7	Cincinnati	OH	0.54249733	0.602717	0.643363
8	Cincinnati	OH	0.536123788	0.57777	0.615082
9	Cincinnati	OH	0.470816356	0.52663	0.557645
10	Cincinnati	OH	0.543928705	0.60627	0.644781
11	Cincinnati	OH	0.517562369	0.580453	0.616157
12	Cincinnati	OH	0.535119744	0.591072	0.633402
1	SanAntonio	TX	0.312950316	0.357793	0.42391
2	SanAntonio	TX	0.250463115	0.305469	0.387371
3	SanAntonio	TX	0.224969147	0.271628	0.357216
4	SanAntonio	TX	0.248887181	0.292538	0.366888
5	SanAntonio	TX	0.262542222	0.304591	0.364688
6	SanAntonio	TX	0.254649717	0.291678	0.344454
7	SanAntonio	TX	0.287936091	0.324586	0.370905
8	SanAntonio	TX	0.270201101	0.302487	0.357471
9	SanAntonio	TX	0.344812111	0.410008	0.481606
10	SanAntonio	TX	0.272594076	0.329044	0.407741
11	SanAntonio	TX	0.294050569	0.359203	0.436564
12	SanAntonio	TX	0.265938134	0.313977	0.375325

Month	City	State	Nat.Gas.IPCC.CO2e.Default.Kg	Nat.Gas.IPCC.CO2e.Min.Kg
1	Boston	MA	0.008934884	0.008642379
2	Boston	MA	0.011102705	0.010739232
3	Boston	MA	0.004369309	0.004226269
4	Boston	MA	0.011686272	0.011303694
5	Boston	MA	0.001348784	0.001304628
6	Boston	MA	0.000190164	0.000183939
7	Boston	MA	5.65E-05	5.47E-05
8	Boston	MA	3.46E-05	3.34E-05
9	Boston	MA	0.000295931	0.000286243
10	Boston	MA	0.00183828	0.0017781
11	Boston	MA	0.007626652	0.007376975
12	Boston	MA	0.011986766	0.011594351
1	Cincinnati	OH	0.01207149	0.011676301
2	Cincinnati	OH	0.011386117	0.011013366
3	Cincinnati	OH	0.007513466	0.007267495
4	Cincinnati	OH	0.040842125	0.039505061
5	Cincinnati	OH	0.036752841	0.03554965
6	Cincinnati	OH	0.029305564	0.028346177
7	Cincinnati	OH	0.052774978	0.051047264
8	Cincinnati	OH	0.053422648	0.051673731
9	Cincinnati	OH	0.038527874	0.037266573
10	Cincinnati	OH	0.044406834	0.042953072
11	Cincinnati	OH	0.033022187	0.031941128
12	Cincinnati	OH	0.006705399	0.006485882
1	SanAntonio	TX	0	0
2	SanAntonio	TX	0	0
3	SanAntonio	TX	0	0
4	SanAntonio	TX	0	0
5	SanAntonio	TX	0	0
6	SanAntonio	TX	0	0
7	SanAntonio	TX	0	0
8	SanAntonio	TX	0	0
9	SanAntonio	TX	0	0
10	SanAntonio	TX	0	0
11	SanAntonio	TX	0	0
12	SanAntonio	TX	0	0

Month	City	State	Nat.Gas.IPCC.CO2e.Max.Kg	Nat.Gas.EPA.CO2e.Kg
1	Boston	MA	0.009302368	0.007949093
2	Boston	MA	0.01155935	0.009877737
3	Boston	MA	0.004549015	0.00388724
4	Boston	MA	0.012166919	0.010396919
5	Boston	MA	0.001404258	0.001199972
6	Boston	MA	0.000197986	0.000169183
7	Boston	MA	5.88E-05	5.03E-05
8	Boston	MA	3.60E-05	3.08E-05
9	Boston	MA	0.000308102	0.00026328
10	Boston	MA	0.001913887	0.001635462
11	Boston	MA	0.007940329	0.006785199
12	Boston	MA	0.012479772	0.01066426
1	Cincinnati	OH	0.012567981	0.010739636
2	Cincinnati	OH	0.011854418	0.01012988
3	Cincinnati	OH	0.007822489	0.006684501
4	Cincinnati	OH	0.042521927	0.03633599
5	Cincinnati	OH	0.038264455	0.032697879
6	Cincinnati	OH	0.030510877	0.026072264
7	Cincinnati	OH	0.054945568	0.046952284
8	Cincinnati	OH	0.055619876	0.047528496
9	Cincinnati	OH	0.040112494	0.034277072
10	Cincinnati	OH	0.04623325	0.039507403
11	Cincinnati	OH	0.034380362	0.02937883
12	Cincinnati	OH	0.006981186	0.005965588
1	SanAntonio	TX	0	0
2	SanAntonio	TX	0	0
3	SanAntonio	TX	0	0
4	SanAntonio	TX	0	0
5	SanAntonio	TX	0	0
6	SanAntonio	TX	0	0
7	SanAntonio	TX	0	0
8	SanAntonio	TX	0	0
9	SanAntonio	TX	0	0
10	SanAntonio	TX	0	0
11	SanAntonio	TX	0	0
12	SanAntonio	TX	0	0

Month	City	State	Fuel.Oil.IPCC.CO2e.Default.Kg	Fuel.Oil.IPCC.CO2e.Min.Kg
1	Boston	MA	0	0
2	Boston	MA	0	0
3	Boston	MA	0	0
4	Boston	MA	0	0
5	Boston	MA	0	0
6	Boston	MA	0	0
7	Boston	MA	0	0
8	Boston	MA	0	0
9	Boston	MA	0	0
10	Boston	MA	0	0
11	Boston	MA	0	0
12	Boston	MA	0	0
1	Cincinnati	OH	0	0
2	Cincinnati	OH	0	0
3	Cincinnati	OH	0	0
4	Cincinnati	OH	0	0
5	Cincinnati	OH	0	0
6	Cincinnati	OH	0	0
7	Cincinnati	OH	0	0
8	Cincinnati	OH	0	0
9	Cincinnati	OH	0	0
10	Cincinnati	OH	0	0
11	Cincinnati	OH	0	0
12	Cincinnati	OH	0	0
1	SanAntonio	TX	0	0
2	SanAntonio	TX	0	0
3	SanAntonio	TX	0	0
4	SanAntonio	TX	0	0
5	SanAntonio	TX	0	0
6	SanAntonio	TX	0	0
7	SanAntonio	TX	0	0
8	SanAntonio	TX	0	0
9	SanAntonio	TX	0	0
10	SanAntonio	TX	0	0
11	SanAntonio	TX	0	0
12	SanAntonio	TX	0	0

Month	City	State	Fuel.Oil.IPCC.CO2e.Max.Kg	Fuel.Oil.EPA.CO2e.Kg
1	Boston	MA	0	0
2	Boston	MA	0	0
3	Boston	MA	0	0
4	Boston	MA	0	0
5	Boston	MA	0	0
6	Boston	MA	0	0
7	Boston	MA	0	0
8	Boston	MA	0	0
9	Boston	MA	0	0
10	Boston	MA	0	0
11	Boston	MA	0	0
12	Boston	MA	0	0
1	Cincinnati	OH	0	0
2	Cincinnati	OH	0	0
3	Cincinnati	OH	0	0
4	Cincinnati	OH	0	0
5	Cincinnati	OH	0	0
6	Cincinnati	OH	0	0
7	Cincinnati	OH	0	0
8	Cincinnati	OH	0	0
9	Cincinnati	OH	0	0
10	Cincinnati	OH	0	0
11	Cincinnati	OH	0	0
12	Cincinnati	OH	0	0
1	SanAntonio	TX	0	0
2	SanAntonio	TX	0	0
3	SanAntonio	TX	0	0
4	SanAntonio	TX	0	0
5	SanAntonio	TX	0	0
6	SanAntonio	TX	0	0
7	SanAntonio	TX	0	0
8	SanAntonio	TX	0	0
9	SanAntonio	TX	0	0
10	SanAntonio	TX	0	0
11	SanAntonio	TX	0	0
12	SanAntonio	TX	0	0

Table A. 10. Monthly Wastewater Data of Boston, Cincinnati, and San Antonio

Month	City	State	Volume.M3	Electricity.MWh	Natural.Gas.therm	Biogas.therm
1	Boston	MA	38845895.89	11679.187	25591	0
2	Boston	MA	32263064.77	10073.465	16116	0
3	Boston	MA	34462389.03	10802.519	12021	0
4	Boston	MA	32342558.42	10650.92	8655	0
5	Boston	MA	36991044.11	11094.101	2224	0
6	Boston	MA	35033986.21	8921.15	195	0
7	Boston	MA	30419569.22	10943.257	43	0
8	Boston	MA	30775397.93	11463.729	35	0
9	Boston	MA	29567851.57	10403.381	289	0
10	Boston	MA	31918592.3	10527.795	3716	0
11	Boston	MA	30835964.52	11190.723	10164	0
12	Boston	MA	40802953.79	11182.497	13989	0
1	Cincinnati	OH	17386396.4	6234.618	244690	0
2	Cincinnati	OH	12117103.17	5212.536	191800	0
3	Cincinnati	OH	18249470.29	6088.33	202730	0
4	Cincinnati	OH	11042046.22	5438.694	140000	0
5	Cincinnati	OH	15285492.85	5478.757	93210	0
6	Cincinnati	OH	8793511.611	5242.74	58340	0
7	Cincinnati	OH	8623168.08	5585.071	58690	0
8	Cincinnati	OH	7850944.073	6211.547	90960	0
9	Cincinnati	OH	9247761.027	5384.626	103360	0
10	Cincinnati	OH	9690654.208	5385.089	88910	0
11	Cincinnati	OH	9088773.732	5010.834	119900	0
12	Cincinnati	OH	14077946.48	5398.205	146220	0
1	SanAntonio	TX	13585589.12	7038.407	0	212296
2	SanAntonio	TX	14645933.73	6587.384	0	259677
3	SanAntonio	TX	14988469.4	6152.58	0	261184
4	SanAntonio	TX	13567886.19	6424.58	0	238342
5	SanAntonio	TX	15604438.66	6223.993	0	208754
6	SanAntonio	TX	13448745.61	7001.031	0	198564
7	SanAntonio	TX	14668590.81	6557.794	0	203960
8	SanAntonio	TX	14673886.03	6609.356	0	211920
9	SanAntonio	TX	15505136.7	6827.017	0	191527
10	SanAntonio	TX	15155580	6026.062	0	198518
11	SanAntonio	TX	13557032.01	6869.357	0	218014
12	SanAntonio	TX	13714729.59	6252.44	0	245269

Month	City	State	Fuel.Oil.gal
1	Boston	MA	23054
2	Boston	MA	33198
3	Boston	MA	13023
4	Boston	MA	3957
5	Boston	MA	4578
6	Boston	MA	19494
7	Boston	MA	27183
8	Boston	MA	10497
9	Boston	MA	54120
10	Boston	MA	84761
11	Boston	MA	36542
12	Boston	MA	55182
1	Cincinnati	OH	0
2	Cincinnati	OH	0
3	Cincinnati	OH	0
4	Cincinnati	OH	0
5	Cincinnati	OH	0
6	Cincinnati	OH	0
7	Cincinnati	OH	0
8	Cincinnati	OH	0
9	Cincinnati	OH	0
10	Cincinnati	OH	0
11	Cincinnati	OH	0
12	Cincinnati	OH	0
1	SanAntonio	TX	0
2	SanAntonio	TX	0
3	SanAntonio	TX	0
4	SanAntonio	TX	0
5	SanAntonio	TX	0
6	SanAntonio	TX	0
7	SanAntonio	TX	0
8	SanAntonio	TX	0
9	SanAntonio	TX	0
10	SanAntonio	TX	0
11	SanAntonio	TX	0
12	SanAntonio	TX	0

Month	City	State	CO2e.Min.Kg	CO2e.Average.Kg	CO2e.Max.Kg
1	Boston	MA	0.123539	0.148318	0.177047
2	Boston	MA	0.12463	0.149944	0.182888
3	Boston	MA	0.123994	0.145853	0.178095
4	Boston	MA	0.133694	0.160247	0.197985
5	Boston	MA	0.103533	0.129215	0.177995
6	Boston	MA	0.086764	0.103944	0.125273
7	Boston	MA	0.131217	0.160873	0.197516
8	Boston	MA	0.144283	0.174314	0.212618
9	Boston	MA	0.126406	0.148073	0.173563
10	Boston	MA	0.125208	0.166144	0.209615
11	Boston	MA	0.130196	0.162915	0.199736
12	Boston	MA	0.103788	0.123646	0.150452
1	Cincinnati	OH	0.360686	0.399951	0.419418
2	Cincinnati	OH	0.438535	0.470633	0.491067
3	Cincinnati	OH	0.334349	0.36771	0.387933
4	Cincinnati	OH	0.462637	0.532164	0.578299
5	Cincinnati	OH	0.35742	0.39375	0.419698
6	Cincinnati	OH	0.576728	0.645251	0.6903
7	Cincinnati	OH	0.625653	0.695104	0.74198
8	Cincinnati	OH	0.797213	0.85914	0.914623
9	Cincinnati	OH	0.555597	0.621461	0.658062
10	Cincinnati	OH	0.539562	0.601402	0.639605
11	Cincinnati	OH	0.531585	0.596179	0.63285
12	Cincinnati	OH	0.381527	0.42142	0.4516
1	SanAntonio	TX	0.31436	0.359404	0.425819
2	SanAntonio	TX	0.254162	0.30998	0.393092
3	SanAntonio	TX	0.226773	0.273806	0.360081
4	SanAntonio	TX	0.280029	0.329141	0.412794
5	SanAntonio	TX	0.231187	0.268214	0.321133
6	SanAntonio	TX	0.301492	0.345331	0.407815
7	SanAntonio	TX	0.271886	0.306493	0.350229
8	SanAntonio	TX	0.274733	0.307561	0.363467
9	SanAntonio	TX	0.258389	0.307245	0.360898
10	SanAntonio	TX	0.229559	0.277097	0.34337
11	SanAntonio	TX	0.276483	0.337743	0.410482
12	SanAntonio	TX	0.264029	0.311722	0.37263

Month	City	State	Nat.Gas.IPCC.CO2e.Default	Nat.Gas.IPCC.CO2e.Min
1	Boston	MA	0.003902	0.003774
2	Boston	MA	0.002959	0.002862
3	Boston	MA	0.002066	0.001998
4	Boston	MA	0.001585	0.001533
5	Boston	MA	0.000356	0.000344
6	Boston	MA	3.30E-05	3.19E-05
7	Boston	MA	8.37E-06	8.10E-06
8	Boston	MA	6.74E-06	6.52E-06
9	Boston	MA	5.79E-05	5.60E-05
10	Boston	MA	0.00069	0.000667
11	Boston	MA	0.001952	0.001888
12	Boston	MA	0.002031	0.001964
1	Cincinnati	OH	0.083361	0.080632
2	Cincinnati	OH	0.093758	0.090689
3	Cincinnati	OH	0.0658	0.063646
4	Cincinnati	OH	0.0751	0.072641
5	Cincinnati	OH	0.03612	0.034937
6	Cincinnati	OH	0.039297	0.038011
7	Cincinnati	OH	0.040314	0.038994
8	Cincinnati	OH	0.068626	0.066379
9	Cincinnati	OH	0.066203	0.064035
10	Cincinnati	OH	0.054345	0.052565
11	Cincinnati	OH	0.07814	0.075582
12	Cincinnati	OH	0.061521	0.059507
1	SanAntonio	TX	0	0
2	SanAntonio	TX	0	0
3	SanAntonio	TX	0	0
4	SanAntonio	TX	0	0
5	SanAntonio	TX	0	0
6	SanAntonio	TX	0	0
7	SanAntonio	TX	0	0
8	SanAntonio	TX	0	0
9	SanAntonio	TX	0	0
10	SanAntonio	TX	0	0
11	SanAntonio	TX	0	0
12	SanAntonio	TX	0	0

Month	City	State	Nat.Gas.IPCC.CO2e.Max	Nat.Gas.EPA.CO2e
1	Boston	MA	0.004063	0.003472
2	Boston	MA	0.00308	0.002632
3	Boston	MA	0.002151	0.001838
4	Boston	MA	0.00165	0.00141
5	Boston	MA	0.000371	0.000317
6	Boston	MA	3.43E-05	2.93E-05
7	Boston	MA	8.72E-06	7.45E-06
8	Boston	MA	7.01E-06	5.99E-06
9	Boston	MA	6.03E-05	5.15E-05
10	Boston	MA	0.000718	0.000614
11	Boston	MA	0.002033	0.001737
12	Boston	MA	0.002114	0.001807
1	Cincinnati	OH	0.08679	0.074164
2	Cincinnati	OH	0.097614	0.083414
3	Cincinnati	OH	0.068506	0.05854
4	Cincinnati	OH	0.078188	0.066814
5	Cincinnati	OH	0.037605	0.032134
6	Cincinnati	OH	0.040914	0.034962
7	Cincinnati	OH	0.041972	0.035866
8	Cincinnati	OH	0.071448	0.061054
9	Cincinnati	OH	0.068925	0.058898
10	Cincinnati	OH	0.05658	0.048349
11	Cincinnati	OH	0.081354	0.069519
12	Cincinnati	OH	0.064052	0.054734
1	SanAntonio	TX	0	0
2	SanAntonio	TX	0	0
3	SanAntonio	TX	0	0
4	SanAntonio	TX	0	0
5	SanAntonio	TX	0	0
6	SanAntonio	TX	0	0
7	SanAntonio	TX	0	0
8	SanAntonio	TX	0	0
9	SanAntonio	TX	0	0
10	SanAntonio	TX	0	0
11	SanAntonio	TX	0	0
12	SanAntonio	TX	0	0

Month	City	State	BioGas.IPCC.CO2e.Default	BioGas.IPCC.CO2e.Min
1	Boston	MA	0	0
2	Boston	MA	0	0
3	Boston	MA	0	0
4	Boston	MA	0	0
5	Boston	MA	0	0
6	Boston	MA	0	0
7	Boston	MA	0	0
8	Boston	MA	0	0
9	Boston	MA	0	0
10	Boston	MA	0	0
11	Boston	MA	0	0
12	Boston	MA	0	0
1	Cincinnati	OH	0	0
2	Cincinnati	OH	0	0
3	Cincinnati	OH	0	0
4	Cincinnati	OH	0	0
5	Cincinnati	OH	0	0
6	Cincinnati	OH	0	0
7	Cincinnati	OH	0	0
8	Cincinnati	OH	0	0
9	Cincinnati	OH	0	0
10	Cincinnati	OH	0	0
11	Cincinnati	OH	0	0
12	Cincinnati	OH	0	0
1	SanAntonio	TX	0.090087	0.076178
2	SanAntonio	TX	0.102215	0.086434
3	SanAntonio	TX	0.100459	0.084949
4	SanAntonio	TX	0.101272	0.085636
5	SanAntonio	TX	0.077124	0.065216
6	SanAntonio	TX	0.085118	0.071976
7	SanAntonio	TX	0.08016	0.067784
8	SanAntonio	TX	0.083258	0.070404
9	SanAntonio	TX	0.071212	0.060218
10	SanAntonio	TX	0.075514	0.063855
11	SanAntonio	TX	0.092709	0.078395
12	SanAntonio	TX	0.103099	0.087181

Month	City	State	BioGas.IPCC.CO2e.Max	BioGas.EPA.CO2e
1	Boston	MA	0	0
2	Boston	MA	0	0
3	Boston	MA	0	0
4	Boston	MA	0	0
5	Boston	MA	0	0
6	Boston	MA	0	0
7	Boston	MA	0	0
8	Boston	MA	0	0
9	Boston	MA	0	0
10	Boston	MA	0	0
11	Boston	MA	0	0
12	Boston	MA	0	0
1	Cincinnati	OH	0	0
2	Cincinnati	OH	0	0
3	Cincinnati	OH	0	0
4	Cincinnati	OH	0	0
5	Cincinnati	OH	0	0
6	Cincinnati	OH	0	0
7	Cincinnati	OH	0	0
8	Cincinnati	OH	0	0
9	Cincinnati	OH	0	0
10	Cincinnati	OH	0	0
11	Cincinnati	OH	0	0
12	Cincinnati	OH	0	0
1	SanAntonio	TX	0.109059	0.051802
2	SanAntonio	TX	0.123741	0.058776
3	SanAntonio	TX	0.121615	0.057766
4	SanAntonio	TX	0.122598	0.058234
5	SanAntonio	TX	0.093365	0.044348
6	SanAntonio	TX	0.103042	0.048945
7	SanAntonio	TX	0.09704	0.046094
8	SanAntonio	TX	0.100791	0.047875
9	SanAntonio	TX	0.086209	0.040949
10	SanAntonio	TX	0.091416	0.043422
11	SanAntonio	TX	0.112232	0.05331
12	SanAntonio	TX	0.124811	0.059285

Month	City	State	Fuel.Oil.IPCC.CO2e.Default	Fuel.Oil.IPCC.CO2e.Min
1	Boston	MA	0.006752	0.006573
2	Boston	MA	0.011708	0.011396
3	Boston	MA	0.0043	0.004185
4	Boston	MA	0.001392	0.001355
5	Boston	MA	0.001408	0.001371
6	Boston	MA	0.006331	0.006162
7	Boston	MA	0.010167	0.009896
8	Boston	MA	0.003881	0.003777
9	Boston	MA	0.020826	0.020271
10	Boston	MA	0.030214	0.029409
11	Boston	MA	0.013483	0.013124
12	Boston	MA	0.015387	0.014977
1	Cincinnati	OH	0	0
2	Cincinnati	OH	0	0
3	Cincinnati	OH	0	0
4	Cincinnati	OH	0	0
5	Cincinnati	OH	0	0
6	Cincinnati	OH	0	0
7	Cincinnati	OH	0	0
8	Cincinnati	OH	0	0
9	Cincinnati	OH	0	0
10	Cincinnati	OH	0	0
11	Cincinnati	OH	0	0
12	Cincinnati	OH	0	0
1	SanAntonio	TX	0	0
2	SanAntonio	TX	0	0
3	SanAntonio	TX	0	0
4	SanAntonio	TX	0	0
5	SanAntonio	TX	0	0
6	SanAntonio	TX	0	0
7	SanAntonio	TX	0	0
8	SanAntonio	TX	0	0
9	SanAntonio	TX	0	0
10	SanAntonio	TX	0	0
11	SanAntonio	TX	0	0
12	SanAntonio	TX	0	0

Month	City	State	Fuel.Oil.IPCC.CO2e.Max	Fuel.Oil.EPA.CO2e
1	Boston	MA	0.006926	0.00608
2	Boston	MA	0.012008	0.010541
3	Boston	MA	0.00441	0.003871
4	Boston	MA	0.001428	0.001253
5	Boston	MA	0.001444	0.001268
6	Boston	MA	0.006493	0.0057
7	Boston	MA	0.010428	0.009154
8	Boston	MA	0.00398	0.003494
9	Boston	MA	0.02136	0.01875
10	Boston	MA	0.030989	0.027204
11	Boston	MA	0.013829	0.01214
12	Boston	MA	0.015782	0.013854
1	Cincinnati	OH	0	0
2	Cincinnati	OH	0	0
3	Cincinnati	OH	0	0
4	Cincinnati	OH	0	0
5	Cincinnati	OH	0	0
6	Cincinnati	OH	0	0
7	Cincinnati	OH	0	0
8	Cincinnati	OH	0	0
9	Cincinnati	OH	0	0
10	Cincinnati	OH	0	0
11	Cincinnati	OH	0	0
12	Cincinnati	OH	0	0
1	SanAntonio	TX	0	0
2	SanAntonio	TX	0	0
3	SanAntonio	TX	0	0
4	SanAntonio	TX	0	0
5	SanAntonio	TX	0	0
6	SanAntonio	TX	0	0
7	SanAntonio	TX	0	0
8	SanAntonio	TX	0	0
9	SanAntonio	TX	0	0
10	SanAntonio	TX	0	0
11	SanAntonio	TX	0	0
12	SanAntonio	TX	0	0

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14. ABSTRACT

Accounting of energy-related GHG emissions in the water sector have largely been conducted at single utilities or cities and rarely at a regional or country scale. In this study, we assess the carbon footprints of operational energy use for 76 wastewater utilities and 64 water utilities across the United States. Additionally, we investigate water-related GHG emissions at a sub-annual scale through three case cities to understand how GHG emissions change at the monthly scale. We estimate the total drinking water and wastewater GHG emissions associated with electricity, biogas, natural gas, and fuel oil consumption across the United States to be 26.5×10^9 and 20.1×10^9 kg CO_{2e} respectively. We find the average GHG emissions per unit drinking water and wastewater emissions to be 0.463 kg CO_{2e}/ m^3 and 0.42 kg CO_{2e}/ m^3, respectively. The research provides insights into operational GHG emissions of the water sector and advances the understanding of temporal variations in the life-cycle of energy use.

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