Carnegie Mellon University

CARNEGIE INSTITUTE OF TECHNOLOGY

THESIS

SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS

FOR THE DEGREE OF Doctor of Philosophy

TITLE Climate Change Decision-Making at the Metropolitan Level: Current Estimates and Future Drivers of Greenhouse Gas Emissions in U.S. Metropolitan Areas

PRESENTED BY Samuel A. Markolf

ACCEPTED BY THE DEPARTMENTS OF

Civil and Environmental Engineering

H. Scott Matthews CO-ADVISOR, MAJOR PROFESSOR	September 18, 2015 DATE
Chris Hendrickson CO-ADVISOR, MAJOR PROFESSOR	September 17, 2015 DATE
David A. Dzombak DEPARTMENT HEAD	September 29, 2015 DATE
Douglas Sicker DEPARTMENT HEAD	September 29, 2015 DATE

APPROVED BY THE COLLEGE COUNCIL

Vijayakumar Bhagavatula DEAN	September 29, 2015 DATE

Climate Change Decision-Making at the Metropolitan Level: Current Estimates and Future Drivers of Greenhouse Gas Emissions in U.S. Metropolitan Areas

Submitted in partial fulfillment of the requirements for the degree of

Doctor of Philosophy

in

Civil and Environmental Engineering

&

Engineering and Public Policy

Samuel A. Markolf

B.S., Chemical Engineering, The University of Texas at Austin
M.S., Civil and Environmental Engineering, Carnegie Mellon University

Carnegie Mellon University
Pittsburgh, PA

September, 2015

COMMITTEE MEMBERS

H. Scott Matthews
Professor, Civil and Environmental Engineering
Professor, Engineering and Public Policy
Carnegie Mellon University
Pittsburgh, PA

Chris Hendrickson
Hamerschlag University Professor
Professor Emeritus, Civil and Environmental Engineering
Carnegie Mellon University
Pittsburgh, PA

Inês Azevedo
Associate Professor, Engineering and Public Policy
Co-Director, Center for Climate and Energy Decision Making
Carnegie Mellon University
Pittsburgh, PA

Michael Blackhurst, PhD
Research Development Manager, University Center for Social & Urban Research
University of Pittsburgh
Pittsburgh, PA

ACKNOWLEDGEMENTS

This research was made possible through the generous support of the Colcom Foundation and the Carnegie Mellon University Steinbrenner Institute U.S. Environmental Sustainability Fellowship Program. Related to this fellowship, I would like to thank John Rohe, Dr. Dave Dzombak, and the other Fellows for their continued intellectual support and stimulating discussions.

I would also like to express my deepest thanks and gratitude to my advisors: Scott Matthews, Chris Hendrickson, and Inês Azevedo. Over the past four years they have given me invaluable support and guidance and have been wonderful mentors and role models. I leave Carnegie Mellon confident that if I apply the same drive, compassion, and caring that they do in their professional and personal lives, I will be well on my way to "living a life worth emulating."

Additionally, I would like thank Dr. Mike Blackhurst for graciously agreeing to serve on my thesis committee and offering terrific feedback and advice. Thank you to Dr. Costa Samaras and Dr. Kelly Klima for their continued mentorship and guidance in matters related to research, teaching, and beyond. Thank you to the staff of EPP and CEE for all the hard work that went into making my time here so comfortable and enjoyable.

Thank you to all of my friends, office mates, roommates and colleagues in and outside of EPP and CEE for bringing so much joy, energy, and excitement to my life on a daily basis.

Last, but certainly not least. I am eternally grateful to all of my family and loved ones. Valerie, thank you so very much for all of the love, laughter, and light you bring into my life. Mom, Dad, and Ian, I can never thank you enough for the never-ending warmth, encouragement, love, and support you have given me. Whether deciding to go to grad school or riding a bike to Alaska, y'all have always been behind me 100% and it has meant the world to me.

ABSTRACT

As concerns and understanding of climate change have continued to grow, cities and local governments have taken a leadership role in developing climate action plans to quantify and reduce greenhouse gas (GHG) emissions. A primary component of most climate action plans is the development of regular or semi-regular GHG inventories. These inventories are typically confined to the city-limits of a given area and report emissions from on-road transportation, electricity generation, residential and commercial buildings, and waste generation and disposal. Although there have been many advances in the data and methods used for forming these inventories, some challenges still remain. For example, the inventories can often be expensive and time consuming, data availability and scope/boundary choices often lead to inconsistencies between inventories across time periods or locations, and over-looked factors like climate and population change may have drastic impacts on emissions in the future. Given these challenges, this thesis seeks to develop a consistent method for evaluating metropolitan-level GHG emissions and some of the key factors that may drive emissions and cities' ability to meet reduction targets moving forward.

First, we use publically available national datasets (e.g. the EPA's National Emissions Inventory, the EPA's Mandatory GHG Reporting Program, etc.) to develop an integrated approach for estimating GHG emissions at the metropolitan level. Overall, this approach allowed us to form consistent production-based GHG estimates for the 100 most populated metropolitan areas in the United States for the years 2002 and 2011. During this time period, the overall GHG emissions for these metropolitan areas decreased by roughly 18%. The largest decreases in emissions were typically driven by decreases in industrial activity, and the largest increases in emissions were typically driven by increases in electricity production and population. We also compared the

emissions estimates from the integrated approach to those reported by the cities in their climate action plans. Overall, the integrated approach generally provides comparable estimates to those reported by the cities. However, this comparison also highlighted some of the uncertainty that can emerge due to scope and boundary choices made while developing an emissions inventory.

Given the uncertainty associated with scope and boundary choices described above, and an increasing push by practitioners to expand their analysis to the regional/mega-regional level (rather than the city-limits), we next sought to gain a better understanding of how scope and boundary decisions impact emission estimates and GHG reduction targets in metropolitan areas. We first identified two categories of under-reported emissions from GHG inventories: 1) "under-reported activities" (industrial processes and transportation between urban and suburban areas), and 2) "under-reported geographies" (emissions within a metropolitan statistical area but outside of the central city/urban core). Using the integrated data from the previous analysis, we found that, on average, under-reported activities account for an additional 24% of emissions and under-reported geographies represent 55% of total metropolitan GHG emissions.

Up to this point, our analysis focused entirely on recent (2011) and past (2002) emissions. However, given the forward looking nature of GHG reduction targets, it is also important to look at how different factors might impact metropolitan GHG emissions and policies in the future. For this component of the analysis, we investigated the implications that projected climatic temperature change, population changes, and the EPA's Clean Power Plan would have on electricity-sector emissions at the metropolitan level. Using regional temperature and electricity demand data, we were able to model strong quadratic relationships between average daily temperature and total daily electricity load. We then applied future temperature projections from climate models to these quadratic relationships to see how electricity demand may change in the future as a result of climate change. Overall, we found that climate change will likely lead to small-to-modest increases in metropolitan electricity sector GHG emissions. Depending on location and climate model, the change in emissions was found to be between -4 and 22% by the year 2030.We also found that changes in population and policy (the EPA's Clean Power Plan) are at least as impactful (if not more impactful) on changes to metropolitan electricity sector GHG emissions by the year 2030.

Overall, the analysis and results from this thesis provide insights into the importance of current and future drivers of metropolitan GHG emissions and help inform decision-making related to GHG mitigation. The integrated approach developed in the first component of our analysis could serve as a less "resource intensive" way for communities to regularly form an initial assessment of their emission profile, compare themselves to their peers, and prioritize their resource and planning efforts. The second component of our analysis reveals that as GHG inventory methods and policies continue to expand in scope and scale, the addition of previously "under-reported" emission sources will require policy makers to re-think how they develop and implement their GHG reduction plans. For example, decision-makers may need to modify the annual reduction rates they target or adjust the time horizon under which they implement their plans. Our analysis also provides a framework for expanding emissions inventories beyond the scale of the city limits. The third component of our analysis shows that the consideration of factors such as climatic temperature change, population change, and policy change should help decision-makers form a more complete understanding of their emission profile in the future and help them decide how best to prioritize their mitigation strategies.

TABLE OF CONTENTS

COMMITTEE MEMBERS i

ACKNOWLEDGEMENTS ii

ABSTRACT iii

1. BACKGROUND AND MOTIVATION 1

2. AN INTEGRATED APPROACH FOR MEASURING GREENHOUSE GAS EMISSIONS IN METROPOLITAN AREAS WITHIN THE UNITED STATES 6

2.1 Introduction 6

2.2 Data 8

2.3 Methods 12

2.4 Results 16

2.5 Conclusions and Implications 32

3. THE IMPLICATIONS OF SCOPE AND BOUNDARY CHOICE ON THE ESTABLISHMENT AND SUCCESS OF METROPOLITAN GREENHOUSE GAS REDUCTION TARGETS IN THE UNITED STATES 35

3.1 Introduction 35

3.2 Data 41

3.3 Methods 42

3.4 Results 44

3.5 Discussion and Implications 51

4. THE IMPLICATIONS OF CLIMATIC TEMPERATURE CHANGE, POPULATION CHANGE, AND POLICY CHANGE ON METROPOLITAN ELECTRICITY DEMAND AND GREENHOUSE GAS EMISSIONS 56

4.1 Introduction 56

4.2 The Importance of Focusing on Metropolitan Areas 60

4.3 Data 61

4.4 Model Specifications 64

4.5 The Relationship between Temperature and Electricity Demand in Various Areas 66

4.7 Impact of Temperature Change on Electricity Demand and Emissions 72

4.8 Sensitivity to Population and Policy Change Scenarios 74

4.9 Discussion and Implications 76

5. SUMMARY, CONCLUSIONS, AND POLICY IMPLICATIONS 80

5.1 Summary 80

5.2 Future Work 82
5.3 Policy Implications and Final Conclusions 86
REFERENCES 89
Appendix A: Supporting Information for Chapter 2 98
A1: Elaboration on Metropolitan Statistical Areas (MSAs) 98
A2: Summary of underlying emission estimates from integrated assessment approach 99
A2: Percent Change in Emissions between 2002 and 2011 105
APPENDIX B: SUPPORTING INFORMATION FOR CHAPTER 3 106
B1: Summary of Communities with GHG Reduction Targets 106
B2: Elaboration on Scope 3 Emissions 110
B3: Summary of the Metropolitan Areas Included in the Analysis in Chapter 3 110
APPENDIX C: SUPPORTING INFORMATION FOR CHAPTER 4 114
C1. Maps of Electricity Service Areas 114
C2. Maps of Climate Projection Regions 115
C3. Additional Description of Temperature Projections and Range of Possible Values 117
C4. Analysis of Accuracy of Regression Results 119

LIST OF TABLES

Table 2-1. Summary of data sources used and sector-based emissions provided by each data source for 2002 estimates. Adapted from (Gurney et al.) ... 9

Table 2-2. Summary of data sources used and sector-based emissions provided by each data source for 2011 estimates (EPA, 2014[C]; EPA, 2014[D;] EIA, 2014; California Energy Commissions, 2015). ... 10

Table 2-3. Average percent change in emissions between 2002 and 2011 for each sector for the 15 MSAs that underwent the largest percent decrease in total emissions during that time frame. ... 22

Table 2-4. Average percent change in emissions between 2002 and 2011 for each sector for the 15 MSAs that underwent the largest percent increase in total emissions during that time frame. 24

Table 3-1. Summary of GHG reduction targets for communities across the United States adapted from (ICLEI USA, 2015[A]) ... 36

Table 4-1. Summary of the % of electricity load for a given ERCOT region or PJM EDC that is generated from power plants within a specific metropolitan area. ... 62

Table 4-2. Summary of current electricity sector GHG emission rate and proposed emission rate under the Clean Power Plan (U.S. EPA, 2014[A]; U.S. EPA, 2014[B]; U.S. EPA, 2015[A]). ... 64

Table 4-3. Second-order polynomial regression between total daily electricity demand and average daily temperature (independent variable) for the San Antonio, Austin, Dallas/Ft Worth, Houston, Chicago, and Pittsburgh metropolitan areas. The units for electricity demand are MWh and the units for temperature are degrees Celsius. ... 69

Table 4-4. Summary of average daily percent difference between predicted and actual electricity load value for two years before and after 2012 (the baseline year for which the regression analysis was performed) ... 70

Table 4-5. "Break Even" values for emission rate and per capita electricity consumption required for each metropolitan area to have 0% growth in their electricity sector GHG emissions between now and the year 2030. Areas marked with "N/A" indicate no additional change in emission rate or per capita electricity use is required to achieve 0% growth in electricity sector GHG emissions between 2010 and 2030. ... 78

Table A1. Summary of population and sector-based GHG emissions for the 100 most populated metropolitan areas in the United States for the year 2002. Emission values are reported in million metric tons of CO2eTable A1. Summary of population and sector-based GHG emissions for the 100 most populated metropolitan areas in the United States for the year 2002. Emission values are reported in million metric tons of CO_2e ... 99

Table A2. Summary of sector-based GHG emissions for the 100 most populated metropolitan areas in the United States for the year 2011. This data corresponds to the 2011a data discussed in Chapter 2. The estimates for the residential and commercial sectors were found by multiplying 2002 per capita values by 2011 population values. The emission estimates are reported million short tons of CO_2e 101

Table A3. Summary of sector-based GHG emissions for the 100 most populated metropolitan areas in the United States for the year 2011. This data corresponds to the 2011b data discussed in Chapter 2. The estimates for the residential and commercial sectors were found by multiplying 2011 state-level per capita values by 2011 MSA population values. The emission estimates are reported million short tons of CO_2e 103

Table B1. Summary of the GHG reduction targets currently in place in various U.S. communities. Replicated from (ICLEI USA, 2015[A]) 106

Table B2. Summary of Communities and MSAs included in analysis 110

LIST OF FIGURES

Figure 2-1. Summary of the 15 metropolitan areas that underwent the largest percent decrease (upper left), largest net decrease (upper right), largest per capita percent decrease (lower left), and largest per capita net decrease (lower right) in total GHG emissions between the years 2002 and 2011. ... 17

Figure 2-2. Summary of the 15 metropolitan areas that underwent the largest percent increase (upper left), largest net increase (upper right), largest per capita percent increase (or smallest decrease in some cases) (lower left), and largest per capita net increase (or smallest decrease in some cases) (lower right) in total GHG emissions between the years 2002 and 2011. ... 18

Figure 2-3. Sector based emissions for years 2002 and 2011 for the four metropolitan areas that underwent the largest percent decrease in total emissions between 2002 and 2011. ... 21

Figure 2-4. Sector based emissions for years 2002 and 2011 for the four metropolitan areas that underwent the largest percent increase in total emissions between 2002 and 2011. ... 23

Figure 2-5. Estimates of 2011 GHG emissions from residential buildings in California metropolitan areas based on three different approaches: 1) estimates from 2002 per capita values (scaled up to 2011 population numbers), 2) estimates based on 2011 EIA state-level per capita estimates (scaled to metropolitan population numbers, and 3) Reported values from the California Energy Commission. ... 26

Figure 2-6. Comparison of total per capita GHG emissions for various metropolitan areas as estimated by different methods/datasets: estimates based entirely on state-level per capita emission values (State), self reported estimates from the cities (Reported), and estimates using our integrated approach for various years (2011a, 2011b, and 2002) ... 29

Figure 2-7. Comparison of how different methods estimate the proportion of total emissions attributable to different sectors: waste, transportation, buildings, and "other." ... 31

Figure 3-1. Profile of total and per capita CO_2e emissions for 41 metropolitan areas as estimated with the integrated data. Emissions estimates for "reported" activities (i.e., the activities commonly reported by cities in their GHG inventories) are shown in blue and the "under-reported" emissions are shown in red (on-road transportation outside the urban core), gold (industrial activity within the urban core). The left side of the figure reports total annual emissions in million metric tons of CO2e and the right side of the figure reports per capita emissions in metric tons CO2e per person. ... 46

Figure 3-2. Profile of total and per capita CO_2e emissions for 41 metropolitan areas as estimated with the integrated data. Emissions estimates for the "urban core" (i.e., central city and area of density) are shown in blue, "central" counties outside of the urban core are shown in orange, and "outlying" counties of the metropolitan area are shown in green. The left side of the figure reports total annual emissions in million metric tons of CO2e and the right side of the figure reports per capita emissions in metric tons CO2e per person. ... 50

Figure 3-3. Illustrative example of GHG reduction policies for Baltimore under different scope scenarios ... 52

Figure 4-1. Total daily electricity demand versus average daily temperature for the year 2012 for the San Antonio (red – upper left), Austin (red- upper right), Dallas/Ft Worth (blue), Houston (orange), Chicago (green), and Pittsburgh (purple) metropolitan areas. Figure created by the authors using data from NOAA, The Electricity Reliability Corporation of Texas (ERCOT), and Pennsylvania, New Jersey, Maryland Interconnect (PJM). ... 67

Figure 4-2. Historical (darker bars) and projected (light bars with black outline) annual frequencies of average daily temperature values for the San Antonio (red – upper left), Austin (red- upper right), Dallas/Ft Worth (blue), Houston (orange), Chicago (green), and Pittsburgh (purple) metropolitan areas. The historical values are the average daily temperatures for the years 1990 to 1999 and the projected values are the average daily temperatures for the years 2025 to 2035. ... 72

Figure 4-3. Historical (darker bars) and projected (light bars with black outline) annual frequencies of total daily electricity generation for the San Antonio (red – upper left), Austin (red- upper right), Dallas/Ft Worth (blue), Houston (orange), Chicago (green), and Pittsburgh (purple) metropolitan areas. The historical values are the average total daily load for the years 1990 to 1999 and the projected values are the average total daily load for the years 2025 to 2035. ... 73

Figure 4-4. Percent change in electricity sector GHG emissions between 2010 and 2030 as a result of various factors – climate change, population change, modified Clean Power Plan (50% of proposed reductions in emission rates), full Clean Power Plan (100% of proposed reductions in emission rates). The first 4 bars (starting at the bottom) for each location show the impact of the specified variable and assume all other variables are held constant (e.g. the "population change" bars show the estimated change in electricity GHG emissions if population were the only thing to change between 2010 and 2030). The "combined effects" bars show the combined results of all of the factors. ... 75

Figure A1. Map of the Pittsburgh MSA included the central county/urban core (Allegheny County) and the suburban counties. ... 98

Figure A2. Percent change in total GHG emissions from 2002 to 2011 for the 100 largest metropolitan areas in the United States. ... 105

Figure C1. Map of regions in ERCOT (Texas) for which baseline electricity usage data were used ... 114

Figure C2. Map of regions in PJM for which baseline electricity usage data were used ... 114

Figure C3. Map of region used to generate temperature projections for the San Antonio and Austin metropolitan areas ... 115

Figure C4. Map of region used to generate temperature projections for the Dallas/Fort Worth metropolitan area 115

Figure C5. Map of region used to generate temperature projections for the Houston metropolitan area 116

Figure C6. Map of region used to generate temperature projections for the Chicago metropolitan area 116

Figure C7. Map of region used to generate temperature projections for the Pittsburgh metropolitan area 116

Figure C8. Average annual historical and projected temperatures for 117

Figure C9. Average daily historical and projected temperature values included upper bound and lower bound estimates for the projected temperature values 118

Figure C10. Comparison of projected daily electricity generation (using regression results from year 2012) to actual daily generation values for the Houston metropolitan area for the years 2010, 2011, 2013, and 2014). 119

1. BACKGROUND AND MOTIVATION

Since the establishment of the Intergovernmental Panel on Climate Change (IPCC) in 1988 and the five Assessment Reports subsequently produced by the organization, knowledge and concerns about climate change have been steadily increasing (IPCC, 1992; IPCC, 1995; IPCC, 2007; IPCC, 2011; IPCC, 2014). In response to these concerns, several international, regional, and national greenhouse gas (GHG) management and reduction policies have been adopted. The most notable of these policies is probably the Kyoto Protocol, which was signed in 1997 and involved 192 nations and was ratified by 83 (United Nations Framework Convention on Climate Change, 2014).

More recently, numerous cities across the world have adopted Climate Action Plans (CAPs) in an attempt to estimate and reduce their greenhouse gas (GHG) emissions. In the United States, over 1000 mayors have committed to the U.S Conference of Mayors Climate Protection Agreement, over 450 local governments have joined the International Council for Local Government Initiatives (ICLEI – Local Governments for Sustainability), and 14 cities in North America have joined the C40 network of global cities striving to reduce GHG emissions (U.S. Conference of Mayors, 2008; ICLEI, 2015[A]; C40 Cities, 2011). Given that over 80% of the United States' population live in metropolitan areas and roughly 75% of the earth's natural resources are consumed in urban areas (U.S. Census Bureau, 2013[A]; Swilling et al., 2013), CAPs provide an important contribution to addressing the challenges posed by climate change – especially when considering that metropolitan mitigation strategies can better address local conditions and be more flexible than a national GHG policy.

The implementation of climate action plans typically involves completing regular GHG inventories. In the United States, GHG inventories are commonly completed with the help of ICLEI's Clean Air Climate Protection (CACP) software, or, more recently, ICLEI's ClearPath software (OpenEI, 2015; ICLEI USA, 2015[B]). Use of this software often results in bottom-up emission estimates for five sectors within a given city:1) Use of electricity by the community, 2) Fuel use in residential and commercial buildings (e.g. natural gas or fuel oil), 3) Fuel use for on-road passenger and freight motor vehicle travel, 4) Energy use in the treatment and distribution of potable water and waste water, and 5) Emissions from the collection and degradation of solid waste generated by the community (ICLEI USA, 2013).

The protocols and resources described above have greatly enhanced the ability of cities to form and assess GHG inventories. However, there are still some challenges with estimating local-level GHG emissions. First, the bottom-up approach commonly employed can be resource intensive. Lack of funds and institutional wherewithal has been described as a primary barrier to the successful implementation of sustainability-oriented actions in metropolitan areas (NRC, 2010; NRC, 2011; NRC, 2013; NRC, 2014). Thus, the time, money, and skills needed to collect and analyze the data necessary for completing a GHG inventory can inhibit the progress of developing and implementing a Climate Action Plan. It is not uncommon for communities to enter into a repetitive cycle of emissions accounting rather than shifting their focus to the implementation of mitigation strategies.

Another issue with current GHG inventories is that they do not necessarily cover the full geographic or sectoral extent of a city's emissions. Inventories are often limited to the city limits and to the five emission-producing activities described above. Thus, emissions from activities like industrial processes, non-road transportation (e.g. rail and airline travel), and on-road commuting between urban and suburban areas are often under reported or omitted. In fact, a study of the GHG footprints of 8 U.S. cities revealed that, on average, “trans-boundary” emissions (emissions from transportation between the city and surrounding areas, airline travel, embodied emissions for goods and services used or purchased in the city, etc.) contributed nearly 50% more to a city’s emissions compared to the emissions from activities that are typically reported (Hillman and Ramaswami, 2010). City practitioners have also stressed the importance of expanding their analysis to the regional or mega-regional level rather than focusing solely on the political boundaries of the city limits (NRC, 2010; NRC, 2013; NRC, 2011; NRC, 2014).

Additionally, forming meaningful comparisons between locations can often be difficult, because there are frequently large discrepancies and inconsistencies between the methods and scopes applied to the inventories of different places (Blackhurst et al., 2011; Ramaswami et al., 2008). Some comparative analyses have been completed, but this work has typically been confined to a limited geographic scope (Blackhurst et al., 2011; Glaeser and Kahn, 2010; Kennedy et al., 2009; Sovacool and Brown, 2010) or a limited set of emission producing activities (Brown, Southworth, and Sarzynski, 2009).

Finally, inventories help practitioners track recent and historical progress. However, climate action plans can often lack elements of forecasting. There are several near-to-long term “extrinsic” factors that may have a considerable impact on the emission profiles of various cities: population change, climate change, technology change, and policy change. Population growth is a particularly important factor in determining the future emissions of a city and the success of any GHG mitigation strategies. Previous work has illustrated the important role that population plays on energy consumption and emissions (York, Rosa, and Dietz, 2003; Wei, 2011; Dietz and Rosa, 1997; Chertow, 2000). Thus, under scenarios of high population growth, it is possible that even highly aggressive GHG mitigation policies and technologies would not be sufficient to achieve desired reductions in a city's emissions.

Another factor that could lead to increased emissions is the increased energy consumption resulting from projected rises in future temperatures due to climate change. The National Climate Assessment projects that average temperatures are likely to rise between 3 and 10^{o}F in the United States over the remainder of the century (USGCRP, 2014). These changes in temperature will affect the demand for space heating and cooling and could potentially lead to increased energy use and emissions as a result. Some areas may undergo a net increase in energy demand and emissions from rising temperatures (i.e. increased cooling demand outpaces decreased heating demand); while the opposite might be true in other locations (i.e. decreased heating demand outpaces increased cooling demand). Regional differences in the balance between changes in cooling and heating demand can lead to interesting decisions related to prioritizing GHG reduction strategies. For example, an area expected to undergo a net increase in energy demand due to space cooling may really want to focus their mitigation efforts on building weatherization and efficient air conditioning units. On the other hand, areas where a net decrease in energy demand is expected may want to focus their mitigation efforts on other areas like transportation.

In addition to changes from rising temperatures, changes in policy, behavior, and technology are likely to lead to decreases in emissions. We focus our attention on the EPA's newly proposed Clean Power Plan aimed at reducing GHG emissions from existing power plants (U.S. EPA, 2014[A]; U.S. EPA, 2014[B]). The Clean Power Plan proposes 30% reduction in electricity-sector GHG emissions by the year 2030 – equivalent to roughly a 10% reduction in total overall U.S. GHG emissions (U.S. EPA, 2015[A]). Although this is a national-level policy, it will still have important implications on GHG emissions at the metropolitan level. For example, the Clean Power Plan will likely have considerable implications on emissions in areas where coal power is predominate (i.e. Pittsburgh, Chicago, Atlanta, etc.), but less of an impact in areas where natural gas or hydro are more prevalent (i.e. Los Angeles, San Francisco, Portland, Seattle, etc.).

Given the issues described above, this thesis seeks to evaluate metropolitan-level GHG emissions and some of the key factors that may drive emissions and cities' abilities to meet reduction targets moving forward. In Chapter 2, we use publically available national data to develop an integrated approach for estimating GHG emissions at the metropolitan level. In Chapter 3, we use census data and the results from our integrated approach to quantify the magnitude of under-reported emissions from GHG inventories and assess the importance that scope and boundary choices can have on the emissions profile of a given metropolitan area. In Chapter 4, we investigate the implications that projected temperature increases, population change, and the EPA's Clean Power Plan have on electricity-sector emissions at the metropolitan level. Finally, Chapter 5 summarizes the key findings and policy implications of this work.

2. AN INTEGRATED APPROACH FOR MEASURING GREENHOUSE GAS EMISSIONS IN METROPOLITAN AREAS WITHIN THE UNITED STATES

2.1 Introduction

In response to growing concerns about climate change, numerous cities across the United States have adopted climate action plans (CAPs) in an attempt to quantify and reduce their greenhouse gas (GHG) emissions. A key component of these CAPs is the implementation of regular GHG inventories, which are typically formed through a bottom-up approach in which data are compiled from local utilities, transportation fuel consumption, and waste disposal. Emission factors associated with each of these activities are then used to form estimates of the GHG emissions for a particular city. Generally speaking, carbon dioxide (CO_2) is the primary component of the GHGs measured in climate action plans. A common exception to this is emissions from waste disposal (i.e. landfills). Unless captured and flared, methane is the primary GHG emitted from landfills. Thus, GHG inventories will typically apply a Global Warming Potential (GWP) value to convert methane emissions to units of CO_2 equivalents (CO_2e). Ultimately, overall city-wide emissions are usually reported in terms of CO_2e.

Previous work has shown that there are large inconsistencies with the methods used to develop inventories and the scopes adopted in the inventories (Blackhurst et al., 2011; Ramaswami et al., 2008). These inconsistencies make it challenging to form meaningful comparisons between the inventories and mitigation strategies adopted by different locations. Some comparative analyses have been completed, but these studies have typically been limited to specific cities or regions (Blackhurst et al., 2011; Glaeser and Kahn, 2010; Kennedy et al., 2009). The few studies that have had a larger geographic extent, have been limited in the number of emission producing activities analyzed (Brown, Southworth, and Sarzynski, 2009). Although some meaningful conclusions can be gathered from the existing work, the results, analysis, and comparisons are not broadly applicable to all metropolitan areas in all scenarios. Having the ability to make such comparisons is important because it allows for better overall assessment of the progress being made across the country, and allows cities to more easily adopt best practices.

In addition to the concerns above, there are also many practical challenges associated with implementing CAPs. Formation of GHG inventories tends to be time consuming and expensive, and cities often require consultants or non- governmental organizations (NGOs) to assist with the process. In a series of National Research Council (NRC) workshops related to urban sustainability, city practitioners stated that the lack of available funding was the primary barrier to implementing sustainability-oriented actions (NRC, 2010; NRC, 2011; NRC, 2013; NRC, 2014). Similarly, they stated that it would be beneficial if the research community could help them lower the costs of compiling and analyzing all the inventory data and help them concentrate on measuring and analyzing the "right things (NRC, 2010)." Turnover in city and consulting personnel can also affect the consistency and quality of the data. For example, discusses with Lindsay Baxter, the former the Sustainability Coordinator for the City of Pittsburgh, revealed that Pittsburgh has completed two GHG inventories since 2006, and each inventory was completed by different people with different levels of transparency in their methodology. Finally, city practitioners expressed the importance of expanding analysis and planning beyond the political boundaries of city limits and focusing more broadly on the "regional or mega-regional level (NRC, 2010; NRC, 2011; NRC, 2013; NRC, 2014)."

Given the above issues, we developed an integrated approach to for using publically available national datasets to estimate production-based GHG emissions by sector at the metropolitan level. We then applied this approach to the 100 most populated metropolitan areas in the United States in order to form GHG emissions estimates for the years 2002 and 2011. The methods and results detailed below allow for consistent comparison of GHG emissions over time, between multiple areas, and across sectors, and can serve as a framework for practitioners to get an initial understanding of their emissions profile without having to fully devote all of the time and resources needed to complete a bottom-up inventory.

The rest of the chapter is organized as follows. Sections 2.2 and 2.3 discuss the data and methods used in our analysis. Section 2.4 describes the results of our emissions estimates and includes comparisons to estimates formed from other methods. Section 2.5 includes policy implications and conclusions.

2.2 Data

The data that served as the basis for our analysis were obtained from a variety of publically available national datasets: the Vulcan database constructed by researchers at Arizona State University, the EPA's National Mobile Inventory Model (NMIM), the EPA's mandatory GHG reporting program, and the EPA's National Emissions Inventory (NEI) – which includes components of the Continuous Emission Monitoring System (CEMS) and Acid Rain Programs (Gurney et al., n.d; The Vulcan Project, n.d.; U.S. EPA, 2010; U.S. EPA, 2013; U.S. EPA, 2014[C]; U.S. EPA, 2014[D]). Estimates for the year 2002 are primarily based on data from the Vulcan database and the 2002 NEI. Table 2-1 provides a summary of the different data sources, the spatial resolution of each source, and the sector-based emissions estimates that each data source provides.

Table 2-1 Summary of data sources used and sector-based emissions provided by each data source for 2002 estimates. Adapted from (Gurney et al.)

Data Source	Data Type	Spatial Resolution	Sector
National Emissions Inventory (NEI), 2002	Point Source	Latitude & Longitude	Industrial Activity
	Non-Point Source	County	Commercial Buildings (non-electricity emissions)
	Non-Point Source	County	Residential Buildings (non-electricity emissions)
	Non-Point Source	County	Non-Road Transportation (boats, rail, etc.)
	Non-Point Source	Latitude & Longitude	Airport Activity (airport operations, airplane takeoff/ landing)
CEMS/Acid Rain Program, 2002	Point Source	Latitude & Longitude	Electricity Production
EPA NMIM/EPA MOVES, 2002	Non-Point Source	County	On-Road Transportation (light and heavy duty vehicles)

Estimates for the year 2011 are primarily based on the EPA's mandatory GHG reporting program and the 2011 NEI. Table 2-2 provides a summary of the different sources, sectors, and spatial resolution of the 2011 data.

Table 2-2 Summary of data sources used and sector-based emissions provided by each data source for 2011 estimates (EPA, 2014[C]; EPA, 2014[D;] EIA, 2014; California Energy Commissions, 2015).

Data Source	Data Type	Spatial Resolution	Sector
EPA GHG Reporting Program, 2011	Point Source	Latitude & Longitude	Industrial Activity
			Electricity Production
			Waste
EIA, EPA, California Energy Commission, 2011	Non-Point Source	County/State	Residential Buildings
			Commercial Buildings
National Emissions Inventory, 2011	Non-Point Source	County	On-Road Transportation

All data use a production-based emissions accounting method, in which emissions are attributed to where they geographically occur. Emissions estimates produced by cities in their CAPs are often accounted as consumption-based emissions: emissions attributed to where the end-use occurs, independent of where it was actually emitted. Normally, the distinction between production-based estimates and consumption-based estimates would make consistent comparison between our approach and other estimates difficult. However, with the exception of electricity-production, the emissions estimates in the city CAPs appear to be comparable to production-based emissions we employ. For example, emissions estimates from transportation are based on where the cars are driven and where the emissions leave the tailpipe. Similarly, for natural gas consumption, emissions are attributed to where the buildings are located (i.e., where the fuel is actually combusted).

As mentioned above, emissions from electricity generation are the only activity where production-based estimates and consumption-based estimates could potentially lead to different results. For example, under a consumption-based approach, a majority of the electricity production emissions would be attributed to the city of Chicago and/or Cook County. However, under a production-based approach, a majority of the electricity production emissions would be attributed to outlying/rural counties in Illinois, Indiana, and Michigan (where the electricity generation facilities are more likely to be) and not necessarily to Cook County and/or the City of Chicago. The difficulties of relating the electricity produced in a county to the electricity consumed in a county were addressed more explicitly by Weber et al (Weber et al., 2010). A regression-based approach to relate the amount of electricity consumed in a county to the amount of electricity produced in a county has also exhibited a fairly large range of uncertainty (Tamayao, Blackhurst, and Matthews, 2014). Our analysis allows for additional comparison between consumption-based and production-based estimates and places any disparities in the context of the overall emissions profile of a metropolitan area.

Years 2002 and 2011 were chosen for the analysis because they were the earliest and most recent years with reliable GHG estimates across all sectors and at the appropriate scale. For example, although the EPA's Mandatory GHG Reporting Program has data from as recent as 2014, it only has data for stationary sources (electricity generators and large industrial facilities) - not transportation or residential/commercial buildings (U.S. EPA, 2014[D]). However, updated NEI data is released every three years, so it is conceivable for the estimates we produce to be systematically updated every three years – beginning with the upcoming release of the 2014 NEI data.

In addition to the datasets described above, we also incorporate population data and compare our estimates to emission values reported directly by cities and states. The population data is at the city, county, and state levels for years 2002 and 2011 (Census citations). The emissions estimates reported directly by the cities were available from the Carbonn Climate Registry, the Carbon Disclosure Project, and the cities themselves (Carbonn Climate Registry, 2014; Carbon Disclosure Project, 2015). The state-level emissions estimates were available from the EPA's 2011 State Energy CO_2 Emissions data set (U.S. EPA, 2015[B]).

2.3 Methods

The Vulcan project, which used similar data sources, converted carbon monoxide (CO) emissions to carbon emissions to form gridded 10km by 10km production-based emissions estimates for the entire United States. The Vulcan results provided insight into how the above data sources could be used, and served as an important starting point for our analysis – especially in forming the 2002 estimates (Gurney et al, n.d.; Gurney et al, 2009). The conversion of CO emissions estimates to carbon (and ultimately CO_2) estimates is based on past work in atmospheric chemistry that has shown that almost all atmospheric CO reacts with OH radicals to form CO_2 over a relatively short time frame (Jaffe, 1968; Weinstock and Niki, 1972; Logan et al., 1981; Khalil and Rasmussen, 1990). Thus, the approach used in Vulcan provides a framework for estimating GHG emissions in the absence of explicit CO_2 estimates/measurements. It is worth noting that this approach is only applied to the 2002 data.

All of our estimates for 2011 are based on explicit CO_2 measurements/estimates (i.e. it was not necessary to start with CO and then convert to CO_2).

The emissions estimates for the seven sectors listed in Table 2-1 – electricity production, industrial activity, residential buildings, commercial buildings, on-road transportation, non-road transportation, and airport activity - were available at a variety of different scales in the data sets we used. For example, emissions associated with industrial activity and electricity generation were provided at the facility level, while emissions associated with residential/commercial buildings, airport activity (i.e. airport operations, airplane takeoff/taxi/landing), and on-road/non-road transportation were provided at the county level. For this study, all of the facility-level data were aggregated to the county level to match the scale of the non-point sources. Then, the county-level emissions estimates were further aggregated to form GHG estimates for Metropolitan Statistical Areas (MSAs). As defined by the United States Census Bureau, MSAs consist of a "substantial population nucleus (of at least 50,000 people), together with adjacent communities having a high degree of economic and social integration with that core (U.S. Census Bureau, 2013[B])." For example, the Pittsburgh MSA consists of the City of Pittsburgh as well as Allegheny, Armstrong, Beaver, Butler, Fayette, Washington, and Westmoreland Counties [see Figure A1 in Appendix A]. Altogether, this aggregation resulted in GHG emissions estimates for the 100 most populated MSAs for the seven emission producing activities described above. For the duration of the report, this data will be referred to as the "integrated data."

The 2011 estimates were formed in a similar manner: facility data was aggregated to the county level, and then county data was aggregated to the MSA level. However, there were a few differences: 1) electricity and industrial activity emissions were collected from the EPA's mandatory greenhouse gas (GHG) Reporting Program, 2) Emissions for waste generation/collection were estimated using the EPA's mandatory reporting program, and 3) the 2011 NEI directly reported on-road transportation emissions in GHGs (as opposed to CO in the 2002 data).

For the 2011 data, the use of the EPA's mandatory GHG reporting program (as opposed to the NEI data) for estimating emissions from industrial processes and electricity production can potentially add some uncertainty to the analysis. Since the NEI and mandatory reporting program are two different data sets, there is the potential for certain facilities to be present in only one of them. For example, in the case where a facility were included in the NEI but not in the mandatory reporting program, the 2002 emission estimates may be larger than the 2011 estimates for a given sector in a given location. Thus, rather than being attributable to a shift in the electricity or industrial processes, the difference between the two estimates (2002 vs. 2011) may be entirely due to the fact that a certain facility is present in one data source but not the other. The same would be true if a facility was included in the mandatory reporting program but not the NEI. In that case, the 2011 estimates would likely be larger than the 2002 estimates due to the inclusion of more facilities in the data set.

We explore the potential for this type of situation by investing the specific power generating facilities present in Texas as included by both the NEI and the mandatory GHG reporting program. The 2011 NEI data contains 127 electricity generating facilities across 70 Texas counties, and the 2011 mandatory GHG reporting program data contains 130 electricity generating facilities across 74 Texas counties (EPA, 2014[C]; EPA, 2014[D]). Of the 74 total counties between the two data sets, 65 counties have the exact same number of facilities in both the NEI and the mandatory reporting. More specifically, between the two data sets, 114 facilities can be directly matched based on facility name and/or address. Therefore, although there is not 100% consistency between the facilities in the NEI and mandatory reporting program, there appears to be enough consistency (close to 90% match rate) to allow for the use of either data set without the introduction of an unacceptable amount of uncertainty. Moving forward, it will be important to perform additional consistency verifications similar to the one described above – especially for multiple locations and different emission producing activities.

Finally, the largest difference between the 2002 and 2011 estimates occurs in the residential and commercial building sector. In contrast to the 2002 data, direct emissions estimates for these two sectors were not available from the 2011 NEI or the EPA's mandatory reporting program. Thus, alternative estimation approaches were applied. For California, county-level natural gas consumption data (for residential and non-residential buildings) was available from the Energy Consumption Data Management System, and was based on values reported by utilities (California Energy Commission, 2015). For the metropolitan areas outside of California, two methods were used to estimate emissions from commercial and residential buildings: 1) we assume that the per capita emissions from the 2002 data remain constant and multiply these values by the 2011 county/MSA populations to get updated estimates; and 2) multiply 2011 county and MSA populations by the state-level per capita residential and commercial building emission values provided by the EIA Form 176 (U.S. EIA, 2014).

2.4 Results

2.4.1 Emission Estimates for 2002 and 2011

Figures 2-1 and 2-2 illustrate changes in overall MSA-level emissions between the years 2002 and 2011. A Full summary of the 2002 and 2011 emission estimates is included in Section A2 of Appendix A. Figure 2-1 depicts the 15 metropolitan areas that underwent the largest decreases in overall net emissions, net emissions per capita, percent change in overall emissions, and percent change in per capita emissions between 2002 and 2011. Figure 2-2 depicts the 15 metropolitan areas that underwent the largest increase (or smallest decrease in some cases) in overall net emissions, net emissions per capita, percent change in overall emissions, and percent change in per capita emissions between 2002 and 2011. The error bars in the figures indicate upper and lower bounds for the estimates. As described in the methods section, these bounds are the result of the two different approaches for estimating emissions from residential and commercial buildings for the year 2011. Figure A2 in Appendix A depicts percent change in emissions between 2002 and 2011 for all analyzed MSAs.

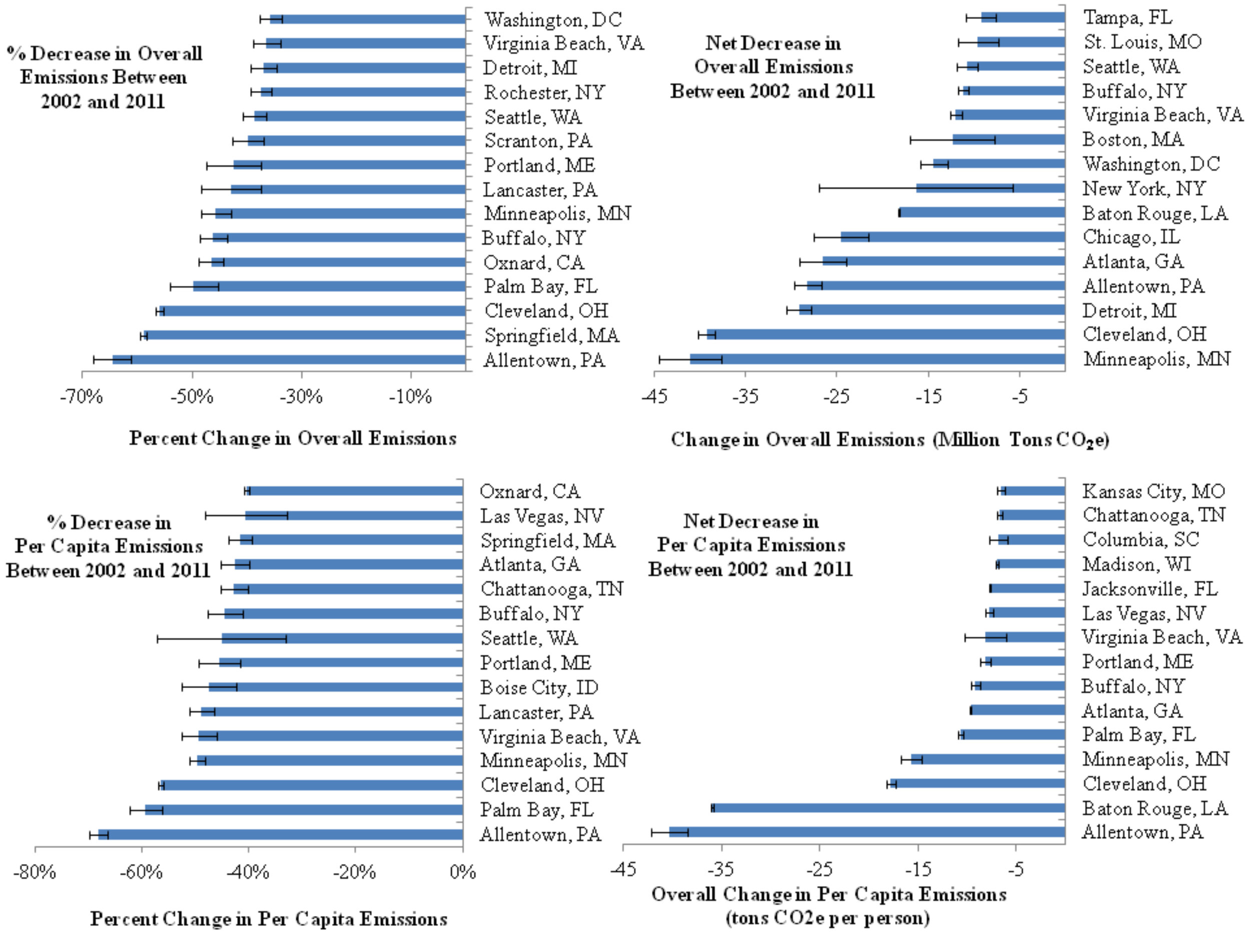

Figure 2-1. Summary of the 15 metropolitan areas that underwent the largest percent decrease (upper left), largest net decrease (upper right), largest per capita percent decrease (lower left), and largest per capita net decrease (lower right) in total GHG emissions between the years 2002 and 2011.

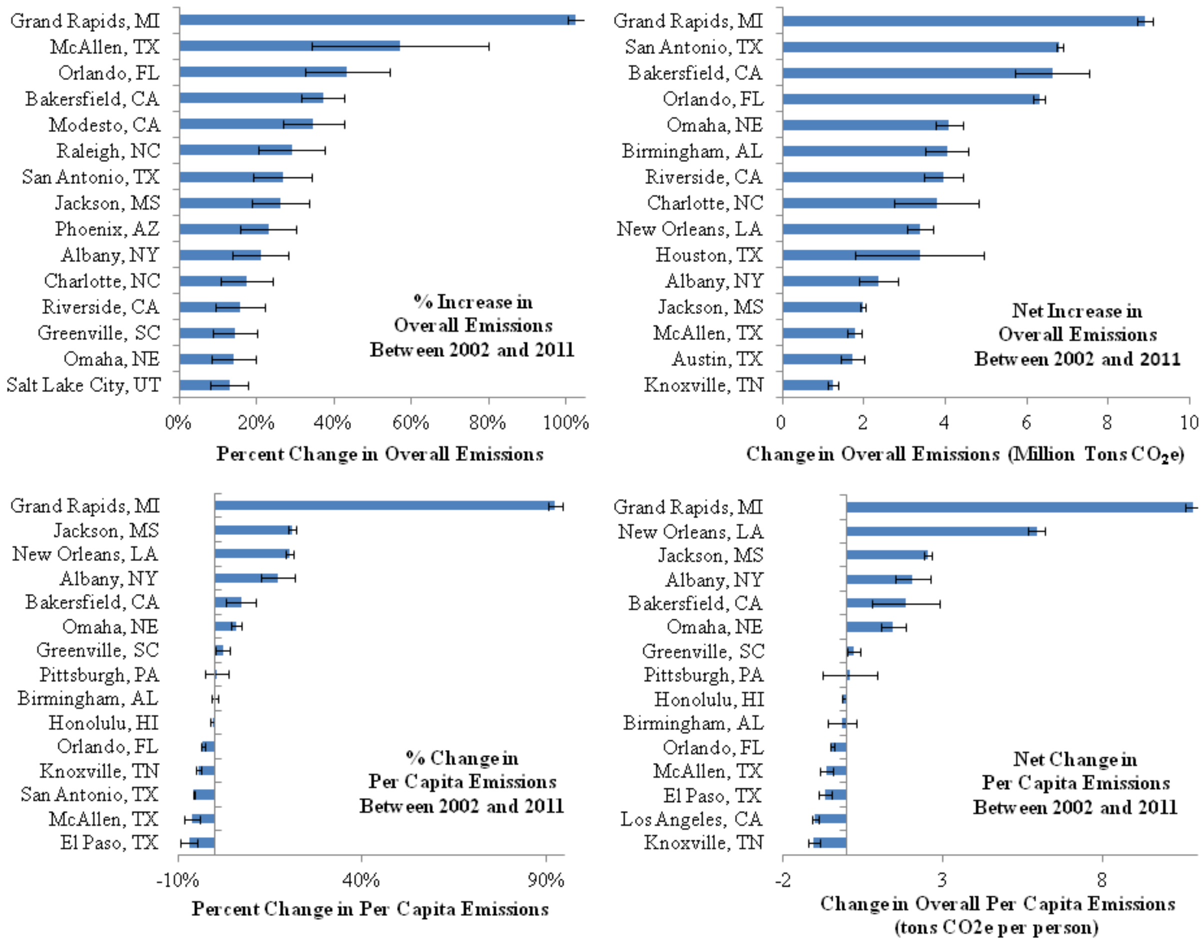

Figure 2-2. Summary of the 15 metropolitan areas that underwent the largest percent increase (upper left), largest net increase (upper right), largest per capita percent increase (or smallest decrease in some cases) (lower left), and largest per capita net increase (or smallest decrease in some cases) (lower right) in total GHG emissions between the years 2002 and 2011.

Although GHG reduction targets are typically framed in terms of a percent reduction in emissions, it is also important to look at how per capita and overall emissions change over time. Generally speaking, large percent reductions in emissions will correspond with large decreases in overall and per capita emissions. However, this interaction appears to be stronger in the case of emission increases rather than emission decreases. Of the 15 MSAs that experienced the largest overall decrease in emissions between 2002 and 2011 (upper right of Figure 2-1), only 5 were in the top 15 for the other emission change categories (percent change in overall emissions, percent change in per capita emissions, and net change in per capita emissions). Similarly, 5 of the top 15 (in terms of overall decrease in emissions) did not appear in the top 15 for any of the other categories. Conversely, of the 15 MSAs that underwent the largest overall increase in emissions between 2002 and 2011 (upper right of Figure 2-2), seven were in the top 15 for the other emission change categories. Additionally, only 2 of the top 15 (in terms of overall decrease in emissions) did not appear in the top 15 for any of the other categories.

Focusing only on percent change in emissions can sometimes give a misleading sense of overall progress – a large percent reduction to a small baseline may be the same as a small percent reduction to a large baseline. From a global perspective, an ideal scenario would be for a majority of the top-emitting areas to experience significant decreases in total and/or per capita emissions. A large percent decrease in emissions would certainly coincide with such an outcome, but it is not necessary for it to occur. For example, the Atlanta MSA had the 5th highest overall emissions in 2011. Its percent decrease in emissions between 2002 and 2011 did not place in the top 15. However, Atlanta experienced the 5th largest overall decrease in total emissions and the 6th largest decrease in per capita emissions. Overall, those changes point to a degree of success in terms of overall GHG reductions. However, if only looking at percent change, this success would not be as apparent.

Including per capita emissions in the analysis is also important in the context of population growth. Areas like Bakersfield, Los Angeles, McAllen, and El Paso experienced fairly large increases in their population but minimal decreases in their per capita emissions between 2002 and 2011. Therefore, decision makers in these areas would do well to seek policies that continue to move per capita emissions downward. Otherwise, the continued growth in population will likely severely undermine any GHG mitigation efforts in the future. Overall, as decision-makers move forward with establishing, implementing, and tracking GHG reduction targets, it will be important for them to frame their progress in the context of both percent and overall net reductions to total and per capita emissions.

For all MSAs analyzed, the average percent change in emissions from 2002 to 2011 was roughly -10% and the average net change was -4.2 million tons CO_2e. Similarly, the average percent change in per capita emissions between 2002 and 2011 was -22% and the average net change in per capita emissions was -4.3 tons CO_2e per person. On average, the alternate approaches to estimating emissions from residential and commercial buildings resulted in an uncertainty range of $\pm$ 4%.

Examining the above emission changes more closely reveals that population change appears to be a major factor for the MSAs that experienced the largest increase in overall emissions. In Figure 2-2, there are multiple cases where increases in net emissions occur in spite of minimal (or even negative) changes in per capita emissions. For example, McAllen, San Antonio, and Knoxville all experienced decreases in per capita emissions but increases in overall emissions between 2002 and 2011. For all MSAs examined, the average population change between 2002 and 2011 was +14%. However, for the 15 MSAs with the largest percent decrease in total emissions (upper-left of Figure 2-1), the average percent change in population was +7%. Similarly, for the 15 MSAs with the largest percent increase in total emissions (upper-left of Figure 2-2), the average percent change in population was +24%.

In addition to population changes, insights about changes in MSA emissions can be gathered from looking more closely at the sector-based emissions for a given MSA over time. Figure 2-3 highlights the sector-based emissions from 2002 and 2011 for the four MSAs that underwent the largest percent decrease in emissions: Allentown, PA; Springfield, MA; Cleveland, OH; and Palm Bay, FL.

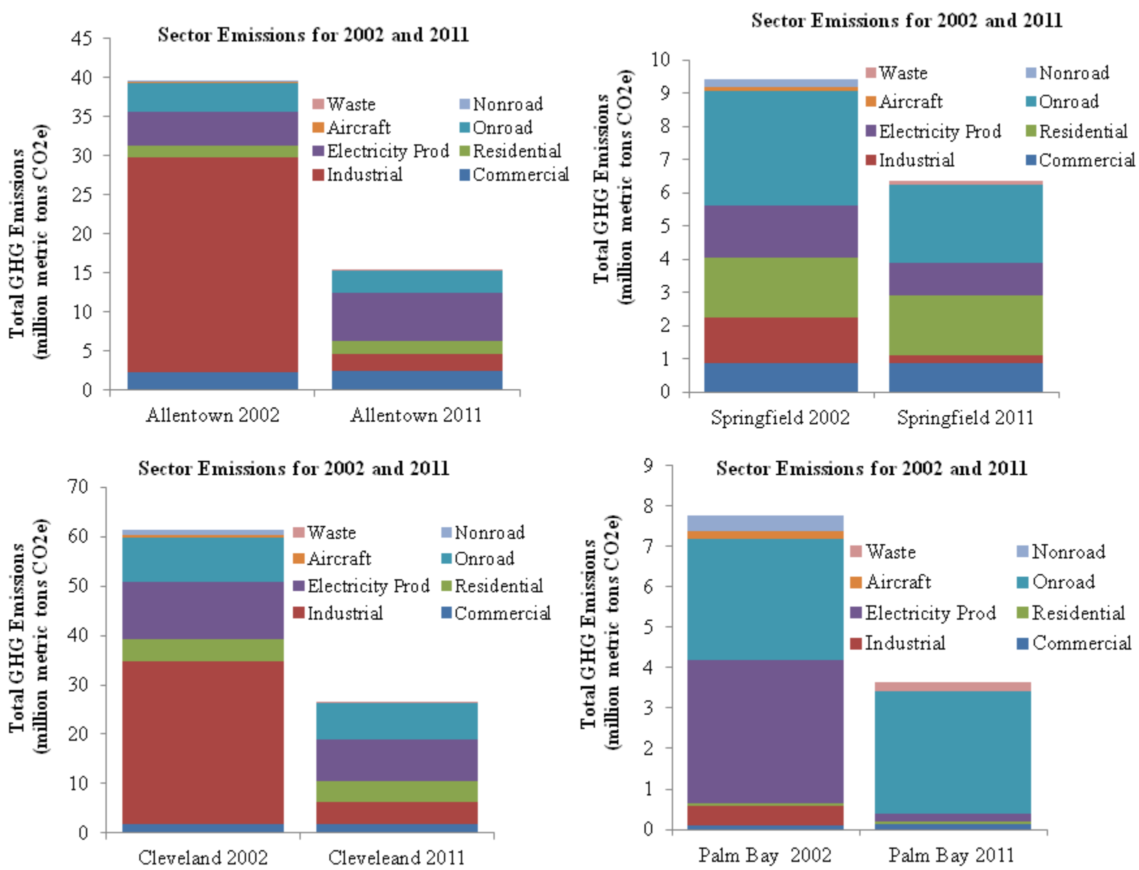

Figure 2-3 Sector based emissions for years 2002 and 2011 for the four metropolitan areas that underwent the largest percent decrease in total emissions between 2002 and 2011.

Figure 2-3 illustrates the large influence that decreased industrial activity and electricity production had on the overall emissions decreases observed in these locations. The four MSAs depicted in Figure 2-3 all appear to have lost a majority of their industrial activity between 2002 and 2011, and Palm Bay also lost a large portion of its emissions from electricity production. Table 2-3 summarizes the average percent change in emissions between 2002 and 2011 for each sector for the 15 MSAs depicted in the upper-left of Figure 2-1.

Table 2-3. Average percent change in emissions between 2002 and 2011 for each sector for the 15 MSAs that underwent the largest percent decrease in total emissions during that time frame.

Sector	Average % Change
Industrial	-62%
Electricity Production	-54%
On-road Transportation	-21%
Commercial Buildings	7%
Residential Buildings	2%

Table 2-3 further illustrates the influence that decreases in industrial and electricity emissions had on overall emission decreases. The average decrease in emissions observed in these two sectors are considerably larger than the average decreases observed in other sectors. While we assume that the decreases in industrial emissions seen above are primarily due to the loss of industrial activities/facilities in a given area, it is possible that these decreases could be partially or fully due to gaps in data between the NEI values used to estimate 2002 emissions and the mandatory GHG reporting values used to estimate 2011 emissions. In Section 2.3, we discussed the strong overlap between NEI and mandatory reporting for electricity facilities in Texas. However, future work on this topic would benefit from also verifying a high degree of overlap between NEI and mandatory reporting for industrial facilities.

Figure 2-4 illustrates the sector-based emissions from 2002 and 2011 for the four MSAs that underwent the largest percent increase in emissions: Grand Rapids, MI; McAllen, TX; Orlando, FL; and Bakersfield, CA.

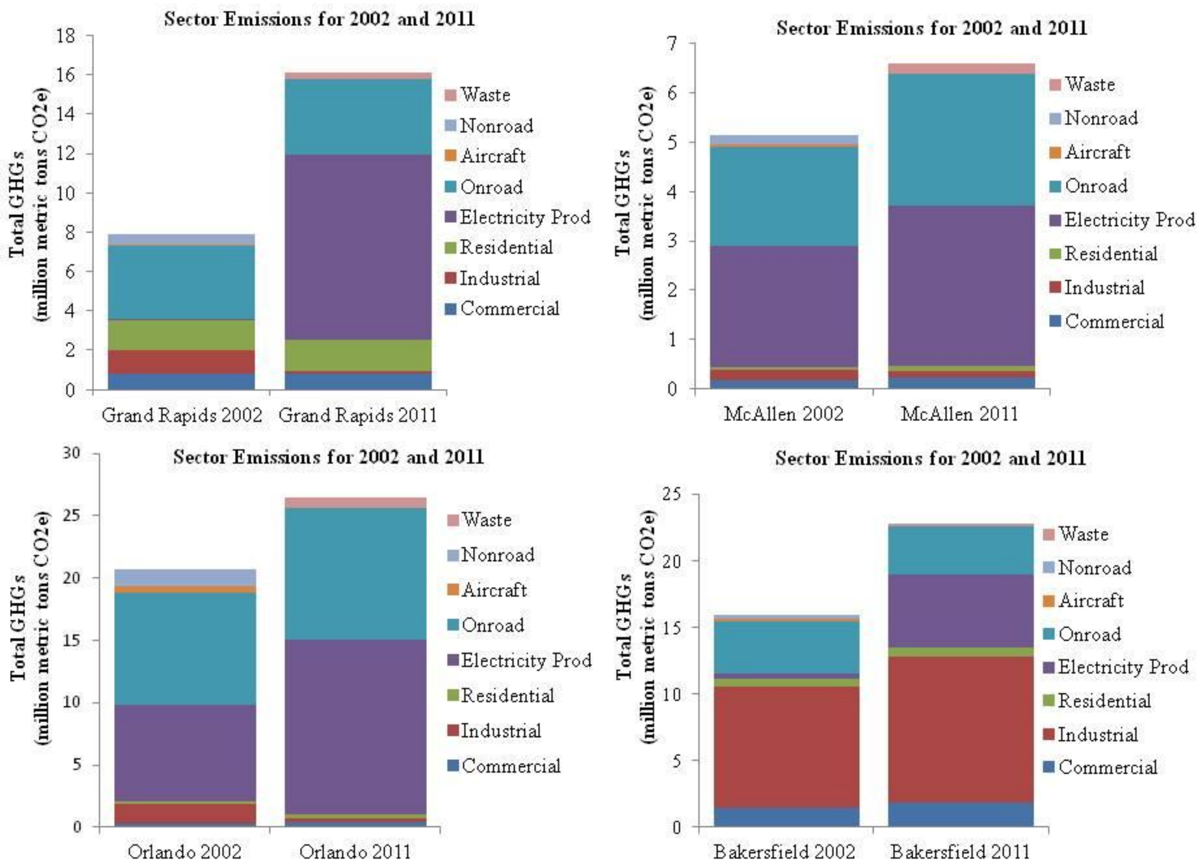

Figure 2-4 Sector based emissions for years 2002 and 2011 for the four metropolitan areas that underwent the largest percent increase in total emissions between 2002 and 2011.

In contrast to Figure 2-3, Figure 2-4 depicts more varied causes of the observed increase in overall emissions. In the cases of Grand Rapids and Bakersfield, the increase in emissions is primarily driven by one or two specific facilities. According to EIA data, the emissions increase in Bakersfield is primarily attributable to the addition of the Pastoria Energy facility and increased usage of the Elk Hills electricity facility (U.S. EIA, 2015). Similarly, the emissions increase in Grand Rapids is primarily due to increased usage of the Zeeland electricity generating facility (U.S. EIA, 2015). On the other hand, population increase in Orlando and McAllen is likely to be a major cause of the observed increases in emissions from the electricity and on-road transportation sectors (and overall emissions). Between 2002 and 2011, the population of the

Orlando MSA increased by 32% and the population of the McAllen MSA increased by roughly 40% (U.S. Census Bureau, 2012[A]).

When examining all 15 MSAs (that underwent the largest percent increase in emissions), increased electricity production appears to have a much larger influence on increased total emissions when compared to other sectors. Table 2-4 summarizes the average percent change in emissions for each sector for the 15 MSAs depicted in the upper-left of Figure 2-2.

Table 2-4 Average percent change in emissions between 2002 and 2011 for each sector for the 15 MSAs that underwent the largest percent increase in total emissions during that time frame.

Sector	Average % Change
Electricity Production	126%
Industrial	15%
Commercial Buildings	14%
Residential Buildings	14%
On-Road Transportation	2%

Overall, the results above highlight the influence that factors like population change and changes to industrial activity and electricity production can have on the overall emissions of a metropolitan area. Large decreases in overall emissions were achieved in locations like Cleveland, Allentown, Springfield, and Palm Bay. From a GHG reduction standpoint, these reductions appear to indicate significant progress. However, given the large decrease in industrial activity required to achieve these reductions, the outcomes would likely not be very desirable or possible in many locations – especially when considering the economic, social, and policy implications likely connected to large scale loss of industrial activity.

From a national and international perspective, it is also important to understand whether the decreases in industrial and electricity emissions are primarily due to the relocation of the facilities or to changes in the efficiency or emission intensity of the processes. Our data does not really have the appropriate level of detail to fully explore this issue, but given the general trend of the U.S. economy shifting toward a more service-based economy; it can be assumed that a majority of changes in industrial emissions are likely due to the relocation of the facilities to other parts of the world. Thus, although the city or MSA may appear to have a large decrease in emissions, there may actually be no net change to global emissions – which is ultimately the goal of any GHG reduction policy. Therefore, as methods and data for estimating metropolitan GHG emissions continue to improve, it will be important for practitioners to take better stock of whether their emission reductions are coming from efficiency and conservation efforts or from a relocation/exportation of activities and processes to other locations.

2.4.2 Comparison of Results to Other Methods

In addition to comparing emission changes over time, we also wanted to examine how our emission estimates compare to estimates from other sources. As mentioned earlier, with the exception of MSAs in California, direct emission estimates from residential and commercial buildings were not available, and thus were estimated using two different approaches: 1) using 2002 per capita emissions (for residential and commercial buildings) and 2011 MSA populations to estimate 2011 MSA emissions, and 2) using 2011 state-level per capita emissions (for residential and commercial buildings) and 2011 MSA populations to estimate 2011 MSA emissions. Given estimates for residential natural gas consumption from the California Energy Commission, Figure 2-5 provides a comparison of our estimates to those reported by the state.

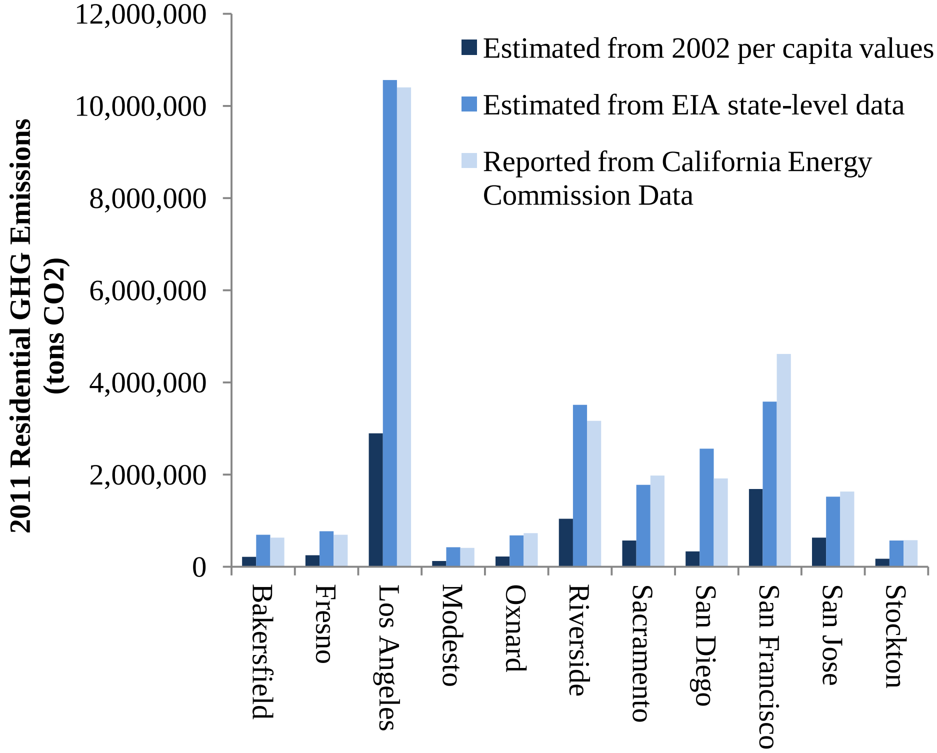

Figure 2-5 Estimates of 2011 GHG emissions from residential buildings in California metropolitan areas based on three different approaches: 1) estimates from 2002 per capita values (scaled up to 2011 population numbers), 2) estimates based on 2011 EIA state-level per capita estimates (scaled to metropolitan population numbers, and 3) Reported values from the California Energy Commission

Figure 2-5 indicates that the estimates based on 2002 per capita values are systematically smaller than the values reported by the California Energy Commission. On the other hand, the estimates based on 2011 state-level per capita values appear to generally coincide well with the values reported by the California Energy Commission. Given that they are based on reported values from utilities, if we assume that the California Energy Commission values are the most accurate, then using state-level per capita values appears to be a reasonable alternative approach. If we expand these observations to other areas outside of California, then we can assume that our estimates based on 2002 per capita values might under estimate actual emissions from residential and commercial buildings, while our estimates based on state-level per capita values may be fairly accurate.

The uncertainty described above is primarily due to modeling constraints within the integrated approach and does not include underlying uncertainty associated with measuring the emissions from different activities. Although not included in this analysis, there is likely to be uncertainty associated with emission estimates from all sectors – not just residential and commercial buildings. Uncertainty in emissions estimates from the electricity and industrial sectors is likely to be rather small given the fact that these estimates are directly measured and/or reported at the facility level. However, given the fact that emission values from the transportation sector are primarily based on county-level vehicle miles traveled (VMT) estimates, the associated uncertainty is likely as large or larger than the uncertainty associated with estimates for residential and commercial buildings. Therefore, decision makers in areas where electricity production and industrial processes account for larger portions of total emissions can likely operate with a fairly high degree of confidence. Practitioners in areas where transportation and/or the building sector account for larger portions of overall emissions will likely want to be more cognizant of some of the potential underlying uncertainty associated with their emission estimates.

Besides comparing our different approaches to each other, comparisons are also made to estimates reported by the cities themselves and to estimates gathered entirely from state-level data. Figure 2-6 shows the per capita emissions estimates for 27 MSAs from 5 different sources: 1) strictly state-level data from the EPA (U.S. EPA, 2015[B]), 2) self reported estimates from the city climate action plans, 3) our integrated approach using 2011 data and 2002 per capita data for residential and commercial buildings (labeled 2011a), 4) our integrated approach using 2011 data and state-level estimates for per capita emissions from residential and commercial buildings (labeled 2011b), and 5) our integrated approach using 2002 data. Note that the dates next to each location in Figure 2-6 correspond to the year in which that particular city conducted their emission inventory.

The MSAs/cities included in Figure 2-6 include all of the urban core areas that have active memberships and GHG reduction targets registered with ICLEI (ICLEI USA, 2015[A]). The emission estimates reported by the cities in the climate action plans were typically compiled using ICLEI's Clean Air Climate Protection (CACP) software (OpenEI, 2015). However, in some cases, cities form and report their estimates without the assistance of CACP. The state-level estimates are based on the EPA's 2011 State Energy CO_2 Emissions data set and 2011 population data from the Census Bureau (U.S. Census Bureau, 2012[B]; U.S. EPA, 2015B).

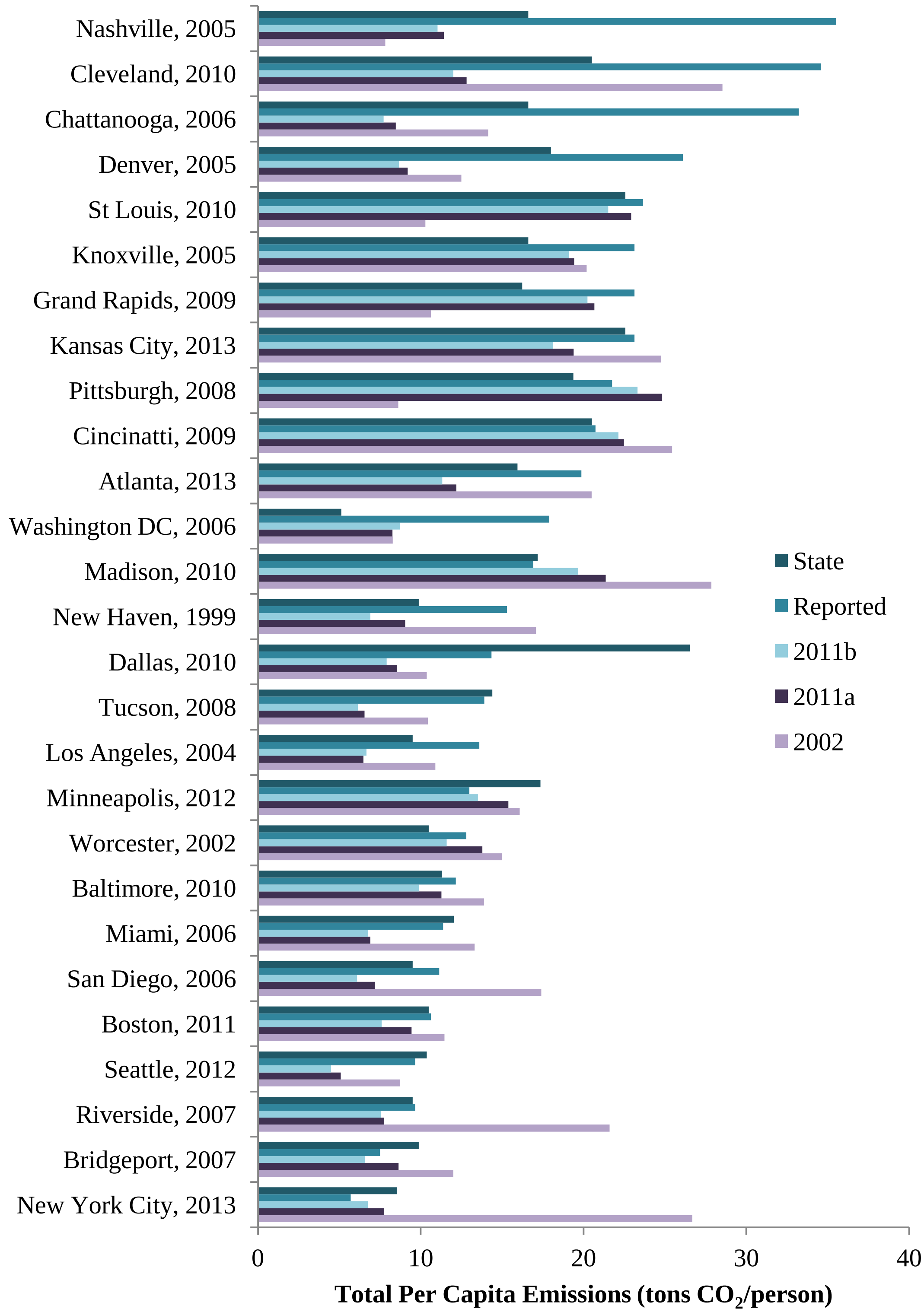

Figure 2-6 Comparison of total per capita GHG emissions for various metropolitan areas as estimated by different methods/datasets: estimates based entirely on state-level per capita emission values (State), self reported estimates from the cities (Reported), and estimates using our integrated approach for various years (2011a, 2011b, and 2002)

Figure 2-6 indicates that for 17 of the 27 MSAs analyzed, the different estimation methods yield comparable results. However, for 5 of the MSAs (Nashville, Cleveland, Chattanooga, Denver, and Washington, DC), the estimates reported by the cities were drastically higher than the estimates from the other methods. On the other hand, for 4 of the MSAs (San Diego, Riverside, Madison, and New York City), the estimates from our integrated approach using the 2002 data were drastically larger than the estimates from the other methods. Finally, for the Dallas MSA, the estimates using state-level per capita data were much larger than the estimates from the other methods.

One of the main factors contributing to the discrepancies observed above could be the different geographic boundaries associated with the different data sets. The emission estimates reported by the cities are confined to the city-limits of a given area, while the emission estimates from the integrated approach are at the MSA level (as described in Section 2.3). As discussed by Tamayao et al., per capita emissions for certain sectors (transportation, residential, commercial) can be significantly different between central and outlying counties (Tamayao et al. 2014). Some of the implications of these geographic differences are discussed further in Chapter 3.

In addition to comparing per capita emissions, we also assessed how different methods estimated the proportion of total emissions attributable to different sectors. Figure 2-7 depicts the percentage of total emissions attributable to waste, transportation, buildings, and “other” for 6 different MSAs as estimated by 4 different methods: 1) our integrated approach using 2002 data, 2) our integrated approach using 2011 data and 2002 per capita data for residential and commercial buildings (labeled 2011a), 3) our integrated approach using 2011 data and state-level per capita estimates for residential and commercial buildings (labeled 2011b), and 4) reported estimates from the city climate action plans. In order to allow for more consistent comparison, the data were aggregated into the broader sectors mentioned above. The transportation sector includes on-road and non-road transportation. The buildings sector includes direct emissions from residential, commercial, and industrial buildings, as well as emissions from electricity generation. The "other" sector primarily includes emissions from industrial processes, but in some cases may include activities such as agriculture.

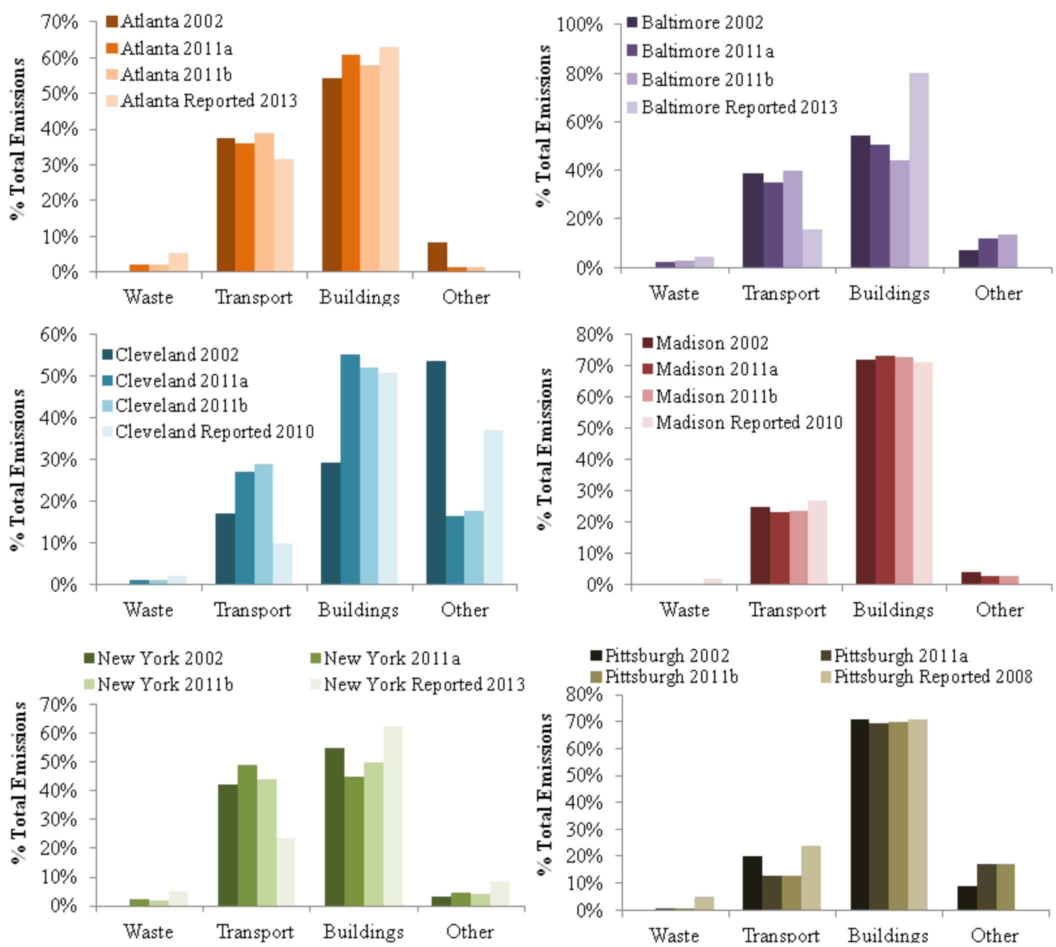

Figure 2-7 Comparison of how different methods estimate the proportion of total emissions attributable to different sectors: waste, transportation, buildings, and "other."

Generally speaking, the proportions estimated by the integrated approach appear to be fairly comparable to those reported by the cities in their climate action plans. However, there appears to be a tendency for the integrated approach estimates for transportation to be higher than the reported values. This observation could likely be attributed to a couple of things. First, the integrated approach accounts for a larger geographic area than the city-reported data, so more transportation activity (i.e. commuting that occurs between the central city and suburban areas) is captured by the integrated approach. Secondly, the integrated approach includes emissions from industrial processes (as classified in the "other" category), while cities typically do not include emissions from industrial processes in their inventories. The impact of the transportation discrepancies appears to be particularly pronounced in Baltimore, New York, and Atlanta. In these cases, the discrepancy between transportation estimates from the integrated approach and the reported data appear to correlate directly with the discrepancies observed for the building sector – if transportation accounts for a higher proportion of emissions under the integrated approach, then the proportion of emissions attributable to other sectors must be lower. Similarly, emissions from industrial processes appear to contribute to the discrepancy between the integrated approach and the reported values in Pittsburgh and Cleveland.

2.5 Conclusions and Implications

In this chapter we have outlined an integrated approach for estimating metropolitan greenhouse gas emissions using publically available national and state datasets. We also compare the estimates from our integrated approach to estimates from state-level per capita data and estimates reported by cities in their climate action plans.

Generally, the integrated approach appears to produce comparable results to the values reported by cities – especially in terms of the proportion of total emissions attributable to specific sectors. In specific instances, there were differences between estimates from the integrated approach and values reported by the cities – especially in terms of total per capita emissions of specific areas. These discrepancies likely arise from differences in the geographic boundaries and emission-producing activities included in the different datasets, and help highlight some of the difficulty and uncertainty associated with comparing the emissions of different locations if they are estimated under different circumstances. The discrepancies also help emphasize one of the primary benefits of our approach: using a uniform method and set of data to form consistent emission estimates across multiple metropolitan areas. The implications of discrepancies from scope and boundary choices are explored further in Chapter 3.

Additionally, our work can contribute to the process of forming GHG inventories and climate action plans at the local level. In complement to the CACP and ClearPath software typically employed by cities, our approach can help decision makers get an initial understanding of the primary contributors to their overall emissions without having to invest heavily in collecting and analyzing "bottom-up" data. In some cases, this initial assessment may be enough for the decision makers to move forward with prioritizing and implementing GHG mitigation strategies. In other cases, the initial assessment can still be valuable in helping the decision makers decide where it may be worthwhile for them to invest time and resources in getting more specific and detailed data. Finally, by having a database of consistently estimated emissions for multiple locations, decision makers could more confidently compare themselves to their peers in whatever manner they see fit.

Carrying this work forward, it would be beneficial to expand the number of locations to which our approach is applied. Here, we only analyze the 100 largest metropolitan areas in the United States, but this analysis could be expanded to the remainder the country. It would also be beneficial to continue to improve the emissions estimates for residential and commercial buildings by getting utility-specific natural gas consumption values for areas of interest. Additionally, with the expected upcoming release of 2014 NEI data, the values presented here could be further updated. Finally, an ultimate goal of this work would be to develop a searchable online database so that researchers and decision makers can more easily access, interpret, and update the data as needed.

3. THE IMPLICATIONS OF SCOPE AND BOUNDARY CHOICE ON THE ESTABLISHMENT AND SUCCESS OF METROPOLITAN GREENHOUSE GAS REDUCTION TARGETS IN THE UNITED STATES

3.1 Introduction

Over the past few decades, cities across the United States have been taking a proactive approach toward addressing climate change by developing climate action plans (CAPs). The basic framework for these CAPs is to conduct a greenhouse gas (GHG) emission inventory, establish GHG emission reduction targets, develop strategies for achieving the reduction target, implement those strategies, monitor results and progress, and make modifications as necessary (ICLEI USA, 2015[A]).

Currently, over 130 communities have partnered with ICLEI, a non-profit organization focused on climate and environmental sustainability issues at the local level, to develop CAPs and GHG reduction targets – see Table B1 in Appendix B for full list. Of these communities, 130 have at least one reduction target, 51 communities have at least two reduction targets, and 27 communities have at least three reduction targets (ICLEI USA, 2015[A]). Table 3-1 provides a summary of the typical reduction values and time frames associated with these targets. For these 130 communities, 2002 typically served as the baseline year.

Table 3-1. Summary of GHG reduction targets for communities across the United States adapted from (ICLEI USA, 2015[A])

	Number of Cities	Typical Planning Horizon	Typical Overall Reduction	Average Annual Reduction Rate
1st Reduction Target	130	~ 2020	~ 20%	1.1%
2nd Reduction Target	51	~ 2025	~ 30%	1.3%
3rd Reduction Target	27	~ 2050	~ 80%	1.6%

Generally speaking, communities have typically compiled their GHG inventories with the help of the Clean Air Climate Protection (CACP) software produced by ICLEI (OpenEI, 2015). By default, the software uses utility information, vehicle miles travelled (VMT) estimates, and waste disposal estimates provided by city officials as inputs. Inventories that use the software typically include five categories: energy consumption (electricity and natural gas) in residential buildings, energy consumption in commercial buildings, energy consumption in industrial buildings, transportation energy consumption (typically related to light-duty vehicle gasoline consumption), and emissions related to the production/disposal of waste generated within the city.

In recent years, considerable work has been done to continually improve the quality, accuracy, and consistency of community GHG inventories. ICLEI's 2013 Protocol for counting and reporting community GHG emissions builds upon the CACP framework discussed above (ICLEI

USA, 2013). The 2013 Protocol states that all emissions inventories should, at a minimum, include estimates on five "Basic Emissions Generating Activities": 1) Use of electricity by the community, 2) Use of fuel in residential and commercial buildings, 3) Use of fuel for on-road passenger and freight motor vehicle travel, 4) Energy use in the treatment and distribution of potable water and waste water, and 5) Emissions from the collection and degradation of solid waste generated by the community (ICLEI USA, 2013). For on-road transportation emissions, the Protocol recommends (and provides guidance for) using an origin-destination demand-based allocation of trips (ICLEI USA, 2013). This approach does a better job of capturing the full scale of transportation emissions related to a city, as opposed to the "in-boundary" (i.e. only within the city limits) emissions that were used in previous frameworks. Although not considered "required" emissions, the 2013 Protocol also provides guidance on estimating emissions from industrial processes and "freight rail, transit, aviation, marine vessels, and off-road equipment (ICLEI USA, 2013)."

Building on this Protocol, ICLEI also launched the ClearPath online emissions management system in 2014 (ICLEI USA, 2015[B]). ClearPath essentially replaces the CACP software previously used and makes it easier for practitioners to measure and report emissions, as well as develop projections of future emissions under different scenarios. As of August 2015, more than 350 local governments have used the ClearPath software (ICLEI USA, 2015[A]). However, the inventories and forecasts produced by these communities are often not readily available to the public. Thus, the most recent sets of inventories that are widely available are still commonly based on the CACP approach. As ClearPath becomes more widely implemented, it is assumed that access to results will become more widely available. Should this occur, it will be very interesting to compare inventories and CAPs conducted with ClearPath to those conducted by CACP. More specifically, it will be beneficial to see if practitioners take advantage of the additional functionality and forecasting tools available in ClearPath.

Internationally, the PAS 2070 protocol produced by the British Standards Institute (BSI) provides guidance on developing city-level emissions estimates that include trans-boundary on-road and non-road transportation and industrial activity (BSI, 2013). Two methods are described for establishing these estimates: the Direct Plus Supply Chain (DPSC) method and the Consumption-Based (CB) method. The DPSC method accounts for direct emissions from within the city boundary and indirect emissions from consumption of goods and services outside the city limits (e.g., grid-supplied electricity, trans-boundary travel, etc.). The CB method accounts for direct and indirect life cycle emissions for "all goods and services consumed by residents of a city (BSI, 2013)."

The protocols discussed above form a strong foundation for developing reliable community-level GHG inventories. Nonetheless, there still appear to be some issues worthy of consideration. For example, nearly all of the inventories examined were confined to the city limits of a given area. However, for activities like on-road commuting between urban and suburban areas, emissions associated with the city but outside the city limit often go under-reported. Similarly, the under-reporting of emissions from non-electricity fuel consumption and industrial processes also appear to be a common occurrence (Ramswami and Chavez, 2013).

With some of these issues in mind, additional approaches for estimating emissions have been demonstrated by various research groups. Ramaswami and Chavez evaluated the GHG emissions and urban energy/carbon intensity indices for 20 different U.S. cities and determined that, for production-based frameworks, normalizing by GDP is more effective approach. On the other hand, for consumption-based approaches, they found that normalizing by population was the more effective approach (Ramaswami and Chavez, 2013). Additionally, researchers at The University of Colorado-Denver and the City and County of Denver, developed a methodology for measuring city-scale emissions on a life-cycle basis. This approach allows for a more comprehensive assessment of a city's emissions by accounting for "trans-boundary" surface transportation (trips that originate or end in a given city but do not necessarily remain with the city-limits for the entire duration of the trip), airline emissions, and embodied emissions for goods consumed within the city (e.g. fuel, food, and water) (Ramaswami et al., 2008; Hillman, Janson, and Ramaswami, 2011). The use of demand-based allocation for transportation fuel use and LCA databases for Scope 3 emissions (indirect emissions associated with an activity or the use/purchase of a good or service - see Section B2 of Appendix B) allowed for the estimation of GHG footprints in 8 U.S. cities. Overall, this study found that "trans-boundary" activities (e.g. on-road and airline travel, scope 3 emissions, etc.), contributed nearly 50% more, on average, to a city's emissions compared to the in-boundary emissions typically reported (Hillman and Ramaswami, 2010).

A majority of the approaches described above rely on bottom-up data collection, which can frequently be resource and time intensive. For example, the approaches proposed in ICLEI's 2013 protocol and implemented by Hillman et al. for estimating "trans-boundary" transportation emissions rely on relatively detailed travel demand data and modeling software (Hillman, Janson, and Ramaswami, 2011). However, local practitioners may not always have the access or the ability to use these datasets and software. Additionally, although captured somewhat by the Scope 3 emission estimates in Ramaswami et al., emissions from industrial processes are commonly omitted from CAPs and local GHG inventories (Ramaswami et al., 2008; Hillman and Ramaswami, 2010).

Finally, although there has been an increased call for analysis and planning at the regional or mega-regional level (NRC, 2010; NRC, 2013; NRC, 2011; NRC, 2014), implementation to this point has been relatively sparse. However, examples of regional GHG inventories and policies have emerged from the San Francisco Bay Area Air Quality Management District (BAAQMD) and the Sacramento Area Council of Governments (SACOG) (BAAQMD, 2015; SACOG, 2015), and may serve as an indication of a more wide-spread shift toward a regional focus moving forward. The expansion to regional emission planning and management is further supported by that fact that, on average, the communities within metropolitan areas that have established GHG reduction targets only account for 13% of the total population of the metropolitan area (U.S. Census Bureau, 2012[A]; U.S. Census Bureau, 2012[B]; ICLEI USA, 2015[A]). In other words, on average, 87% of the total metropolitan population lives in communities that do not have an established GHG reduction target.

This chapter explores these issues more closely and determines the importance of limiting analysis to the city limits and to certain emission producing activities. More specifically, we use metropolitan-level GHG estimates gathered from publically available data sources to determine how the inclusion of under-reported emissions (i.e. emissions from outside the central city limits, emissions from activities like industrial processes and urban-suburban transportation, etc.) effects the ability of different locations to meet their GHG reduction targets.

The remainder of this chapter is organized as follows. Sections 3.2 and 3.3 discuss the data and methods used in our analysis. Section 3.4 quantifies and analyzes the significance of under-reporting emissions from industrial processes, on-road transportation, and confining analysis to the city-limits of a given area. Finally, section 3.5 discusses some policy implications and conclusions of our analysis.

3.2 Data

The emissions estimates used in this analysis are based on the same data and methods used in Chapter 2. Production-based GHG estimates were formed from a combination of data from the EPA's mandatory GHG reporting program, the EPA's National Emissions Inventory, and natural gas consumption data from the California Energy Commission and the U.S. Energy Information Administration (EIA) (U.S. EPA, 2010; U.S. EPA, 2013; U.S. EPA, 2014[C]; U.S. EPA, 2015[B]; California Energy Commission, 2015; U.S. EIA, 2014). Overall, we end up with production-based GHG estimates for the year 2011 for the 100 largest metropolitan areas in the United States. The estimates include emissions from industrial activity, electricity production, waste generation and disposal, on-road transportation, natural gas consumption in residential buildings, and natural gas consumption in commercial buildings. For the duration of this report, these data will be referred to as the "integrated data."

Information about the magnitude and timing of various community-level GHG reduction targets was available from ICLEI's 2015 progress report (ICLEI USA, 2015[A]). Information and data regarding GHG inventories of individual cities was available from the Carbonn Climate Registry, the Carbon Disclosure Project, and the cities themselves (Carbonn Climate Registry, 2014; Carbon Disclosure Project, 2015). It is important to note that the actual emission data from these sources are not the primary focus of this analysis. We mainly used these sources to gain a better understanding of the sector scopes and geographic boundaries commonly used in GHG inventories reported by cities. In order to ensure consistent comparisons and allow for the analysis of numerous locations, the integrated data serves as the primary source of quantitative data for this chapter. However, comparisons between the integrated data and the estimates reported by cities are included in Chapter 2.

Finally, population data from the U.S. Census Bureau were used to compare the populations of various locations and develop per capita emissions estimates. These population values are for the year 2011 and were available at the city, county, and metropolitan level (U.S. Census Bureau, 2012[A]; U.S. Census Bureau, 2012[B]; U.S. Census Bureau, 2012[C]).

3.3 Methods

We started with the 130 communities that have partnered with ICLEI to form and report their GHG reduction targets. However, we were primarily interested in metropolitan areas, so we limited our analysis to communities that are within one of the 100 largest metropolitan areas as defined by the U.S. Census Bureau. Under this constraint, 87 communities qualified and were contained within 41 Metropolitan Statistical Areas (MSAs) – see Section B3 in Appendix B.

Thus, all of the results and emissions estimates discussed below are developed from the integrated data for the 41 MSAs of interest.

The first part of our analysis focused on quantifying the emissions from activities that are frequently under-reported by cities in their GHG inventories: industrial activity and on-road transportation within the metropolitan area but occurring outside the urban core. Thus, we classified the total MSA GHG emissions into 3 categories: 1) “Reported” emissions, 2) “Under-reported” industrial emissions, and 3) “Under-reported” on-road emissions. Although on different geographical scales, the “reported” emissions are meant to serve as a proxy for the activities frequently included by cities in their inventories: electricity production at the MSA level, waste at the MSA level, residential and commercial natural gas consumption at the MSA level, and on-road transportation within the urban core. The under-reported industrial emissions include industrial activity within the urban core. This component was limited to the urban core, because we could not envision a scenario in which a government entity might be able to influence industrial facilities outside of its jurisdiction. Finally, the “under-reported” on-road emissions include light and heavy duty vehicle activity within the metropolitan area but outside of the urban core. These boundaries were chosen to approximate emissions that result from commuting and the transfer of goods between urban and suburban parts of a metropolitan area. In contrast to industrial activity, we thought the entire MSA was an appropriate scale for transportation emissions, because planning and policy efforts within the central city or urban core can reasonably be expected to impact transportation activity and emissions throughout a metropolitan area (e.g. increased densification, implementation of public transit, etc.). Once estimates were formed for each of these 3 categories, we evaluated how total MSA emissions change when the "under-reported" estimates are added to the "reported" estimates. We then evaluate how the emission reduction plan would need to be altered to accommodate the addition of these added emission sources.

The second part of our analysis focuses on the implications of cities confining their inventories and planning to the city limits. Thus, when evaluating emissions from a given metropolitan area, we form three different categories: 1) the urban core county/counties, 2) the central counties outside the urban core, and 3) the outlying counties of the MSA. For our analysis, we classified the "urban core" as the county (or counties) that house(s) the primary city of an MSA. We maintain the central and outlying classifications specified by the Census Bureau. Using the San Francisco-Oakland-Fremont, CA MSA as an example, San Francisco County serves as the urban core; Alameda, Marin, and San Mateo counties serve as the central counties outside the urban core, and Contra Costa County serves as the outlying county. Once estimates were formed for each of these 3 categories, we evaluated how total MSA emissions change when the "central" and "outlying" estimates are added to the "urban core" estimates. We then evaluate how the emission reduction plan would need to be altered to accommodate the emissions from the additional geographic areas.

3.4 Results

*3.4.1 Quantification of Under-reported Emissions Based on Integrated Data***.**

As mentioned above, there are two emission producing activities that we quantify as commonly under-reported in city reported inventories: 1) on-road transportation that occurs within the MSA but outside the urban-core, and 2) emissions from industrial processes (i.e., non-utility energy consumption) that occur within the urban core. We denote these emissions as "under-reported activities," and quantify them using the integrated data.

Based on emissions estimates from the integrated data, the under-reported activities were found to account for between 0.1 (in the Bridgeport, CT MSA) and 51 million metric tons of CO_2e (in the New York City MSA), with an average of roughly 9 million metric tons of CO_2e per MSA across all MSAs. These omitted categories account for between 1% (in Bridgeport-Stamford-Norwalk, CT MSA) and 44% (in the Portland, OR MSA) of total production-based emissions within an MSA, and average roughly 24% of the total production-based emissions across all MSAs. Similar percentages hold on a per capita basis, and emissions range from roughly 0.1 metric tons CO_2e per person (in the Bridgeport, CT MSA) to roughly 8.1 metric tons CO_2e person (in the Cleveland, OH MSA). Given these results, it appears that by not fully accounting for these activities, certain metropolitan areas may be missing key opportunities to reduce their overall GHG emissions.

Figure 3-1 uses the integrated data to depict the "under-reported" and "reported" production-based emissions for 41 metropolitan areas in the United States. The "reported" emissions represent a proxy for the emissions that are most frequently reported in city GHG inventories, while the "under-reported" emissions represent the activities that cities do not commonly report - as discussed earlier. The figure also includes per capita emissions for each MSA.

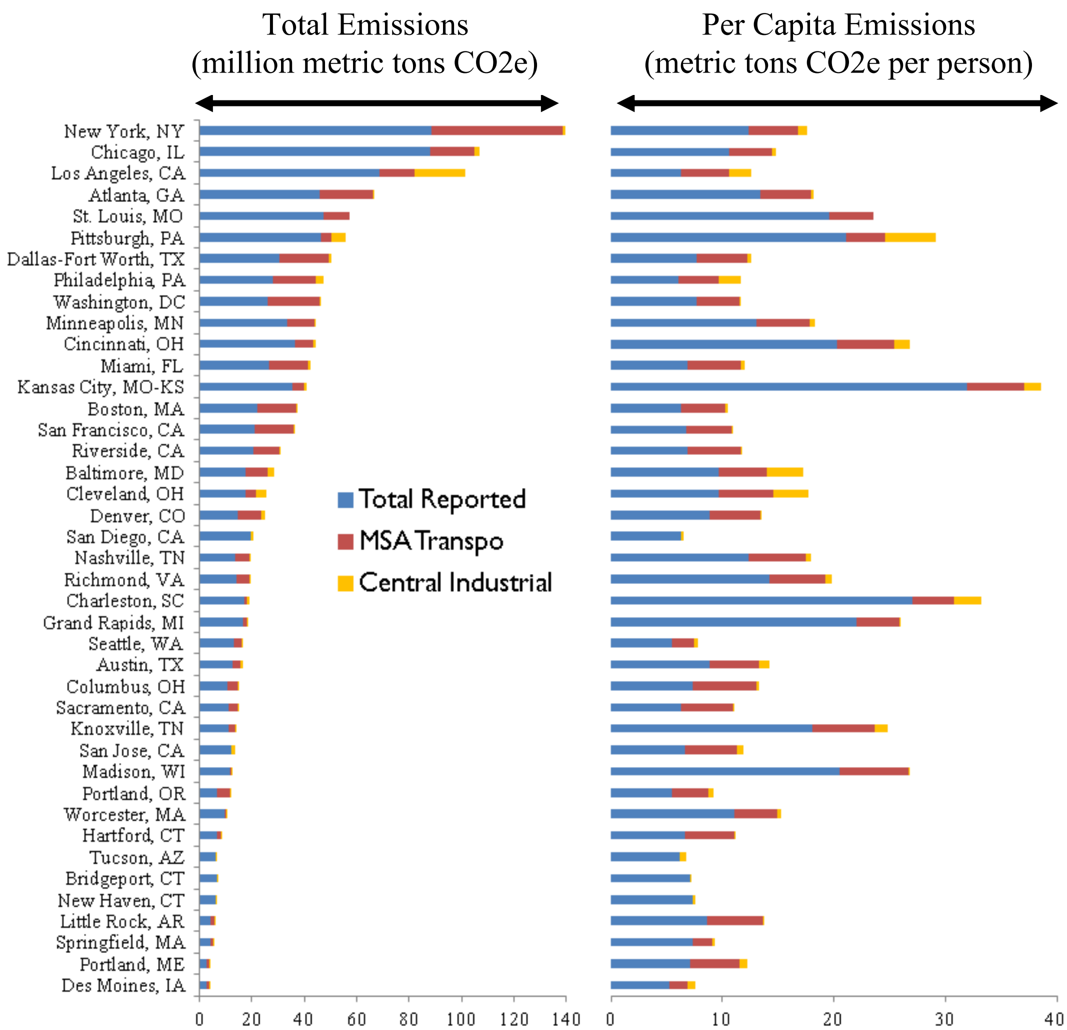

Figure 3-1 Profile of total and per capita CO_2e emissions for 41 metropolitan areas as estimated with the integrated data. Emissions estimates for "reported" activities (i.e., the activities commonly reported by cities in their GHG inventories) are shown in blue and the "under-reported" emissions are shown in red (on-road transportation outside the urban core), gold (industrial activity within the urban core). The left side of the figure reports total annual emissions in million metric tons of CO2e and the right side of the figure reports per capita emissions in metric tons CO2e per person.

Figure 3-1 shows that "under-reported" emissions can vary widely between metropolitan areas and can be rather large in certain cases. For a majority of the MSAs, on-road transportation outside the central county/urban core comprises the largest portion of total under-reported emissions. However, for places like Los Angeles, Cleveland, Pittsburgh, and Baltimore, emissions from industrial activity within the central county/urban core are as large as (or larger) than on-road transportation emissions. The large contribution from industrial activity in these locations is somewhat surprising given that industrial activity is typically expected to be located outside of the urban core for an MSA – particularly in the United States.

Care should be taken when interpreting our results for industrial activity. Our data is only granular to the level of the county in which the central urban core is located. Less concern is warranted in instances where the city comprises all (or a majority) of the county for which emissions are reported (e.g. Denver County, Miami-Dade County, etc.). Similarly, if county-level industrial emissions are low or negligible, city-level industrial emissions can also be considered to be low or negligible. However, there is the potential for over estimating if our approach is used to estimate industrial emissions that only occur within a given city limits that comprise only a small portion of the central county. One way to address this issue would be to allocate the county-level industrial emissions to a given city based on GDP data. Alternatively, since industrial emissions are based on point source estimates, more refined emissions values for a given city could be derived from facility-reported data in the EPA's National Emissions Inventory or the EPA's Mandatory GHG reporting program (U.S EPA, 2014[C] ; U.S. EPA, 2014[D]).

Scope 3 emissions are frequently described as outside the bounds of analysis in GHG inventories. Thus, even if one does not fully agree with the boundary of analysis employed here, the emissions estimates for otherwise omitted activities can at least serve as an initial lower-bound estimate of the Scope 3 emissions for various cities and help allow for their inclusion in the inventory and CAP process.

3.4.2 Quantification of Urban Core Versus Metropolitan Emissions Using Integrated Data.

In addition to quantifying emissions from under-reported activities, we also quantified metropolitan emissions that are under-reported due to cities limiting their analysis and planning to the city limits. The population of the communities that have developed GHG reduction targets is only roughly 15% of the U.S. population. Thus, in order to get a better understanding of the implications that geographic boundary choices have on the emissions profile of a given area, we use the integrated data to estimate and compare three different categories of emissions: 1) the "urban core", 2) the "central" counties outside the urban core, and 3) the "outlying" counties within the MSA. For this analysis, the estimates for the "urban core" are assumed to be comparable to those reported by a given city, while the "central" and "outlying" estimates are assumed to be under-reported by cities due to their boundary choices.

Based on the estimates from the integrated data, the "non urban core" MSA emissions (i.e. emissions from central and outlying MSA counties) were found to account for between 0 metric tons CO_2e (in the New Haven, CT, Bridgeport, CT, San Diego, CA, and Tucson, AZ MSAs) and 116 million metric tons CO_2e (in the Chicago, IL MSA), with an average of roughly 23 million metric tons of CO_2e per MSA across all MSAs. These non-urban core categories account for between 0% (in the New Haven, CT, Bridgeport, CT, San Diego, CA, and Tucson, AZ MSAs) and 98% (in the St. Louis, MO MSA) of total production-based emissions within an MSA, and average roughly 55% of the total production-based emissions across all MSAs.

On a per capita basis, the "non urban core" emissions range from 0 metric tons CO_2e per person (in the New Haven, CT, Bridgeport, CT, San Diego, CA, and Tucson, AZ MSAs) to roughly 30 metric tons CO_2e person (in the Charleston, SC MSA). In terms of proportion of total MSA per capita emissions, the "non urban core" emissions account for between 0% (in the New Haven, CT, Bridgeport, CT, San Diego, CA, and Tucson, AZ MSAs) and 98% (in of the St. Louis, MO MSA) total MSA per capita emissions.

Figure 3-2 uses the integrated data to depict the production-based emissions for the "urban core", "central" counties (outside the urban core), and "outlying" counties for 41 metropolitan areas in the United States. The "urban core" emissions represent a proxy for the emissions that are reported in city GHG inventories, while the "central" and "outlying" emissions represent potentially "under-reported" emissions. The figure also includes per capita emissions estimates.

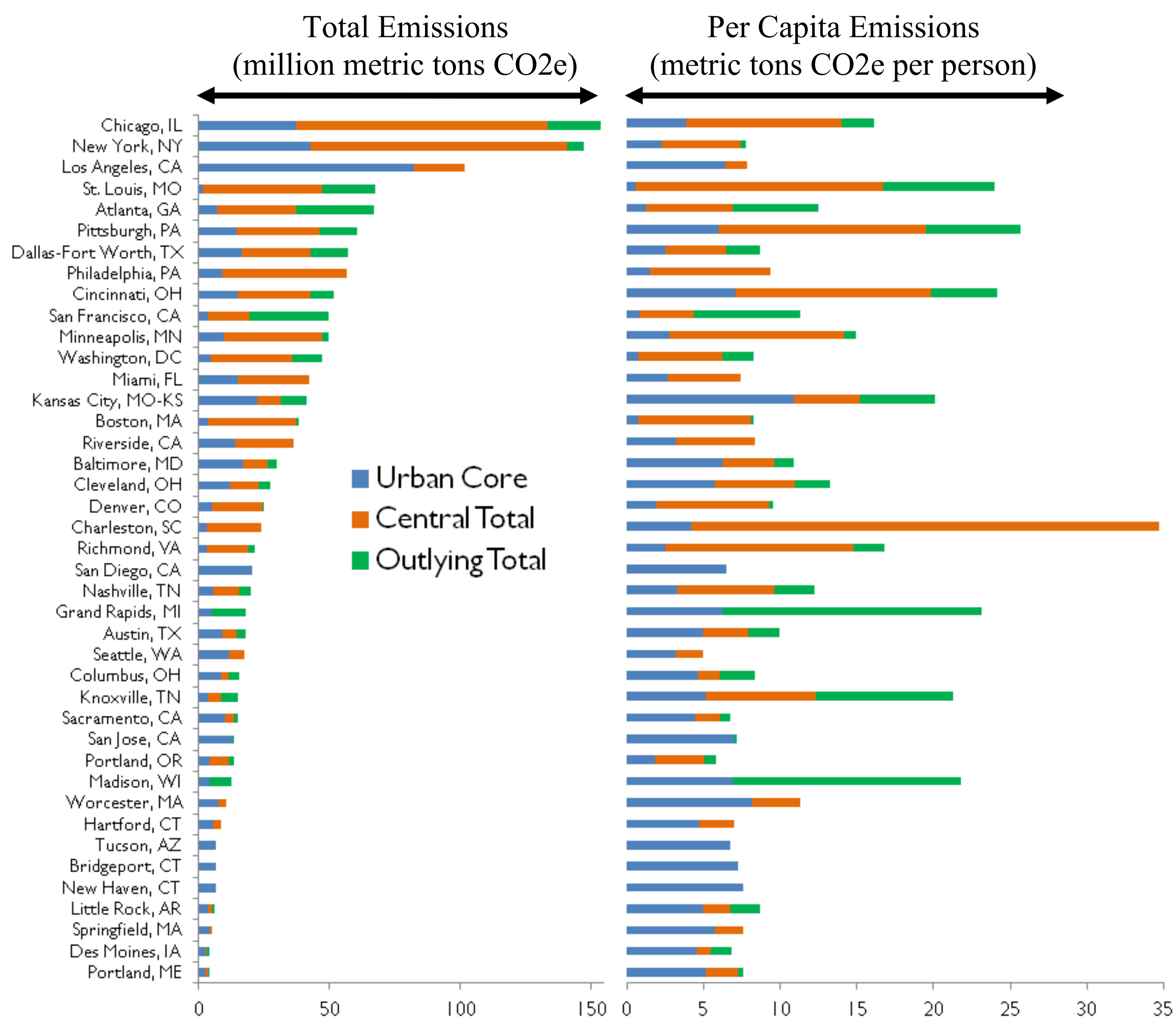

Figure 3-2 Profile of total and per capita CO_2e emissions for 41 metropolitan areas as estimated with the integrated data. Emissions estimates for the "urban core" (i.e., central city and area of density) are shown in blue, "central" counties outside of the urban core are shown in orange, and "outlying" counties of the metropolitan area are shown in green. The left side of the figure reports total annual emissions in million metric tons of CO2e and the right side of the figure reports per capita emissions in metric tons CO2e per person.

Figure 3-2 shows that, in most cases, the vast majority of emissions within a metropolitan area come from outside the urban core. Thus, although it is important for the central cities to develop CAPs and GHG reduction plans, failure to expand and develop analysis and policies at the metropolitan level could lead to sub-optimal results in terms of achieving desired emission reduction targets. The figure also indicates that the central counties appear to have a much larger contribution to total emissions than the outlying counties – on average, 84% of emissions come from central counties (including the urban core). Thus, if steps were taken to expand CAPs beyond city limits, it might be more effective in the short-term to focus on communities within the central counties and the central counties themselves before expanding to outlying counties.

3.5 Discussion and Implications

The analysis above helps illustrate how commonly under-reported emissions can be estimated and incorporated into GHG inventories and climate action plans. It also helps to highlight implications that may arise from adding these “under-reported” emissions into the analysis and planning process. As organizations like ICLEI continue to provide updated protocols and inventory software and more communities adopt a regional planning approach similar to those of Sacramento Area Council of Governments and the San Francisco Bay Area Air Quality Management District, decision-makers will likely need to revaluate how they develop and implement their GHG reduction targets. To further demonstrate this point, Figure 3-3 provides an illustrative example of potential GHG reduction pathways for Baltimore that could occur with and without the inclusion of the “under-reported” emissions.

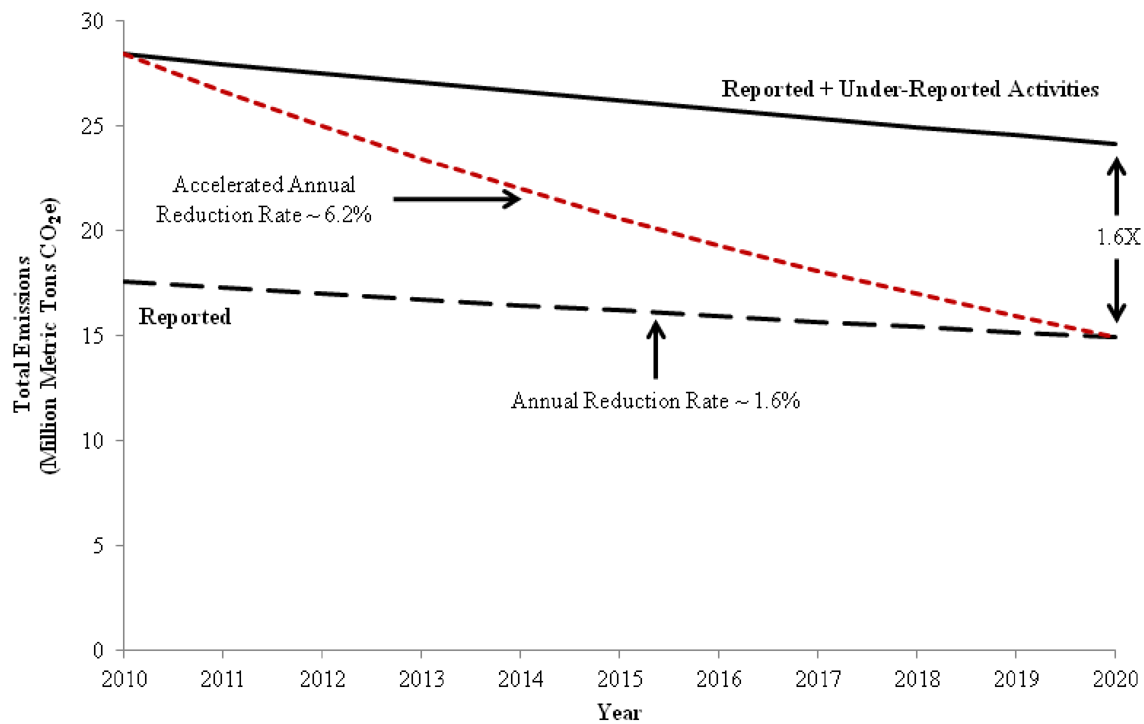

Figure 3-3. Illustrative example of GHG reduction policies for Baltimore under different scope scenarios

The City of Baltimore has pledged to reduce its emission to 15% below 2010 values by the year 2020 (ICLEI USA, 2015[A]). Based on the integrated data, this equates to moving from roughly 17.6 million metric tons CO2e in 2010 to roughly 14.9 million metric tons in 2020. This level of reduction equates to roughly a 1.6% annual reduction rate over the ten year period (this baseline scenario is depicted by the dashed black line in Figure 3-3). If Baltimore decision makers decided they wanted to follow the ICLEI 2013 Protocol more thoroughly and expand their scope to include emissions from industrial processes within the city limits and on-road transportation within the metropolitan area but outside the city limits, its baseline emissions undergo a 1.6 fold increase (depicted as the solid black line in Figure 3-3). Under this new emission regime, the decision makers would then have to decide what emission rate they want to pursue. One option would be to maintain the original overall reduction of 15%. Another option would be to maintain the original emission target (14.9 million metric tons in 2020). Under the first option, the 2020 emissions would be roughly 24 million metric tons, but would be more representative of the full scale of emissions within the Baltimore metropolitan area. Under the second option, the community would need to adopt highly aggressive and comprehensive emission reduction measures in order to achieve an annual reduction rate of 6.2% (red dashed line in Figure 3-3), as opposed to the original annual reduction rate of 1.6%. It is important to note that these scenarios were evaluated in the absence of changes to population and technology/policy. As will be discussed in Chapter 4, these factors can have a major influence on emissions moving forward. Thus, with the inclusion of population change, annual reduction rates would likely need to be even larger than 6.2% if the goal were to reach the originally proposed emission levels by the year 2020.

Assuming all of the analyzed communities have a 30% reduction target (comparable to the average mid-term reduction targets currently being pursued in several areas). Inclusion of the "under-reported" activities of industrial processes and on-road transportation outside the urban core would require, on average, an additional reduction of roughly 17% to achieve the same emission levels as the original target. Similarly, inclusion of "non urban core" metropolitan emissions would require, on average, an additional reduction of roughly 40% to achieve the same emission levels as the original target. In other words, to reach the equivalent emission value achieved from a 30% reduction at the reported/urban-core level, the average MSA would have to achieve a 70% reduction in emissions if non-urban core counties were included in the planning and analysis, and a roughly 50% reduction in emissions if the "under-reported" activities were included in the planning and analysis.

Achieving a roughly 2% annual reduction rate may prove to be quite challenging for local governments. Historically, the City of Pittsburgh was able to achieve a 30% reduction in emissions over a 30 year period. But, in order to achieve such reductions, the city lost 25% of its population and 40% of its value-added industrial activity (Hoesly et al., 2012). More recently, The City of Portland and Multnomah County have been able to achieve an annual emission reduction rate of roughly 2.2% between the years 2000 and 2013, while also experiencing increases in population and number of jobs (City of Portland and Multnomah County, 2015). However, it is unclear whether such a reduction rate can be sustained over the course of multiple decades. Additionally, moving from an annual reduction rate of roughly 2% to one that is 7-8% would likely require an unprecedented effort. Between 1990 and 2013, the largest single year decrease in national GHG emissions in the U.S. was roughly 7%, between 2008 and 2009 (U.S. EPA, 2015[B]). The largest average annual decrease in national emissions over a 10 year period was roughly 4%, between 2003 and 2012 (U.S. EPA, 2015[B]). Thus, if cities were to expand their analysis to cover "under-reported" emissions, they would likely require extraordinary levels of commitment, policies, and economic transformation in order to achieve the originally desired levels of GHG reduction.

Given the emerging cases and continued calls for GHG analysis and policies at the regional or mega-regional level, this analysis provides an initial framework for inclusions that could be made to develop more comprehensive metropolitan level GHG emission estimates. Additionally, the analysis presented above highlights some key issues that may arise as local-level GHG policies continue to evolve and technology and data management advancements allow for more complete and accurate assessment of GHG emissions in metropolitan areas. As policies expand in geographic scope and include more emission-producing activities, GHG reduction targets will also likely need to change. For example, GHG reduction plans may need to become more aggressive in terms of annual reduction rates, adjust the overall emission value targeted, or increase the number of years in which to achieve the desired emission reduction.

The continued expansion of the scope and boundaries of local GHG reduction plans can play a major factor in national-level GHG emissions reduction efforts. For example, the sum of the emissions from under-reported activities in the 41 metropolitan areas analyzed was roughly 5% of total U.S. GHG emissions in 2011. Similarly, the sum of the "non-urban core" emissions from the 41 metropolitan areas analyzed was roughly 14% of total U.S. GHG emissions in 2011. Therefore, there appears to be much to gain from continuing to expand the scope and boundaries of local-level GHG reduction policies and the manner in which these policies evolve will help determine their overall influence on efforts to mitigate global climate change.

4. THE IMPLICATIONS OF CLIMATIC TEMPERATURE CHANGE, POPULATION CHANGE, AND POLICY CHANGE ON METROPOLITAN ELECTRICITY DEMAND AND GREENHOUSE GAS EMISSIONS

4.1 Introduction

The most recent IPCC Assessment Report estimates that average temperatures across the United States are projected to rise between 0.5 and 5^{o} C by the end of the century (IPCC, 2013). These projections are based on extensive work undertaken to understand and quantify the relationship between greenhouse gas (GHG) concentrations and rising temperatures (IPCC, 1992; IPCC, 1995; IPCC, 2007; IPCC, 2011; IPCC, 2014). As opposed to analyzing the impact that GHG emissions might have on increasing temperatures, the work presented here takes the approach of analyzing a less studied effect - how increasing temperatures will affect the level of electricity demand and subsequent emissions. More specifically, we first establish the relationship between observed temperatures and observed electricity demand in six metropolitan areas in the United States (San Antonio, Austin, Houston, Dallas/Fort Worth, Chicago, and Pittsburgh). We then apply data from statistically downscaled climate models to estimate how electricity demand might change as a result of increases in future temperatures. Other key factors that may substantively affect the level of total emissions in metropolitan areas are changes in population and changes in emission intensity in the electricity grid (York, Rosa, and Dietz, 2003; Wei, 2011; Dietz and Rosa, 1997; Chertow, 2000; Blackhurst et al., 2011; Tamayao et al.2014). Thus, we develop first order estimates of how changes in population and emission intensity impact future metropolitan electricity emission levels and compare these results to the impacts that climate change may have. Compared to Chapters 2 and 3, which focus more on current aspects of GHG inventories and reduction policies, this chapter investigates some of the forward-looking components of forecasting and planning for emissions in the future.

The relationship between temperature and energy demand has been studied for at least the past three decades (Quayle and Diaz, 1979; Le Comte and Warren, 1981; Warren and LeDuc, 1981; Downton, Stewart, and Miller, 1988; Badri, 1992; Lehman, 1994; Lam, 1998; Yan, 1998; Morris, 1999; Pardo et al., 2002). These studies used regression-based analyses to evaluate the influence of heating and/or cooling degree days on energy consumption. The studies covered a variety of different time-scales (multiple decades to monthly), geographic scales (national to city-level), end-uses (electricity versus natural gas), and sectors (residential, industrial, and commercial). Some of the studies only look at the impacts of temperature, while others look at the impacts of temperature in conjunction with other variables like population or price. Regardless of the scope of these analyses, the studies all show the strong influence that temperature has on energy demand.

All of the studies described above were retrospective and did not use their results to forecast future conditions. With a few exceptions, the incorporation of long-term projections across U.S. regions to understand how energy demand is likely to be affected by climatic temperature change has been few and recent. For example, Baxter and Calandri performed one of the first forward-looking analyses by estimating California’s annual electricity use and peak demand by the year 2010 under two climate change scenarios (Baxter & Calandri, 1992), and Amato et al. employed a degree-day methodology and econometric analysis to estimate how projected changes in temperature might impact energy demand in the state of Massachusetts (Amato et al., 2005). In a similar vein, Hadley *et al.* modeled the potential implications that projected monthly average temperatures would have on population-weighted heating/cooling degree days and subsequent energy use and corresponding fossil fuel CO_2 emissions for the nine Census Divisions in the United States between the years 2003 and 2025 (Hadley et al., 2006). Franco and Sanstad used temperature data from four California cities and electricity generation data for the state of California to estimate the impacts of two climate change scenarios on annual and peak electricity consumption between 2005 and 2099 (Franco and Sanstad, 2008). Sathaye et al. employed a similar approach, but used temperature data from across the state of California, as opposed to only four cities. They ultimately ended up assessing how projected changes in temperature might impact peak demand in the month of August by the year 2099 (Sathaye et al., 2013).

Our work builds on these previous studies in a few different ways. First, our analysis is at a finer geographic and temporal scale than the studies mentioned above. All of the works described above are at the national, state, or census division level. In contrast, our work is at the intra-state/metropolitan scale. Similarly, most previous works employ monthly or annual data, while our work is based on daily temperature and electricity demand data. Also, with the exception of Hadley et al., the previous works only focus on one state or region. Our work is novel in that it analyzes multiple areas across the United States using the same method. Additionally, with the exception of Hadley et al., our analysis estimates projected changes in GHG emissions in addition to electricity demand. Along these lines, our study is the first, to our knowledge, that estimates the GHG implications of changing temperatures using facility specific and regional emission intensity values (as opposed to national averages). Finally, to our knowledge, this is the first study to place the GHG implications of changing temperatures in the context of changing populations and emission intensity policies.

Ultimately, the work presented here strives to determine how projected changes in temperature due to climate change will impact metropolitan electricity use and subsequent GHG emissions. As a secondary objective, we also aim to form a link between temperature-induced changes in GHG emissions and changes that occur under different population and policy scenarios. Gaining a better understanding of the linkage between these factors can help the implementation of local and state emission reduction strategies and energy source/capacity planning. Finally, our exploration of multiple locations is important because it allows for a better understanding of how underlying climate, fuel mix, grid mix, economic profile, and population changes can impact the influence that temperature changes have on GHG emissions and reduction targets.

The remainder of the chapter is organized as follows. Section 4.2 explains the importance of focusing on metropolitan areas. Sections 4.3 and 4.4 describe the primary data sources and methods used in our analysis. Section 4.5 discusses the relationship between temperature and electricity demand. Section 4.6 summarizes the projected changes in temperature between now and the year 2035 for the geographic areas of interest. Section 4.7 discusses how the projected changes in temperature might affect electricity demand. Section 4.8 compares the effect of temperature change to the effect of population and policy changes. Finally, section 4.9 discusses some key conclusions and implications.

4.2 The Importance of Focusing on Metropolitan Areas

In contrast to previous studies that have focused on state, national, or regional levels, our analysis focuses on metropolitan areas. Climate varies greatly across a state, so performing the analysis at a more refined geographic scale can better capture the impacts that location can have on energy demand and projected changes in climate. Additionally, over 80% of people in the United States live in metropolitan areas (U.S. Census Bureau, 2013[A]). On a global scale, the proportion of people living in urban areas was estimated to be roughly 54% in the year 2014 and is projected to increase to 66% by the year 2050 (UN Department of Economic and Social Affairs, 2014). This level of urbanization results in high levels of resource consumption via complex and interdependent systems - roughly 75% of the earth's natural resources are consumed in urban areas (Swilling et al., 2013).

The concentration of people, infrastructure, and resource consumption make metropolitan areas prime locations to implement both climate change mitigation and adaptation strategies. For example, the large building stocks and transportation networks contained in metropolitan areas present many opportunities for reducing GHG emissions. Similarly, the large concentration of people and critical infrastructure enhance the vulnerability that metropolitan areas have to extreme events caused by climate change.

In response to these rising concerns over climate change, numerous cities across the world have developed Climate Action Plans (CAPs) in an attempt to quantify and reduce their GHG emissions and adapt to the impacts of climate change. This analysis will inform decision makers on the effects of several factors on future electricity demand and emissions in their region.

Additionally, although outside the scope of this work, our analysis could potentially aid in adaptation efforts by helping decision-makers anticipate time periods when their citizens and electricity infrastructure might be especially vulnerable to the effects of rising temperatures.

4.3 Data

The baseline temperature data for each location was available from the National Climatic Data Center produced by the National Oceanic and Atmospheric Administration (NOAA) (NOAA, 2015). For each area of interest, temperature data is available from Weather Bureau Army Navy (WBAN) weather stations located at the appropriate airport (i.e., temperature data for the Dallas metropolitan area is from DFW International Airport). For each location, daily high and low temperature observations for the year 2012 were used develop daily average temperature values.

The baseline electricity load data for each location comes from their respective Independent System Operators (ISO) and Regional Transmission Organizations (RTO). For the metropolitan areas in Texas, historical daily electricity generation data is available from the Electric Reliability Council of Texas (ERCOT) (ERCOT, 2015), while for the Chicago and Pittsburgh regions, historical daily electricity generation is available from the PJM RTO (PJM, 2015). For ERCOT, historical daily electricity load values are available at regional levels. San Antonio and Austin are within the South Central region, Dallas is within the North Central Region, and Houston is within the Coastal Region (see Figure C1 in Appendix C). For PJM, historical electricity load values are available for each electric distribution company (EDC) within the PJM operational area. More specifically, ComEd is the EDC that serves the Chicago metropolitan area, and Duquesne Light is the EDC that serves the Pittsburgh metropolitan area (See Figure C2 in Appendix C). For each of the regions specified above, we use daily historical electricity load data for the year 2012.

Although the geographic extent of these regions do not coincide exactly with the geographic extent of the metropolitan areas, they serve as a reasonable proxy for electricity demand within the metropolitan area (we could not find any daily electricity demand data that was limited only to the geographic extent of a given metropolitan area). Table 4-1 summarizes the ERCOT Region or PJM EDC that corresponds to each metropolitan area and the % of the total region/EDC load that is generated from plants within the metropolitan area. For this analysis, the load values are taken from data presented by PJM and ERCOT and the generation data is taken from eGRID (PJM, 2015; ERCOT, 2015; U.S. EPA, 2014[E]).

Table 4-1 Summary of the % of electricity load for a given ERCOT region or PJM EDC that is generated from power plants within a specific metropolitan area.

ERCOT Region/ PJM EDC	Metropolitan Area	% of Load Generated in Metro
South Central (ERCOT)	San Antonio/Austin	70%
North Central (ERCOT)	Dallas/Ft Worth	40%
Coast (ERCOT)	Houston	85%
ComEd (PJM)	Chicago	50%
Duquesne Light	Pittsburgh	380%*

*The Duquesne Light service area is smaller than the Pittsburgh MSA as a whole. Thus, the generation produced within the MSA is much larger than the demand within Duquesne Light.

Projected temperature values are gathered from NOAA's Geophysical Fluid Dynamics Laboratory (GFDL). More specifically, we use projected daily surface temperature values from the GFDL-CM3and GFDL-ESM2G climate models under the RCP 8.5 scenario (NOAA GFDL, 2014). From these models, we ultimately end up with daily projections for high and low temperatures for the years 2025-2035. The data are statistically downscaled using the BCCA technique and are available at a resolution of 1/8 degree (U.S. Bureau of Reclamation, 2014). Where necessary, the downscaled temperature data were spatially averaged to provide projections for geographic regions that are consistent with the six electricity load regions described in the previous paragraph (see Figures C3 through C7 in Appendix C).

These two models, GFDL-CM3 and GFDL-ESM2G, were chosen as a starting point for our analysis because they performed well in the IPCC's evaluation of CMIP5 climate models. For measuring surface air temperatures, GFDL-CM3 was found to have a relative space-time root-mean-square error (RMSE) between 0 and -10%, meaning that the RMSE for GFDL-CM3 is up to 10% smaller compared to the median RMSE of all CMIP5 models. Similarly, GFDL-ESM2G has a relative RMSE between 0 and +10% (Flato et al., 2013). We choose models that were based in the United States with the assumption that these would be better suited for regional downscaling due to a better knowledge of localized conditions. The time frame for analysis is 2025 to 2035, and was chosen to align with the planning horizon that many cities employ for their climate action plans and GHG reduction targets. This time horizon also corresponds well with population projection data and the proposed implementation of the EPA's Clean Power Plan.

Population projection data were gathered from the state governments of the metropolitan areas analyzed. For the Texas metropolitan areas, county-level population projections were produced by the Texas State Data Center (Texas State Data Center, 2015). For the Pennsylvania metropolitan areas, county-level population projections were produced by the Pennsylvania State

Data Center (Pennsylvania State Data Center, 2010). For the Chicago metropolitan area, Illinois county-level population projections were produced by the Illinois State Government (Illinois Department of Public Health, 2014). All county-level data were then aggregated to the appropriate Metropolitan Statistical Area (MSA), as defined by the United States Census Bureau. All population projections are for the year 2030.

Future emission intensity values (lbs CO_2e/MWh) under the Clean Power Plan are provided by technical support documentation for the EPA's proposed Rule 111d (i.e. Clean Power Plan) (U.S. EPA, 2014[A]; U.S. EPA, 2014[B]; U.S. EPA, 2015[A]). Table 4-2 summarizes the current and proposed emission intensity rates for the states of interest in this study.

Table 4-2 Summary of current electricity sector GHG emission rate and proposed emission rate under the Clean Power Plan (U.S. EPA, 2014[A]; U.S. EPA, 2014[B]; U.S. EPA, 2015[A]).

State	2012 Emission Rate (Fossil, RE, and Nuclear) (lbs CO_2/MWh)	Final 2030 Goal (lbs CO_2/MWh)
Texas	1284	791
Pennsylvania	1531	1052
Illinois	1894	1271

Plant-specific GHG emission data (total emissions and emission intensity) within each metropolitan area were available from eGRID for the year 2010 (U.S. EPA, 2014[E]).

4.4 Model Specifications

The first step in our analysis was to gain a better understanding of the relationship between temperature and electricity demand for the areas of interest. To do so, we pair location specific daily average temperature values for the year 2012 with location specific total daily electricity demand for the year 2012, and estimate the relationship between these variables by performing a second-order polynomial regression.

We then use the temperature projection data from the climate models and the regression results to estimate future electricity demand under climate change. For each of the climate models, we forecast daily electricity consumption for the years 2025 to 2035.

Although the regression values we use are based on 2012 data, we wanted to evaluate future conditions against a larger and more established set of baseline data. Thus, we incorporate historical temperature values for each day of the year between 1990 and 1999 (~3650 total data points). Although the climate record goes much further back, this time period was chosen as the baseline period of analysis due to lack of available electricity demand and temperature data at the appropriate scale and frequency. For our baseline analysis, we compare the average daily electricity demand from the historical temperature data (1990-1999) to the average daily electricity demand estimates from the projected temperature data (2025-2035). We then assess the frequencies of various historical and projected electricity demands (See Figure 4-3). Next, we sum the daily values and form an estimate of average annual historical and projected electricity demand and determine the percent change in annual electricity demand likely to be caused by increasing temperatures.

Finally, we employ current and possible future emission intensity and population values to get a range of estimates for metropolitan electricity sector GHG emissions in the year 2030 under varying conditions of climate change, population change, and technology/policy change. Overall, we evaluate the impacts of these different conditions in 6 different scenarios: four scenarios look at the GHG impacts of changing one of the factors independent of all other factors (e.g. determining the impact that climate change may have on emissions while assuming population and emission rates remain constant) and two scenarios look at the GHG impacts that occur when all factors are changing at the same time. When analyzing the potential impacts of the Clean Power Plan, two separate options were analyzed: 1) A “modified” case in which the regulation is only half as stringent as originally proposed (i.e. Texas would only need to get its average emission rate from 1284 lbs CO_2e/MWh to 1037 lbs CO_2e/MWh), and 2) A “full” case in which the regulation is implemented as proposed (i.e. the states are required to reduce their emission rates to the values presented in Table 4-2). Similar analysis could potentially be completed by performing a regression that includes temperature, population, and emission rate. However, the data for these parameters are not available on consistent time scales – the electricity load and temperature data are at a daily time scale, while population and emission intensity values are only available at annual/semi-annual time scales. As a result, we believe scenario analysis to be better suited to our purposes.

4.5 The Relationship between Temperature and Electricity Demand in Various Areas

Using temperature data from NOAA and electricity load data from various Independent System Operators (ISO) and Regional Transmission Organizations (RTO), we established the relationship between total daily electricity demand and daily average temperatures for the year 2012 for six metropolitan areas in the United States – San Antonio, Austin, Dallas/Ft Worth, Houston, Chicago, and Pittsburgh – as illustrated in Figure 4-1. It is worth noting that due to geographic constraints of the data, the San Antonio and Austin metropolitan areas were analyzed within the same region of ERCOT (see Figure C1 in Appendix C). Thus, the results presented below for these two metropolitan areas are identical.

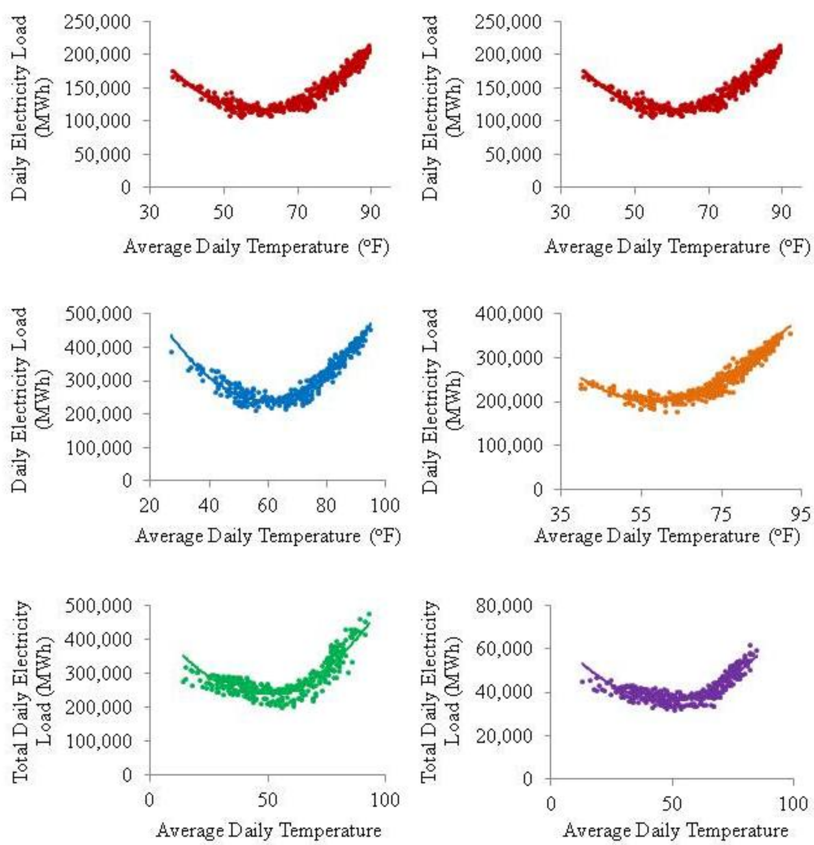

Figure 4-1 Total daily electricity demand versus average daily temperature for the year 2012 for the San Antonio (red – upper left), Austin (red- upper right), Dallas/Ft Worth (blue), Houston (orange), Chicago (green), and Pittsburgh (purple) metropolitan areas. Figure created by the authors using data from NOAA, The Electricity Reliability Corporation of Texas (ERCOT), and Pennsylvania, New Jersey, Maryland Interconnect (PJM).

Figure 4-1 illustrates that a quadratic relationship holds for all locations. The U-shaped curves seen in Figure 4-1 are similar to those produced by Sathaye et al. and Pardo et al. (Sathaye et al., 2013; Pardo, Meneu, and Valor, 2002). A second-order polynomial regression was performed for each location (see Table 4-3). Generally speaking, electricity demand increases as temperatures move toward the extremes (either hotter or colder), and decreases toward a minimum as temperatures become more moderate (approximately 55 - 65^{o} F depending on the location). The minimum points are slightly different in each of the curves. For the locations in Texas, the minimums appear to occur around 65-70^{o} F, while the minimums in Pittsburgh and Chicago appear to be closer to 55 or 60^{o} F. These differences in minimums may illustrate different levels of personal comfort preferences in various locations. Although outside the scope of this analysis, it would be interesting to study these preferences further and see how flexible they may be under different conditions. For example, if someone moved from Houston to Pittsburgh, would they maintain their original "comfort profile" (a minimum in the U-curve occurring around 60^{o} F) or would they shift to a "comfort profile" similar to what is observed in Pittsburgh (a minimum in the U-curve occurring closer to 50^{o} F)? Similarly, as temperatures continue to rise due to climate change, and people in colder areas become more adapted to higher temperatures, will the U-curves in Chicago and Pittsburgh start to more closely resemble the U-curves currently seen in Texas?

Compared to the four Texas metropolitan areas, the slopes on the left-hand side of the curves appear to be a little flatter for Pittsburgh and Chicago. This is likely due to the fact that natural gas is more heavily used as a fuel for space heating in these two metropolitan areas compared to the four in Texas. More specifically, electricity is used as the primary source for space heating in roughly 50% of households in Texas. In Illinois and Pennsylvania, electricity is the primary source for space heating in only 13% and 27% of households, respectively (U.S. EIA, 2009). Thus, if analyzing total energy consumption rather than electricity consumption, the relationships seen in Figure 4-1 would likely look very different. Additionally, if space heating and cooling become increasingly decoupled from the electricity and/or natural gas sector – as might be the case if the use of heat pumps increased drastically – the U-shaped curves presented in Figure 4-1 would become increasingly uncertain. Due to the lack of consistent natural gas consumption data at the appropriate geographic and temporal scale, we were unable to incorporate this component into our analysis. However, the primary policy change we analyze (i.e. the Clean Power Plan) is aimed at reducing electricity sector emissions, so the omission of natural gas in our study does not appear of critical importance.

Table 4-3 Second-order polynomial regression between total daily electricity demand and average daily temperature (independent variable) for the San Antonio, Austin, Dallas/Ft Worth, Houston, Chicago, and Pittsburgh metropolitan areas. The units for electricity demand are MWh and the units for temperature are degrees Celsius.

MSA	Regression	R-squared	Standard Error	SE % of Average Daily Generation
San Antonio/Austin	$Y = 339.0x^2 – 10,472x + 197,140$	0.94	7,088	5%
Dallas/Ft. Worth	$Y = 599.9x^2 – 18,371x + 380,029$	0.93	16,194	5%
Houston	$Y = 498.4x^2 – 14,642x + 308,521$	0.93	12,006	5%
Pittsburgh	$Y = 49.4x^2 – 782x + 39,754$	0.73	2,917	7%
Chicago	$Y = 324.4x^2 – 5,535x + 263,015$	0.76	24,433	9%

Based on the R-square and standard error values from the regressions, the equations in Table 4-3 generally fit the data very well. For the four Texas metropolitan areas, the R^2 values are all about 0.9. For Chicago and Pittsburgh, the fit is not quite as strong with R^2 values of approximately 0.75 for both metropolitan areas.

In order to further verify the goodness of fit provided by the regression equations, we compared projected generation values to actual generation values for four additional years of data (2010, 2011, 2013, and 2014) - see Appendix C. The relationship between electricity consumption and temperature was robust across years, and thus we only present the results for 2012 in the main manuscript.

Table 4-4 summarizes the average daily percent difference between predicted and actual electricity load values for various locations and years. The predicted values are found by plugging historical average daily temperature values for a given year into the regression equations presented in Table 4-3. The actual electricity load values for the Texas metropolitan areas are available from ERCOT and the actual electricity load values for Pittsburgh and Chicago are available from PJM – see Section C4 of Appendix C.

Table 4-4 Summary of average daily percent difference between predicted and actual electricity load value for two years before and after 2012 (the baseline year for which the regression analysis was performed)

MSA	2010 Data	2011 Data	2013 Data	2014 Data
San Antonio/Austin	+3%	+3%	+1%	-2%
Dallas/Ft. Worth	+3%	0%	-3%	-5%
Houston	+2%	-4%	-1%	-4%
Pittsburgh	+4%	+2%	+3%	+5%
Chicago	+1%	0%	+2%	+5%

The average daily percent difference between the regression-predicted and actual electricity load values range between 0% and +5%. The average percent difference values appear to be slightly lower for the two years immediately before and after 2012. Overall, the results in Table 4-4 appear to provide further evidence supporting the quality of the regression models in determining the relationship between temperature and electricity load.

4.6 Projected Changes in Temperature in Various Metro Areas

We used statistically downscaled climate models from NOAA's Geophysical Fluid Dynamics Laboratory (GFDL) to estimate how temperatures are likely to change over the next 20 years as a result of climate change. Figure 4-2 presents frequency distributions of average daily historical (1990-1999) and projected (2025-2035) temperatures for the six metropolitan areas of interest. The darker bars represent the historical data and the lighter bars outlined in black represent the projected data. Additional descriptions of the temperature projections and the range of possible temperatures are included in Section C3 of Appendix C. As shown in Figure 4-2, with the exception of Chicago, the distribution of daily temperatures is generally projected to shift to the right (hotter). The implications of these projected temperature shifts on electricity demand are further discussed in the next sections.

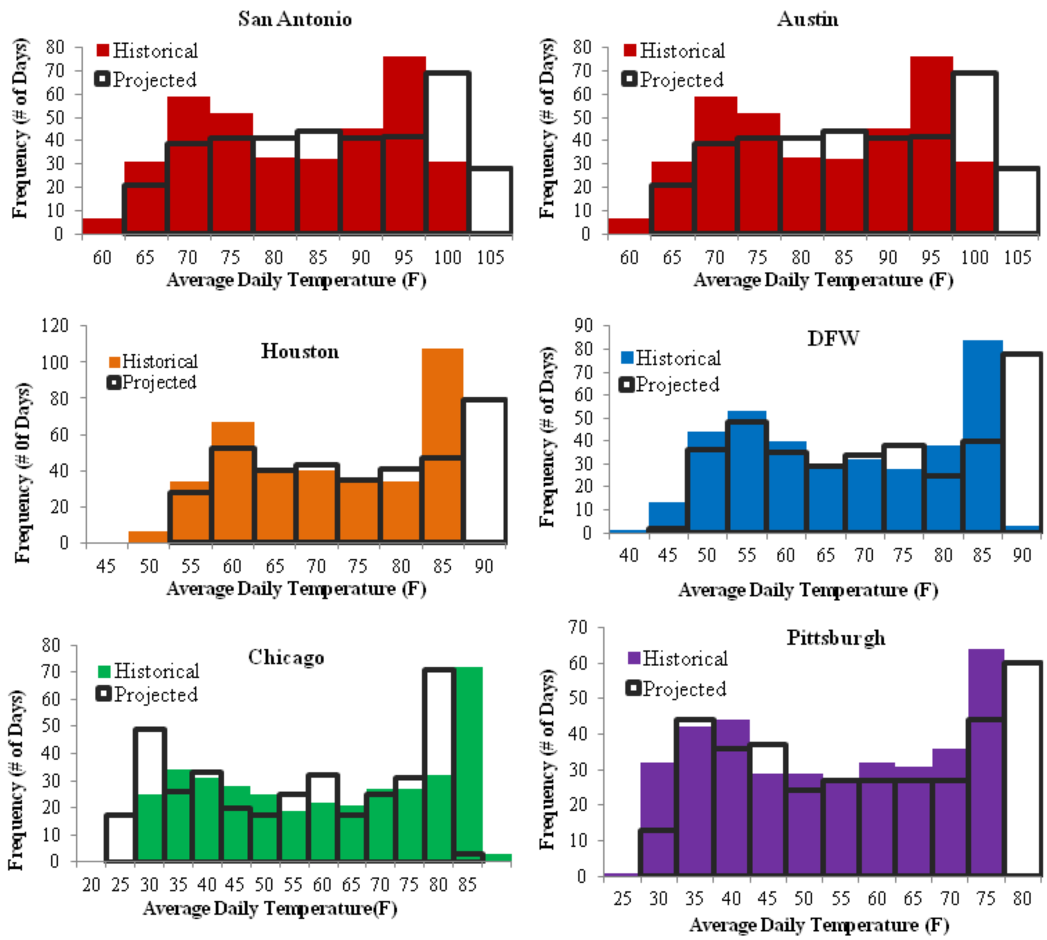

Figure 4-2 Historical (darker bars) and projected (light bars with black outline) annual frequencies of average daily temperature values for the San Antonio (red – upper left), Austin (red- upper right), Dallas/Ft Worth (blue), Houston (orange), Chicago (green), and Pittsburgh (purple) metropolitan areas. The historical values are the average daily temperatures for the years 1990 to 1999 and the projected values are the average daily temperatures for the years 2025 to 2035.

4.7 Impact of Temperature Change on Electricity Demand and Emissions

Using the regression results and the projected daily temperatures from the climate models, we estimate projected metropolitan electricity demand, as shown in Figure 4-3. Figure 4-3 also includes historical levels of electricity demand for the metropolitan areas of interest.

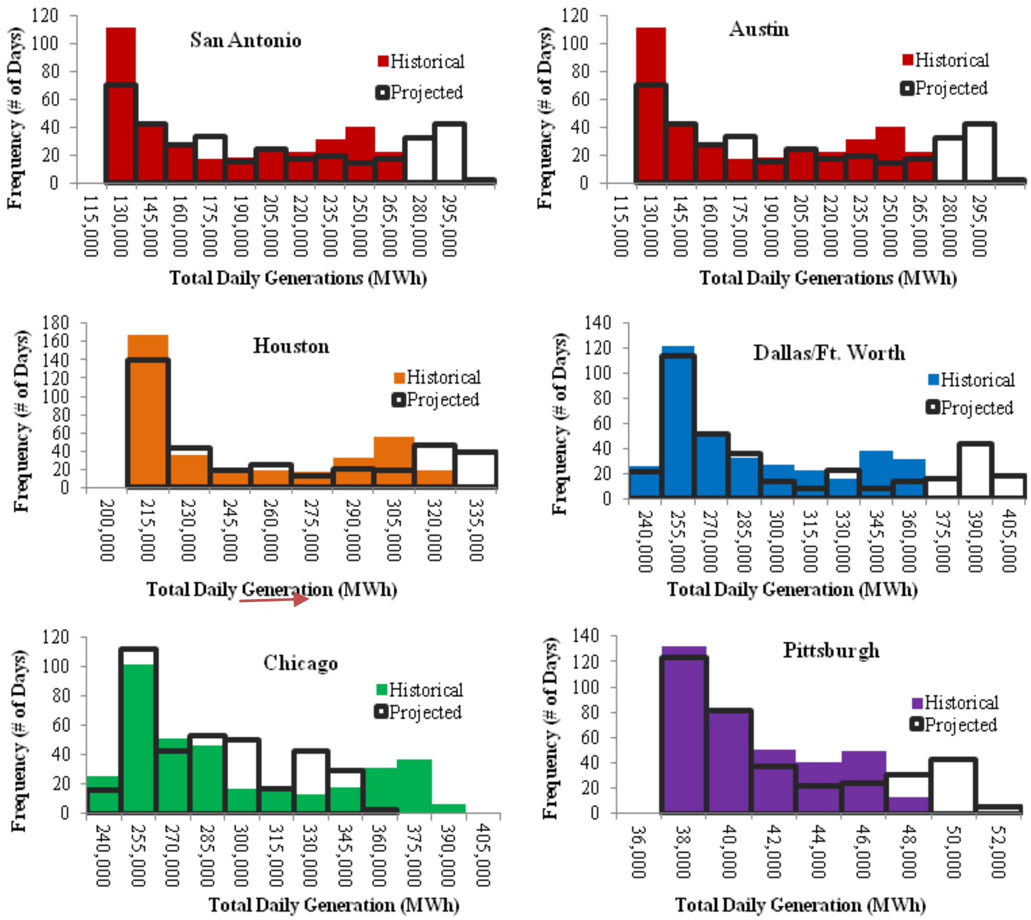

Figure 4-3 Historical (darker bars) and projected (light bars with black outline) annual frequencies of total daily electricity generation for the San Antonio (red – upper left), Austin (red- upper right), Dallas/Ft Worth (blue), Houston (orange), Chicago (green), and Pittsburgh (purple) metropolitan areas. The historical values are the average total daily load for the years 1990 to 1999 and the projected values are the average total daily load for the years 2025 to 2035.

The figure generally illustrates electricity generation shifting to the right (more demand). With the exception of Chicago, all metropolitan areas are expected to undergo an increase in electricity demand as a result of climate change. San Antonio and Austin face an average increase of 12% in total annual electricity demand during the years 2025- 2035 when compared to 1990-1999. Dallas/Fort Worth and Houston are expected to see an estimated increase of 5% and 4% in total annual electricity demand, respectively. In Pittsburgh, the increase in electricity consumption is expected to be more moderate - a 3% increase in 2025-2035 when compared to

1990-1999. The relatively small estimated changes in electricity demand for Dallas, Chicago, and Pittsburgh are likely due to the fact that a majority of the increase in demand for space cooling (in the summer) is offset by the decrease in demand for space heating (in the winter). Relatively speaking, San Antonio and Austin have fewer cold days, so this offset is minimized in these two locations – explaining the larger increase in electricity demand for these two areas compared to the others. In comparing San Antonio and Austin to Houston, the relatively small change in Houston is possibly due to the fact that it experiences less fluctuation in temperatures compared to other others – likely a result of its proximity to the Gulf of Mexico. For example, although Houston has a higher annual average temperature than San Antonio (69.1^{o}F compared to 68.7^{o}F), San Antonio actually has a higher average annual maximum temperature (79.8^{o}F compared to 78.3^{o}F) (U.S. Climate Data, 2015[A]; U.S. Climate Data, 2015[B]).

4.8 Sensitivity to Population and Policy Change Scenarios

Figure 4-4 presents the percent change in metropolitan electricity GHG emissions under varying scenarios: 1) only climate change; 2) only population change; 3) a "modified" version of the EPA's Clean Power Plan (CPP) in which states are only required to achieve 50% of the originally proposed reduction in average emission rates; 4) a full version of the EPA's Clean Power Plan in which the states are required to achieve the reductions in average emission rates currently proposed by the regulation; 5) the combined effect of climate change, population change, and the "modified" Clean Power Plan; and 6) the combined effect of climate change, population change, and the "full" Clean Power Plan. Where possible, we also added upper and lower bounds to certain values (indicated by the red uncertainty bars in the figure). The upper and lower bound values primarily come from the climate and population projections. The minimum values under the climate change scenario are based on the lower average daily temperature between the two climate models and the upper bound values under the climate scenario are based on the higher average daily temperature between the two climate models. For the population change scenario, the upper and lower bound values come from population projections under high and low emigration scenarios (these values were only available for the State of Texas).

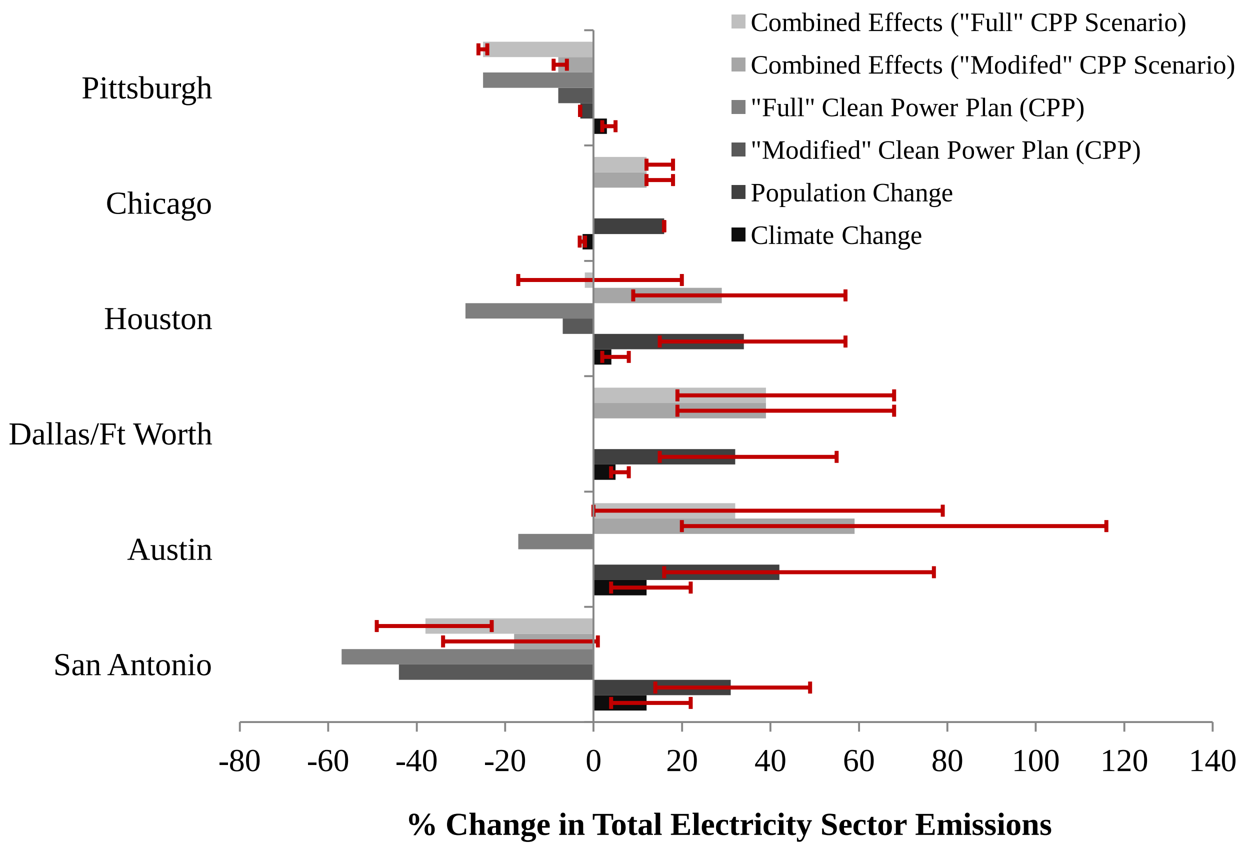

Figure14-4. Percent change in electricity sector GHG emissions between 2010 and 2030 as a result of various factors – climate change, population change, modified Clean Power Plan (50% of proposed reductions in emission rates), full Clean Power Plan (100% of proposed reductions in emission rates). The first 4 bars (starting at the bottom) for each location show the impact of the specified variable and assume all other variables are held constant (e.g. the "population change" bars show the estimated change in electricity GHG emissions if population were the only thing to change between 2010 and 2030). The "combined effects" bars show the combined results of all of the factors.

Based on the "Full CPP" and "Combined Effects (Full CPP Scenario)" bars, electricity GHG emissions in San Antonio, Houston, and Pittsburgh are expected to be heavily impacted by the

Clean Power Plan. Even with climate change and population growth, electricity GHG emissions in these three areas are likely to decrease between now and 2030. Thus, these areas may be better suited focusing their mitigation efforts on other sectors of need (e.g. transportation). On the other hand, the other three metropolitan areas are expected to be heavily impacted by population change. In these cases, even when considering climate change and EPA regulations, changes to population are likely to lead to an overall increase in electricity GHG emissions. Thus, in the absence of more aggressive policies that limit population influx/growth, mitigation strategies in these locations will likely want to focus on conservation and efficiency efforts that drive down per capita electricity use and/or emissions as much as possible.

4.9 Discussion and Implications

The analysis and results presented above help to highlight how climate change may impact the effectiveness of local, state, and national mitigation efforts moving forward. This paper illustrates the potential for "climate rebound" that may undermine the absolute effectiveness of mitigation efforts and planning. For example, without considering the impacts of climate change, the Clean Power Plan is estimated to reduce total annual GHG emissions from Austin power plants by 17% by the year 2030. However, when adding in the impacts of climate change, the Clean Power Plan is estimated to reduce total annual GHG emissions from Austin MSA power plants by only 7%. Thus, the "climate rebound" for this scenario is roughly 10%.

Additionally, the analysis not only helps place the impacts of climate change in the context of other factors that might impact emissions, but also helps illustrate the importance of incorporating forecasting into any type of climate related policy. The results in Figure 4-4 show the true difficulty that certain areas may face in reaching their GHG reduction targets. Even with the help of the Clean Power Plan, electricity sector emissions are projected to increase in the Austin, Dallas, and Chicago metropolitan areas. When adding in emissions from other sectors like transportation, the increases will likely become even larger. Thus, it will become increasingly important for decision-makers to fully understand and plan for the impacts of factors like population growth and climate change if they are going to have any reasonable chance of meeting their GHG reduction goals moving forward.

Table 4-5 further illustrates this point by showing the “break even” values for either the emission rate or the per capita electricity consumption that each metropolitan area would have to achieve in order for their net electricity sector GHG emissions to change by 0% between now and the year 2030. The break-even values presented in Table 4-5 assume that climate change and population change both occur. For example, assuming climate change results in a 12% increase in electricity demand and Austin’s population increases 42% between 2010 and 2030, the emission rate of Austin power plants would need to decrease by roughly 40% (roughly 20 percentage points more than the estimated reduction from the Clean Power Plan) in order for electricity sector GHG emissions to have 0% growth during that period. Similarly, per capita electricity usage would need to decrease by roughly 25% in order for electricity sector GHG emissions to have 0% growth during that period.

Table 4-5 "Break Even" values for emission rate and per capita electricity consumption required for each metropolitan area to have 0% growth in their electricity sector GHG emissions between now and the year 2030. Areas marked with "N/A" indicate no additional change in emission rate or per capita electricity use is required to achieve 0% growth in electricity sector GHG emissions between 2010 and 2030.

Metropolitan Area	Emission Rate (lbs CO2/MWh)	Per Cap Electricity (MWh/Person)
San Antonio	N/A	N/A
Austin	-37%	-25%
Dallas/Ft Worth	-28%	-29%
Houston	N/A	N/A
Chicago	-11%	-11%
Pittsburgh	N/A	N/A

Overall, it appears that climate change will result in increased electricity demand and subsequent emissions in most metropolitan areas. However, the magnitude of this increase varies greatly by location. The largest increases are likely to occur in warmer and drier metropolitan areas like San Antonio and Austin. Smaller increases are seen in cooler and/or wetter areas like Chicago and Pittsburgh. Extrapolating these results to other locations would likely mean that places in the southwestern and western parts of the United States should be more concerned with the impacts of temperature change on electricity demand – especially considering the fact that increased demand in northern and eastern locations will likely be offset by decreases in demand for heating. Similarly, areas with high population growth and/or a relatively low baseline emission rate are likely to experience net emission increases, while areas with low population growth and/or a relatively high baseline emission rate are likely to experience net emission decreases.

In addition to expanding this analysis to more metropolitan areas, we would also like to incorporate natural gas usage in addition to the analysis of electricity demand described above. Due to the high usage of natural gas for heating in the northern parts of the country, the incorporation of natural gas into the analysis would likely result in a net decrease in GHG emissions for metropolitan areas in colder parts of the country. However, as mentioned above, we were unable to find sufficient data to support this task. Finally, climate induced changes in energy demand will impact more than GHG emissions. Thus, it would also be interesting to study the impacts on criteria pollutants and the implementation of any regulations aimed at improving air quality.

5. SUMMARY, CONCLUSIONS, AND POLICY IMPLICATIONS

5.1 Summary

This thesis explored the estimation of GHG emissions at the metropolitan level and the impacts that various scope, boundary, and forecasting choices can have on the emission profile and successful reduction of GHGs in a given location. We began by developing an integrated approach for estimating emissions at the metropolitan level and comparing the results to other estimation approaches. We then compared the results from the integrated approach to estimates reported by cities in order to assess the magnitude and implications of emissions that may be under-reported by current methods. Finally, we evaluated the impact the climatic temperature change might have electricity demand and GHG emissions in the future, and compared the results to the projected impact of population change and policy change in certain metropolitan areas.

Chapter 2 used publically available national datasets to form production-based GHG estimates for the 100 largest metropolitan areas in the United States. These estimates allowed for the consistent comparison of emissions over time and across locations. Between the years 2002 and 2011, the overall GHG emissions for these metropolitan areas decreased by an average of roughly 10%. The largest decreases in emissions during this time period were typically driven by a large decrease in industrial activity. The largest increases in emissions during this time period were typically driven by increases in electricity production and population.

Chapter 3 expanded upon the results of Chapter 2 by evaluating the magnitude and potential implications of "under-reported" GHG emission estimates from certain activities and from geographic boundary choices. On average, it was found that emissions estimates from "under-reported" activities, like industrial processes and on-road transportation within the MSA but outside the urban core, accounted for roughly 24% of total emissions. Similarly, it was found that MSA emissions from outside the urban core account for an average of 55% of total MSA emissions. These results highlight the importance of continuing to improve and expand the manner in which local-level climate action plans are developed and implemented. It also highlights the large potential that still exists for developing climate action plans at the metropolitan or regional level.

Chapter 4 used regional data to assess the relationship between average daily temperature and total daily electricity demand. Projected future temperatures from climate models were combined with the electricity demand versus temperature relationships to predict the impacts of climatic temperature change on future electricity demand. Generally speaking, we found that climatic temperature change will have a relatively large impact on electricity demand in warm/dry areas like San Antonio and Austin, and a much smaller impact in colder/wetter areas like Pittsburgh and Chicago. When adding the projected impacts of population change and the EPA's Clean Power Plan, electricity sector GHG emissions are expected to go up by roughly 12-40% in Chicago, Dallas, and Austin and decrease by roughly 2-40% in Pittsburgh, Houston, and San Antonio.

5.2 Future Work

5.2.1 Expanded scale and scope of analysis

The primary results of this thesis include GHG emission estimates for the 100 most populated metropolitan areas in the United States for the years 2002, 2011, and 2030. However, there is opportunity to expand on these estimates by adding data from the 2005 and 2008 National Emissions Inventory (U.S. EPA, 2014[C]). Additionally, the analysis could be expanded beyond the 100 most populated metropolitan areas in order to form a more comprehensive analysis of GHG emissions in U.S. metropolitan areas over the past decade and a half. It is possible to create GHG emission estimates for all counties and metropolitan areas in the United States for the years 2002, 2005, 2008, 2011, and 2014 (as soon as the newest NEI data is released from the EPA). The analysis could also be expanded to include location-specific sources of frequently under-reported emissions. For example, the Pittsburgh region has a large number of legacy mines and natural gas wells. If methane were leaking undetected from some of these locations, the emission profile of the city/metropolitan area would be considerably higher – especially considering the higher global warming potential of methane compared to carbon dioxide.

The impact of our results could be improved by adding additional socio-economic and demographic data to our emission data. For example, information about each metropolitan area's population trends, geographic area (in terms of square miles or square kilometers), climate zone, economic activity, and region of the country could be coupled with the emission data to allow for a more complete analysis of underlying trends that may be impacting a metropolitan area's emissions. Ultimately, it would be ideal if the inclusion of this additional data could be placed on a searchable web-based platform to allow for more informative comparisons between locations, the establishment of situation/location specific best practices, and the creation of innovative policy solutions for reducing emissions. It might also be beneficial to collaborate with ICLEI and see if any of the approaches and findings developed in this thesis might complement their efforts in the continued development of the ClearPath software and GHG reporting protocols.

Finally, there is wide regional variation in fuel use for residential and commercial buildings. Thus, in addition to the impacts on electricity consumption described in Chapter 4, it would be beneficial to also model the impacts that climate change, policy change, and population change have on natural gas and fuel oil consumption. The inclusion of the impacts on natural gas and fuel oil consumption and emissions would provide additional insights into the true impact that climate change may have on regional energy demand and emissions. In several locations, it is likely that climatic temperature change will result in decreased natural gas/fuel oil demand for space heating. If these decreases are larger than the increased demand for space cooling, then climate change will likely provide a "net benefit" in terms of reducing overall energy demand and emissions from the building sector. By gaining a more complete understanding of this phenomenon, decision makers may decide that it is more beneficial for them to concentrate their mitigation efforts on other sectors (e.g. transportation).

5.2.2 Analysis of energy use, fuel consumption, and criteria air pollutants

Our analysis focuses almost entirely on GHG emissions. However, other impacts such as energy use and criteria air pollutants (ammonia, carbon monoxide, nitrogen oxides, particulate matter, sulfur dioxide and volatile organic compounds) could be estimated using similar methods. In contrast to GHGs, criteria pollutants remain much more confined to the region in which they are produced and can have a much more localized impact. Thus, the inclusion of criteria pollutants could be especially beneficial given our focus on metropolitan areas. NEI provides emissions estimates for the years 2002, 2005, 2008, and 2011 (U.S. EPA, 2014[C]). Thus, data aggregation and analysis similar to the ones demonstrated in this thesis could be used to develop estimates of criteria air pollutants in metropolitan areas across the United States. The estimates of GHGs and criteria air pollutants could then be paired with economic impact models like the Air Pollution Emission Experiments and Policy analysis (APEEP) model developed by Muller et al. or the health and environmental assessment conducted by Siler-Evans et al. (Muller, Mendelsohn, and Nordhaus, 2011; Siler-Evans, Azevedo, and Morgan, 2012; Siler-Evans et al., 2013). Incorporating this economic component could be very beneficial to the overall decision-making process. By gaining a better understanding of the financial benefits of certain mitigation efforts allows for an easier comparison to the costs of said mitigation actions. Thus, the coupled climate, environment, economic, and human health analysis could be rather influential on the manner in which climate and environmental policies are implemented in various locations. Given the regional differences in end-uses, fuel uses, and overall energy consumption, this proposed analysis may help certain locations decide that it is better for them to focus their efforts on reducing criteria pollutants, while other areas may prefer to focus their efforts on reducing GHGs. This proposed analysis could also provide valuable insights into quantifying the co-benefits (environmental and climate) of various mitigation strategies.

5.2.3 Improved forecasting efforts

Although this thesis primarily focuses on historical emissions estimates (i.e. estimates for the years 2002 and 2011), there is some forward-looking analysis to the year 2030 – especially in Chapter 4. The emissions estimates presented in Chapters 3 and 4 are a “snap-shot” of results we form from certain scenarios and assumptions. In other words, we evaluate emissions in the year 2030 under a given set of scenarios, but don't necessarily estimate emissions in the years leading up to 2030 or under all possible scenarios.

Using our analysis as a starting point, future work could make significant contributions by forming more dynamic and comprehensive forecasts of metropolitan GHG emissions. The work in Chapter 3 could be enhanced by incorporating different population and policy scenarios into the analysis of emission reduction targets in the future.

Similarly, Chapter 4 could be enhanced if, in addition to the population and policy components we evaluated, factors such as economic activity and technological changes/disruptions could also be included in the forecasts. Similar to the previous sub-section, the forecasting efforts could also be expanded to include criteria pollutants in addition to GHGs. Rather than only developing "snap-shot" estimates for the years 2011 and 2030, it would also be beneficial to develop estimates for the interim (years 2015-2030) in order to get a better sense of what changes and disruptions might have the largest influence on the emission levels that ultimately occur in the year 2030 and beyond. This type of forecasting and forward-looking analysis might be well suited for applying principles of Robust Decision Making (RDM) (Bryant and Lempert, 2010; Lempert and Collins, 2007). Under such an application, local decision makers could get a better idea of the full range of potential emission outcomes under different scenarios, and then base their policy efforts and decisions on avoiding the underlying circumstances that lead to the most undesirable outcomes. Overall, developing more descriptive and informative forecasts of emissions under different scenarios could be very beneficial to local practitioners as they continue to develop and revise their climate action plans and GHG reduction targets.

5.3 Policy Implications and Final Conclusions

The integrated approach employed in Chapters 2 and 3 allows for a consistent comparison of GHG emissions from the 100 most populated metropolitan areas in the United States for the years 2002 and 2011. In many cases, this approach appears to provide comparable results to the emission estimates reported by cities – especially when assessing the proportion of total emissions attributable to different emission-producing sectors. Therefore, the integrated approach could serve as a less “resource intensive” way for communities to regularly get an initial assessment of their emission profile and more effectively prioritize their resource and planning efforts (i.e. decide where to expend more resources for collecting better data and/or where to expend resources for mitigation efforts).

The methods and results outlined in Chapters 2 and 3 also help illustrate some of the implications that may result from expanding analysis to the metropolitan level and including emissions from activities that were previously under-reported. In comparing 2011 MSA emissions estimates to 2002 estimates, many of the large decreases in emissions were attributable to the loss of large amounts of industrial activity. Although effective in terms of reducing overall emissions, loss of industrial activity may not be a feasible or sustainable mitigation strategy for many metropolitan areas moving forward. In some cases, the economic implications of lost industry would be undesirable, while in other cases, potential reductions may be limited due to the low presence of industrial activity in the first place. These observations stress how important it will be for decision makers to develop strategies that strike a balance between achieving emission reductions and maintaining certain economic and social standards.

Emissions at the urban core accounted for only roughly 45% of total metropolitan emissions, on average. Thus, the clamoring expressed by some local practitioners for expanding analysis and planning to the regional or mega-regional level appear to be well founded. Instead of acting in isolation, collaboration between cities and counties within a metropolitan area could allow for more effective sharing of resources and best practices and result in a much larger overall reduction in emissions. However, if analysis and planning were expanded to the metropolitan level or to “under-reported” activities, it is likely that alterations would need to be made to GHG reduction plans as they currently exist. More specifically, in order to achieve the same overall reduction in emissions, annual GHG reduction rates will need to be much more aggressive. Otherwise, communities may find it beneficial to modify the overall percent reduction they hope to achieve or extend the time frame in which they plan to meet a certain reduction target. Even with all of these considerations, a widespread expansion of analysis and planning to the metropolitan level would be a large step in the right direction toward meeting national and international GHG reduction goals, and the approaches outlined in this thesis can serve as a starting point for quantifying and evaluating the implications of metropolitan-level climate action plans.

Finally, it appears that the impacts of climate change are worth including in emission forecasts and climate action plans - especially in hotter/drier areas like Texas, where increases in cooling demand seem like they will outweigh decreases in heating demand. Consideration of the impacts of climate change is especially important in the context of energy efficiency and the Clean Power Plan, because there appears to be the strong possibility for a “climate rebound effect” – actual emissions reductions from various policies will be lower than projected reductions due to increased cooling demand caused by temperature increases. Even in places like Chicago, where climate change is expected to decrease overall electricity demand, considering climate change in emission and energy demand forecasts can be beneficial. If it appears that there will be a “natural” decrease in energy demand and emissions from the building stock due to climate change, then it may be more beneficial to focus mitigation efforts on other sectors like transportation.

The analysis and results from this thesis provide insights into the importance of current and future drivers of metropolitan GHG emissions and help inform decision-making related to GHG mitigation. In areas where population change is expected to have the largest impact, mitigation efforts could be focused on the highest per-capita emission activities or land use policies that encourage dense development. In areas where temperature increase is expected to have a large impact, efforts could be focused on building stock insulation and/or installation of high efficiency air conditioning units. In areas where on-road transportation is a large contributor to overall emissions, partnerships between the central city and the surrounding communities/counties could be formed to encourage high density growth and the use of public/mass transit. Ultimately, by gaining a better understanding of the impact that various scope, boundary, and forecasting decisions can have on the emission profile of a given metropolitan area, decision-makers can start moving beyond a repetitious cycle of emissions accounting and begin to better prioritize and implement their GHG mitigation efforts.

REFERENCES

Amato, A. D., Ruth, M., Kirshen, P., & Horwitz, J. (2005). Regional Energy Demand Responses to Climate Change: Methodology and Application to the Commonwealth of Massachusetts. *Climatic Change , 71*, 175-201.

Arizona State School of Life Sciences - The Vulcan Project. (n.d.). *Research Data*. Retrieved from The Vulcan Project Website: http://vulcan.project.asu.edu/index.php

Badri, M. A. (1992). Analysis of Demand for Electricity in the United States. *Energy , 17* (7), 725-733.

Baxter, L. W., & Calandri, K. (1992). Global Warming and Electricity Demand: A Study of California. *Energy Policy , 20* (3), 233-244.

Bay Area Air Quality Managment District (BAAQMD). (2015, January). *Bay Area Emissions Inventory Summary Report: Greenhouse Gases.* Retrieved September 23, 2015, from BAAQMD Website: http://www.baaqmd.gov/~/media/Files/Planning%20and%20Research/Emission%20Inventory/BY2011_GHGSummary.ashx?la=en

Blackhurst, M., Matthews, H. S., Sharrard, A., Hendrickson, C., & Azevedo, I. L. (2011). Preparing US Community Greenhouse Gas Inventories for Climate Action Plans. *Environmental Research Letters*.

British Standards Institution. (2013). *PAS 2070:2013 - Specification for the assessment of greenhouse gas emissions of a city: Direct plus supply chain and consumption-based methodologies.* BSI Standards Limited.

Brown, M. A., Southworth, F., & Sarzynski, A. (2009). The Geography of Metropolitan Carbon Footprints. *Policy and Society , 27* (4), 285-304.

Bryant, B. P., and Lempert, R. J., "Thinking inside the box: A participatory, computer assisted approach to scenario discovery." Technological Forecasting and Social Change, 77(1), 34-49, 2010.

C40 Cities Climate Leadership Group. (2011). *About C40: Sustainable Action on Climate Change*. Retrieved November 2013, from C40 Website: http://www.c40.org/about

California Energy Commission. (2015). *Energy Consumption Data Managment System (ECDMS): Gas Consumption by County*. Retrieved September 7, 2015, from ECDMS Website : http://www.ecdms.energy.ca.gov/gasbycounty.aspx

Carbon Disclosure Project (CDP). (2015). *Reports and Data*. Retrieved September 8, 2015, from CDP Website: https://www.cdp.net/reports

Carbonn Climate Registry. (2014). *Entity Data: United States*. Retrieved September 8, 2015, from Carbonn Climate Registry Website: http://carbonn.org/data/

Chertow, M. (2000). The IPAT Equation and Its Variants. *Journal of Industrial Ecology , 4* (4), 13-29.

City of Portland and Multnomah County. (2015). *Cliamte Action Plan Summary 2015: Local Strategies to Address Climate Change.* Retrieved September 8, 2015, from City of Portland Website: https://www.portlandoregon.gov/bps/article/531994

Downton, M. W., Stewart, T. R., & Miller, K. A. (1988). Estimating Historical Heating and Cooling Needs: Per Capita Degree Days. *Journal of Applid Meteorology , 27*, 84-90.
Franco, G., & Sanstad, A. H. (2008). Climate Change and Electricity Demand in California. *Climatic Change , 87*, S139-S151.

Dietz, T., & Rosa, E. A. (1997). Effects of Population and Affluence on CO2 Emissions. *Proceedings of the National Academy of Sciences of the United States (PNAS) , 94* (1), 175-179.

ERCOT. (2015, April 9). *Hourly Load Data Archieves*. Retrieved April 16, 2015, from ERCOT Web Site: http://www.ercot.com/gridinfo/load/load_hist/

Flato, G., J. Marotzke, B. Abiodun, P. Braconnot, S.C. Chou, W. Collins, P. Cox, F. Driouech, S. Emori, V. Eyring, C. Forest, P. Gleckler, E. Guilyardi, C. Jakob, V. Kattsov, C. Reason and M. Rummukainen, 2013: Evaluation of Climate Models. In: Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change

Glaeser, E. L., & Kahn, M. E. (2010). The greenness of cities: Carbon dioxide emissions and urban development. *Journal of Urban Economics, 67*(3), 404-418. doi:10.1016/j.jue.2009.11.006

Greenhouse Gas Protocol. (2012). *Calculation Tools - Frequently Asked Questions*. Retrieved October 1 2014, 2014, from Greenhouse Gas Protocol Website: http://www.ghgprotocol.org/calculation-tools/faq

Gurney, K. R., Mendoza, D., Geethakumar, S., Zhou, Y., Chandrasekaran, V., Miller, C., Godbole, A., Sahni, N., Seib, B., Ansley, W., et al. (n.d.). *Vulcan Science Methods Documentation, Version 2.0.* Retrieved from Vulcan Project Website: http://vulcan.project.asu.edu/pdf/Vulcan.documentation.v2.0.online.pdf

Hadley, S. W., Erickson III, D. J., Hernandez, J. L., Broniak, C. T., & Blasing, T. J. (2006). Responses of Energy Use to Climate Change: A Climate Modeling Study. *Geophysical Research Letters , 33*.

Hillman, T., & Ramaswami, A. (2010). Greenhouse Gas Emission Footprints and Energy Use Benchmarks for Eight U.S. Cities. *Environmental Science & Technology , 44* (6), 1902-1910.

Hillman, T., Janson, B., & Ramaswami, A. (2011). Spatial Allocation of Transportation Greenhouse Gas Emissions at the City Scale. *Journal of Transportation Engineering , 137* (6), 416-425.

Hoesly, R., Blackhurst, M., Matthews, H. S., Miller, J. F., Maples, A., Pettit, M., et al. (2012). Historical Carbon Footprinting and Implications for Sustainability Planning: A Case Study of the Pittsburgh Region. *Environmental Science & Technology , 46*, 4283-4290.

ICLEI - Local Governments for Sustainability USA. (July 2013). *U.S. Community Protocol for Accounting and Reporting of Greenhouse Gas Emissions - Version 1.1*

ICLEI - Local Governments for Sustainability USA[A]. (2015, August 6). *Measuring Up 2015: How US Cities are Accelerating Progress Toward National Climate Goals.* Retrieved September 7, 2015, from ICLEI USA Website: http://icleiusa.org/wpcontent/uploads/2015/08/Measuring_Up_2015.pdf

ICLEI USA[B]. (2015). *ClearPath*. Retrieved September 7, 2015, from ICLEI USA Website: http://icleiusa.org/clearpath/

Illinois Department of Public Health. (2014). *IDPH Population Projections 2014 Edition*. Retrieved September 8, 2015, from State of Illinois Data Portal: https://data.illinois.gov/dataset/IDPH-Population-Projections-For-Illinois-Counties-/ntyz-weef

Intergovernmental Panel on Climate Change (IPCC). (2007). *Climate Change 2007: Synthesis Report.* Retrieved September 7, 2015, from IPCC Website: http://www.ipcc.ch/pdf/assessment-report/ar4/syr/ar4_syr_full_report.pdf

Intergovernmental Panel on Climate Change (IPCC). (1992). *First Assessment Report - Overview Chapter.* Retrieved September 7, 2015, from IPCC Website: http://www.ipcc.ch/ipccreports/1992%20IPCC%20Supplement/IPCC_1990_and_1992_Assessments/English/ipcc_90_92_assessments_far_overview.pdf

Intergovernmental Panel on Climate Change. (2011). *Climate Change 2001: Synthesis Report (Third Assessment Report).* Retrieved September 7, 2015, from IPCC Website: http://www.grida.no/publications/other/ipcc_tar/

IPCC, 2013: Summary for Policymakers. In: Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change

Intergovernmental Panel on Climate Change. (2014). *Climate Change 2014: Synthesis Report.* Retrieved September 7, 2015, from IPCC Website: http://www.ipcc.ch/pdf/assessment-report/ar5/syr/SYR_AR5_FINAL_full.pdf

Intergovernmental Panel on Climate Change. (1995). *IPCC Second Assessment: Climate Change 1995.* Retrieved September 7, 2015, from IPCC Website: http://www.ipcc.ch/pdf/climate-changes-1995/ipcc-2nd-assessment/2nd-assessment-en.pdf

Jaffe, L. S. (1968). Ambient Carbon Monoxide and its Fate in the Atmosphere. *Journal of the Air Pollution Control Association , 18* (8), 534-540.

Kennedy, C., Steinberger, J., Gasson, B., Hansen, Y., Hillman, T., Havránek, M., Pataki, D., Phdungsilp, A., Ramaswami, A., & Mendez, G. V. (2009). Greenhouse Gas Emissions from Global Cities. *Environ. Sci. Technol.*, *43*(19), 7297-7302. doi:10.1021/es900213p

Khalil, M. A., & Rasmussen, R. (1990). The Global Cycle of Carbon Monoxide: Trends and Mass Balance. *Chemosphere , 20* (1-2), 227-242.

Lam, J. C. (1998). Climatic and Economic Influences on Residential Electricity Consumption. *Energy Conversion and Management , 39* (7), 623-629.

Le Comte, D. M., & Warren, H. E. (1981). Modeling the Impact of Summer Temperatures on National Electricity Consumption. *Journal of Applied Meteorology* (20), 1415-1419.

Lehman, R. L., & Warren, H. E. (1994). Projecting Monthly Natural Gas Sales for Space Heating Using a Monthly Updated Model and Degree-days from Monthly Outlooks. *Journal of Applied Meterorology , 33* (1), 96-106.

Lempert, R., and Collins, M. (2007). "Managing the Risk of Uncertain Threshold Responses: Comparison of Robust, Optimum, and Precautionary Approaches." Risk Analysis, 27(4), 2007.

Logan, J. A., Prather, M. J., Wofsy, S. C., & McElroy, M. B. (1981). Tropospheric Chemistry: A Global Perspective. *Journal of Geophysical Research , 86* (C8), 7210-7254.

Morris, M. (1999, September). *The Temperature Trends on Short-Term Energy Demand.* Retrieved September 8, 2015, from U.S. EIA Website: http://www.eia.gov/forecasts/steo/special/pdf/temptrnd.pdf

Muller, N. Z., Mendelsohn, R., & Nordhaus, W. (2011). Environmental Accounting for Pollution in the United States Economy. *American Economic Review , 101* (5), 1649-1675.

National Oceanic and Atmospheric Administration (NOAA). (2015). *National Climatic Data Center*. Retrieved April 16, 2015, from NOAA Web Site: http://www.ncdc.noaa.gov/cdo-web/

National Research Council (NRC): Committee on the Challenge of Developing Sustainable Urban Systems. (2010). *Pathways to Urban Sustainability: Research and Development of Urban Systems - Summary of a Workshop.* Washington, D.C.: The National Academies Press.

National Research Council (NRC): Committee on Regional Approaches to Urban Sustainability. (2011). *Pathways to Urban Sustainability: Lessons from the Atlanta Metropolitan Region - Summary of a Workshop.* Washington, D.C.: The National Academies Press.

National Research Council (NRC): Committee on Pathways to Urban Sustainability. (2013). *Pathways to Urban Sustainability: A Focus on the Houston Metropolitan Region - Summary of a Workshop.* Washington, D.C.: The National Academies Press.

National Research Council (NRC): Committee on Regional Approaches to Urban Sustainability. (2014). *Pathways to Urban Sustainability: Perspective from Portland and the Pacific Northwest - Summary of a Workshop.* Washington, D.C.: The National Academies Press.

NOAA Geophysical Fluid Dynamics Laboratory (GFDL). (2014, September 23). *Coupled Physical Model, CM3*. Retrieved September 8, 2015, from GFDL Website: http://www.gfdl.noaa.gov/coupled-physical-model-cm3

Open Energy Information (OpenEI). (2015). *International Council for Loacl Environmental Initiatives (ICLEI) Clean Air and Climate Protection Software Tools*. Retrieved September 7, 2015, from OpenEI Website: http://en.openei.org/wiki/International_Council_for_Local_Environmental_Initiatives_(ICLEI)_Clean_Air_and_Climate_Protection_Software_Tools

Pardo, A., Meneu, V., & Valor, E. (2002). Temperature and Seasonality Influences on Spanish Electricity Load. *Energy Economics , 24* (1), 55-70.

Pennsylvania State Data Center (PaSDC). (2010, October 10). *Pennsylvania County Population Projections, 2010-2040*. Retrieved September 8, 2015, from PaSDC Website: https://pasdc.hbg.psu.edu/Data/Projections/tabid/1013/Default.aspx

PJM. (2015, April 13). *Metered Load Data*. Retrieved April 16, 2015, from PJM Markets & Operations Web Site: https://www.pjm.com/markets-and-operations/ops-analysis/historical-load-data.aspx

Quayle, R. G., & Diaz, H. F. (1980). Heating Degree Day Data Applied to Residential Heating Energy Consumption. *Journal of Applied Meteorology , 19*, 241-246.

Ramaswami, A., Hillman, T., Janson, B., Reiner, M., & Thomas, G. (2008). A Demand-Centered, Hybrid Life-Cycle Methodology for City-Scale Greenhouse Gas Inventories. *Environ. Sci. Technol., 42*(17), 6455-6461. doi:10.1021/es702992q

Ramaswami, A., & Chavez, A. (2013). What metrics best reflect the energy and carbon intensity of cities? Insights from theory and modeling of 20 US cities. *Environmental Research Letters , 8* (3).

Sacramento Area Council of Governments (SACOG). (n.d.). *The Greenhouse Gas Regional Inventory Protocol: Sacramento Area Council of Governments.* Retrieved September 23, 2015, from SACOG Website: http://www.sacog.org/about/committees/lunr/grip.pdf

Sathaye, J. A., Dale, L. L., Larsen, P. H., Fitts, G. A., Koy, K., Lewis, S. M., et al. (2013). Estimating Impacts of Warming Temperatures on California's Electricity System. *Global Environmental Change , 23*, 499-511.

Siler-Evans, K., Azevedo, I. L., Morgan, M. G., & Apt, J. (2013). Regional Variations in the Health, Environmental, and Climate Benefits of Wind and Solar Generation. *Proceedings of the National Academy of Sciences of the United States of America (PNAS) , 110* (29), 11768-11773.

Siler-Evans, K., Azevedo, I. L., & Morgan, M. G. (2012). Marginal Emissions Factors for the U.S. Electricity System. *Environmental Science & Technology , 46* (9), 4742-4748.

Sovacool, B. K., & Brown, M. A. (2010). Twelve Metropolitan Carbon Footprints: A Preliminary Comparative Global Assessment. *Energy Policy , 38* (9), 4856-4869.

Swilling, M., Robinson, B., Marvin, S., & Hodson, M. (2013). *City-Level Decoupling: Urban resource flows and the governance of infrastructure transitions.* UNEP.

Tamayao, M. M., Blackhurst, M. F., & Matthews, H. S. (2014). Do US Metropolitan Core Counties Have Lower Scope 1 and 2 CO2 Emissions than Less Urbanized Counties? *Environmental Research Letters , 9*.

Texas State Data Center. (2015). *Texas Population Projections Program*. Retrieved April 16, 2015, from Texas State Data Center Web Site: http://txsdc.utsa.edu/Data/TPEPP/Projections/Index.aspx

U.S. Bureau of Reclamation. (2014, July 25). *Downscaled CMIP3 and CMIP5 Climate and Hydrology Projections*. Retrieved September 8, 2015, from U.S. Bureau of Reclamation Website: http://gdo-dcp.ucllnl.org/downscaled_cmip_projections/dcpInterface.html

U.S. Census Bureau. (2012, May 16) [A]. *Population Estimates: Metropolitan and Micropolitan Statistics*. Retrieved September 7, 2015, from U.S. Census Bureau Website: https://www.census.gov/popest/data/metro/totals/2011/

U.S. Census Burearu. (2012, April 5) [B]. *Population Estimates: County Totals - Vintage 2011*. Retrieved September 7, 2015, from U.S. Census Bureau Website: http://www.census.gov/popest/data/counties/totals/2011/

U.S. Census Bureau. (2012, June 27) [C]. *Population Estimates - City and Town Totals: Vintage 2011*. Retrieved September 23, 2015, from U.S. Census Bureau Website: http://www.census.gov/popest/data/cities/totals/2011/

U.S. Census Bureau. (2013, March 7) [A]. *2010 Census Urban Area Facts*. Retrieved September 7, 2015, from US Census Bureau Website: http://www.census.gov/geo/reference/ua/uafacts.html
U.S. Census Bureau. (2012, June 27). *City and Town Totals: Vintage 2011*. Retrieved September 8, 2015, from U.S. Census Website: http://www.census.gov/popest/data/cities/totals/2011/

U.S. Census Bureau. (2013, February 2013) [B]. *About Metropolitan and Micropolitan Statistical Areas*. Retrieved September 23, 2015, from U.S. Census Bureau Website: http://www.census.gov/population/metro/about/

U.S. Climate Data. (2015). *Houston Weather Averages*. Retrieved September 8, 2015, from U.S. Climate Data Website: http://www.usclimatedata.com/climate/houston/texas/united-states/ustx0617

U.S. Climate Data. (2015). *San Antonio Weather Averages*. Retrieved September 8, 2015 , from U.S. Climate Data Website: http://www.usclimatedata.com/climate/san-antonio/texas/united-states/ustx1200

The U.S. Conference of Mayors. (2008). *U.S. Conference of Mayors Climate Protection Agreement*. Retrieved November 2013, from Mayor Climate Protection Center Website: http://www.usmayors.org/climateprotection/agreement.htm

U.S. Energy Information Administration (EIA). (2009). *Residential Energy Consumption Survey (RECS) - 2009 RECS Survey Data*. Retrieved September 8, 2015, from U.S. EIA RECS Website: http://www.eia.gov/consumption/residential/data/2009/

U.S. Energy Information Administration (EIA). (2014, October). *Natural Gas Annual Respondent Query System: EIA-176 Data through 2013*. Retrieved September 7, 2015, from U.S. EIA Website:
http://www.eia.gov/cfapps/ngqs/ngqs.cfm?f_report=RP1&f_sortby=ACI&f_items=101TVL,102TVL,103TVL,104TVL,105TVL,106TVL&f_year_start=2011&f_year_end=2011&f_show_compid=Name&f_fullscreen=

U.S. Energy Information Administration (EIA). (2015, March 25). *Form EIA-923 Detailed Data with Previous Form Data (EIA-906/920)*. Retrieved September 23, 2015, from U.S. EIA Website: http://www.eia.gov/electricity/data/eia923/

U.S. Environmental Protection Agency. (2010, March 5). *2002 National Emissions Inventory Data and Documentation*. Retrieved October 1, 2014, from Technology Transfer Network Clearinghouse for Inventories and Emissions Factors: http://www.epa.gov/ttn/chief/net/2002inventory.html#inventorydata

U.S. Environmental Protection Agency. (2013, May 30). *National Mobile Inventory Model (NMIM)*. Retrieved October 3, 2014, from U.S. EPA Modeling and Inventories Website: http://www.epa.gov/otaq/nmim.htm

U.S. Environmental Protection Agency[A]. (2014, October 28). *Carbon Pollution Standards: Developing Carbon Pollution Standards Under the Clean Air Act*. Retrieved April 16, 2015, from U.S. EPA Web Site: http://www2.epa.gov/carbon-pollution-standards/what-epa-doing#developing

U.S. Environmental Protection Agency[B]. (2014). *Regulatory Impact Analysis for the Proposed Carbon Pollution Guidelines for Existing Power Plants and Emission Standards for Modified and Reconstructed Powe Plants.* Research Triangle Park, North Carolina: Office of Air Quality Planning and Standards.

U.S. Environmental Protection Agency[C]. (2014, September 11). *Emission Inventories*. Retrieved October 1, 2014, from Technology Transfer Network Clearinghouse for Inventories and Emissions Factors: http://www.epa.gov/ttn/chief/eiinformation.html

U.S. Environmental Protection Agency[D]. (2014, Septermber 30). *GHG Reporting Program Data Sets*. Retrieved October 3, 2014, from U.S. EPA Website: http://www.epa.gov/ghgreporting/ghgdata/reportingdatasets.html

U.S. Environmental Protection Agency[E]. (2014). *eGRID 9th Editiion Version 1.0: Year 2010 Summary Tables.*

U.S. Environmental Protection Agency[A]. (2015, March 25). *Carbon Pollution Standards: Clean Power Plan*. Retrieved April 16, 2015, from U.S. EPA Web Site: http://www2.epa.gov/carbon-pollution-standards

U.S. Environmental Protection Agency (U.S. EPA)[B]. (2015, July 8). *State Energy CO2 Emissions*. Retrieved September 7, 2015, from U.S. EPA Climate and Energy Program Website: http://epa.gov/statelocalclimate/resources/state_energyco2inv.html

U.S. Global Change Research Program (USGCRP). (2014). *Climate Change Impacts in the United States: The Third National Climate Assessment.*

United Nations (UN) Department of Economic and Social Affairs. (2014). *World Urbanization Prospects - 2014 Revision.* Retrieved September 8, 2015, from UN Economic and Social Affairs Website: http://esa.un.org/unpd/wup/Highlights/WUP2014-Highlights.pdf

United Nations Framework on Climate Change (UNFCC). (2014). *Status of Ratification of the Kyoto Protocol*. Retrieved September 7, 2015, from UNFCC Website: http://unfccc.int/kyoto_protocol/status_of_ratification/items/2613.php

Warren, H. E., & LeDuc, S. K. (1981). Impact of Climate on Energy Sector in Economic Analysis. *Journal of Applied Meteorology , 20*, 1431-1439.

Wei, T. (2011). What STIRPAT Tells About Effects of Population and Affluence on the Environment? *Ecological Economics , 72*, 70-74.

Weinstock, B., & Niki, H. (1972). Carbon Monoxide Balance in Nature. *Science , 176* (4032), 290-292.

Yan, Y. Y. (1998). Climate and Residential Electricity Consumption in Hong King. *Energy , 23* (1), 17-20.

York, R., Rosa, E. A., & Dietz, T. (2003). STIRPAT, IPAT, and ImPACT: Analytical Tools for Unpacking the Driving Forces of Environmental Impacts. *Ecological Economics , 46* (3), 351-365.

Appendix A: Supporting Information for Chapter 2

A1: Elaboration on Metropolitan Statistical Areas (MSAs)

Metropolitan Statistical Areas (MSAs) include the Central County (urban core) and surrounding suburban counties. For example, the Pittsburgh MSA (as illustrated below) includes Allegheny as the Central County (urban core) and Beaver, Butler, Armstrong, Westmoreland, and Washington Counties the suburban counties.

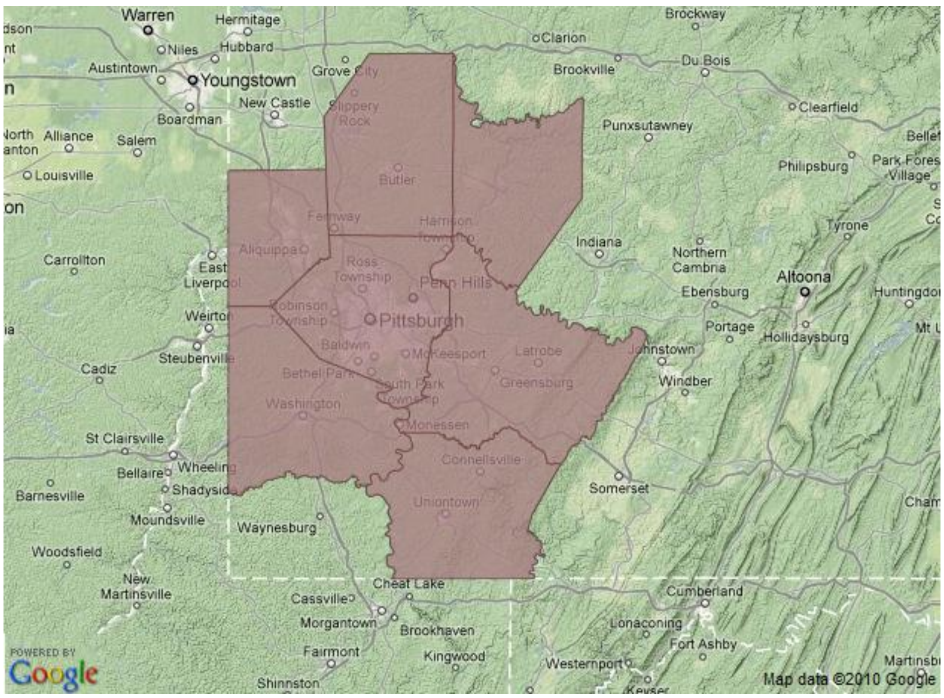

Figure A1. Map of the Pittsburgh MSA included the central county/urban core (Allegheny County) and the suburban counties.

A2: Summary of underlying emission estimates from integrated assessment approach

Table A1 Summary of population and sector-based GHG emissions for the 100 most populated metropolitan areas in the United States for the year 2002. Emission values are reported in million metric tons of CO2eTable A1. Summary of population and sector-based GHG emissions for the 100 most populated metropolitan areas in the United States for the year 2002. Emission values are reported in million metric tons of CO_2e

MSA Code	MSA Title	Population	Total	Commercial	Industrial	Residential	Electricity Prod	Onroad	Aircraft	Nonroad
10420	Akron, OH	694,960	7.22	0.58	1.19	1.47	0.00	3.54	0.12	0.33
10580	Albany-Schenectady-Troy, NY	825,875	9.06	0.80	0.63	1.60	0.96	4.56	0.16	0.33
10740	Albuquerque, NM	729,649	7.57	0.62	0.44	1.04	0.77	4.13	0.24	0.33
10900	Allentown-Bethlehem-Easton, PA-NJ	740,395	39.64	2.20	27.62	1.44	4.27	3.68	0.11	0.32
12060	Atlanta-Sandy Springs-Marietta, GA	4,247,981	87.08	2.93	7.08	4.75	39.67	28.95	1.15	2.55
12260	Augusta-Richmond County, GA-SC	499,684	7.91	0.22	2.82	0.41	1.39	2.73	0.08	0.25
12420	Austin-Round Rock, TX	1,249,763	14.82	0.78	1.16	0.60	4.75	6.50	0.23	0.79
12540	Bakersfield, CA	661,645	15.92	1.44	9.12	0.55	0.45	3.86	0.18	0.33
12580	Baltimore-Towson, MD	2,552,994	35.47	3.06	2.45	3.90	12.27	12.28	0.43	1.07
12940	Baton Rouge, LA	705,973	67.79	0.27	46.57	0.42	16.67	3.43	0.09	0.33
13820	Birmingham-Hoover, AL	1,052,238	50.15	0.71	3.70	0.90	37.39	6.66	0.19	0.60
14260	Boise City-Nampa, ID	464,840	5.07	0.45	1.35	0.64	0.00	2.10	0.18	0.35
14460	Boston-Cambridge-Quincy, MA-NH	4,391,344	50.34	4.70	8.14	10.99	6.84	17.26	0.68	1.74
14860	Bridgeport-Stamford-Norwalk, CT	882,567	10.59	1.02	0.16	2.02	3.22	3.63	0.09	0.46
15380	Buffalo-Niagara Falls, NY2/	1,170,111	21.91	0.89	4.27	2.45	8.37	5.29	0.20	0.44
16700	Charleston-North Charleston, SC	549,033	20.54	0.28	2.35	0.30	14.04	3.04	0.15	0.38
16740	Charlotte-Gastonia-Concord, NC-SC	1,330,448	18.19	0.95	1.62	1.29	6.19	6.66	0.45	1.04
16860	Chattanooga, TN-GA	476,531	6.74	0.49	2.20	0.36	0.00	3.38	0.08	0.24
16980	Chicago-Naperville-Joliet, IL-IN-WI	9,098,316	165.05	9.94	42.21	19.57	48.81	36.00	4.25	4.28
17140	Cincinnati-Middletown, OH-KY-IN	2,009,632	51.13	1.61	3.21	3.28	31.31	10.06	0.63	1.01
17460	Cleveland-Elyria-Mentor, OH	2,148,143	61.30	1.85	32.93	4.43	11.68	9.01	0.35	1.06
17820	Colorado Springs, CO	537,484	8.40	0.53	0.26	0.87	4.09	2.23	0.15	0.27
17900	Columbia, SC	647,158	12.23	0.34	1.69	0.37	5.04	4.25	0.14	0.40
18140	Columbus, OH	1,612,694	16.49	1.54	1.88	3.17	0.61	7.89	0.39	1.00
19100	Dallas-Fort Worth-Arlington, TX	5,161,544	53.52	4.32	7.11	3.21	8.78	25.63	1.41	3.07
MSA Code	MSA Title	Population	Total	Commercial	Industrial	Residential	Electricity Prod	Onroad	Aircraft	Nonroad
19380	Dayton, OH	848,153	9.33	0.75	1.60	1.51	0.94	3.96	0.15	0.40
19740	Denver-Aurora, CO1/	2,179,240	27.21	1.91	2.70	3.54	6.54	10.54	0.73	1.27
19780	Des Moines, IA	481,394	5.34	0.72	0.50	0.85	0.01	2.77	0.10	0.41
19820	Detroit-Warren-Livonia, MI	4,452,557	73.14	3.91	9.14	10.35	24.52	22.57	0.87	1.78
21340	El Paso, TX	679,622	5.73	0.28	1.46	0.52	0.98	2.19	0.08	0.21
23420	Fresno, CA	799,407	6.20	0.43	0.74	0.70	0.02	3.75	0.14	0.42
24340	Grand Rapids-Wyoming, MI	740,482	7.87	0.79	1.23	1.49	0.06	3.69	0.12	0.48
24660	Greensboro-High Point, NC	643,430	7.08	0.34	0.86	0.66	0.84	3.87	0.10	0.40
24860	Greenville, SC	559,940	5.28	0.31	1.44	0.21	0.00	2.88	0.10	0.33
25420	Harrisburg-Carlisle, PA	509,074	5.81	0.57	0.56	0.94	0.04	3.41	0.06	0.24
25540	Hartford-West Hartford-East Hartford, CT	1,148,618	11.47	1.48	0.53	2.78	0.62	5.38	0.19	0.48
26180	Honolulu, HI	876,156	8.96	0.12	0.99	0.06	4.46	2.75	0.29	0.29
26420	Houston-Baytown-Sugar Land, TX	4,715,407	119.33	3.54	49.19	2.52	37.44	22.79	1.01	2.82
26900	Indianapolis, IN	1,525,104	22.00	1.78	2.40	2.25	5.54	8.62	0.28	1.13
27140	Jackson, MS	497,197	5.49	0.18	0.53	0.33	0.90	3.17	0.13	0.25
27260	Jacksonville, FL	1,122,750	25.27	0.43	2.78	0.15	13.46	7.35	0.32	0.77
28140	Kansas City, MO-KS	1,836,038	45.42	2.00	3.16	3.06	25.83	9.86	0.36	1.16
28940	Knoxville, TN	616,079	12.44	0.33	0.86	0.50	5.90	4.35	0.13	0.37
29460	Lakeland-Winter Haven, FL	483,924	12.98	0.10	0.66	0.06	9.03	2.72	0.12	0.30
29540	Lancaster, PA	470,658	5.54	0.48	1.90	0.81	0.00	2.03	0.05	0.27
29820	Las Vegas-Paradise, NV	1,375,765	23.71	0.59	0.56	1.11	16.21	3.54	0.53	1.17
30780	Little Rock-North Little Rock, AR	610,518	6.66	0.68	1.02	0.66	0.18	3.56	0.18	0.38
31100	Los Angeles-Long Beach-Santa Ana, CA	12,365,627	92.35	1.99	19.73	9.19	8.73	45.98	2.13	4.60
31140	Louisville, KY-IN	1,161,975	32.36	0.96	3.00	1.63	18.33	7.52	0.23	0.70
31540	Madison, WI	501,774	13.47	1.01	0.48	0.88	7.75	2.80	0.11	0.43

Table A1 Continued. Summary of population and sector-based GHG emissions for the 100 most populated metropolitan areas in the United States for the year 2002. Emission values are reported in million metric tons of CO_2e

MSA Code	MSA Title	Population	Total	Commercial	Industrial	Residential	Electricity Prod	Onroad	Aircraft	Nonroad
32580	McAllen-Edinburg-Pharr, TX	569,463	5.15	0.17	0.21	0.07	2.45	2.00	0.05	0.21
32820	Memphis, TN-MS-AR	1,205,204	16.03	0.63	1.17	1.28	4.94	6.93	0.41	0.67
33100	Miami-Fort Lauderdale-Miami Beach, FL	5,007,564	42.64	1.01	4.68	0.65	10.52	22.11	1.10	2.58
33340	Milwaukee-Waukesha-West Allis, WI	1,500,741	24.13	2.31	2.33	2.77	8.63	6.99	0.31	0.79
33460	Minneapolis-St. Paul-Bloomington, MN-WI	2,968,806	85.26	6.53	27.73	5.68	26.48	15.68	1.40	1.76
33700	Modesto, CA	446,997	3.49	0.22	0.35	0.35	0.16	2.12	0.05	0.23
34980	Nashville-Davidson--Murfreesboro, TN	1,311,789	22.41	0.73	2.70	1.11	7.02	9.65	0.33	0.87
35300	New Haven-Milford, CT	824,008	8.55	0.93	0.23	1.96	1.71	3.29	0.07	0.35
35380	New Orleans-Metairie-Kenner, LA	1,316,510	35.13	0.66	19.53	1.00	8.62	4.41	0.22	0.70
35620	New York-Northern New Jersey-Long Island, NY-NJ-PA	18,323,002	152.74	18.18	3.96	35.44	30.74	56.18	1.81	6.44
36420	Oklahoma City, OK	1,095,421	15.03	1.12	2.41	1.35	1.93	7.34	0.25	0.63
36540	Omaha-Council Bluffs, NE-IA	767,041	17.79	0.86	1.56	1.30	9.43	3.76	0.15	0.72
36740	Orlando, FL	1,644,561	20.66	0.33	1.50	0.21	7.79	8.96	0.59	1.28
37100	Oxnard-Thousand Oaks-Ventura, CA	753,197	7.80	0.41	1.09	0.67	2.37	2.75	0.16	0.36
37340	Palm Bay-Melbourne-Titusville, FL	476,230	7.75	0.10	0.48	0.06	3.52	2.99	0.22	0.37
37980	Philadelphia-Camden-Wilmington, PA-NJ-DE	5,687,147	62.45	6.35	10.81	10.67	9.70	22.09	0.73	2.10
38060	Phoenix-Mesa-Scottsdale, AZ	3,251,876	28.01	2.55	1.04	1.03	3.68	16.22	1.17	2.32
38300	Pittsburgh, PA	2,431,087	58.31	2.50	4.98	4.95	34.24	10.14	0.57	0.93
38860	Portland-South Portland, ME	487,568	7.95	0.59	0.40	1.48	1.99	3.11	0.10	0.28
38900	Portland-Vancouver-Beaverton, OR-WA	1,927,881	17.13	1.29	4.01	1.43	0.61	8.24	0.45	1.10
39100	Poughkeepsie-Newburgh-Middletown, NY	621,517	9.43	0.40	0.39	1.10	3.55	3.56	0.21	0.22
39300	Providence-New Bedford-Fall River, RI-MA	1,582,997	24.15	2.02	2.72	3.82	9.79	4.95	0.24	0.60
39580	Raleigh-Cary, NC	797,071	7.17	0.51	0.29	0.70	0.00	4.89	0.21	0.57
40060	Richmond, VA	1,096,957	23.70	0.89	5.37	1.17	8.45	7.05	0.18	0.59
40140	Riverside-San Bernardino-Ontario, CA	3,254,821	29.35	1.59	5.31	2.62	1.78	15.31	0.80	1.94

MSA Code	MSA Title	Population	Total	Commercial	Industrial	Residential	Electricity Prod	Onroad	Aircraft	Nonroad
40380	Rochester, NY	1,037,831	11.22	0.84	1.02	1.89	1.61	5.19	0.14	0.52
40900	Sacramento--Arden-Arcade--Roseville, CA	1,796,857	18.42	5.34	0.44	1.57	1.20	8.33	0.42	1.12
41620	Salt Lake City, UT	968,858	10.33	0.28	1.40	2.33	0.73	4.77	0.36	0.46
41700	San Antonio, TX	1,711,703	29.79	1.05	1.45	0.46	17.23	8.39	0.39	0.83
41740	San Diego-Carlsbad-San Marcos, CA	2,813,833	25.90	5.22	0.73	0.98	3.65	13.32	0.56	1.45
41860	San Francisco-Oakland-Fremont, CA	4,123,740	43.08	2.00	7.36	5.28	8.10	17.65	0.84	1.85
41940	San Jose-Sunnyvale-Santa Clara, CA	1,735,819	13.78	1.14	1.46	1.96	0.05	7.94	0.37	0.87
42540	Scranton--Wilkes-Barre, PA	560,625	5.76	0.60	0.51	1.24	0.46	2.69	0.07	0.19
42660	Seattle-Tacoma-Bellevue, WA	3,043,878	26.59	2.30	3.50	2.95	0.24	15.15	0.85	1.61
44140	Springfield, MA	680,014	9.43	0.85	1.41	1.78	1.58	3.44	0.11	0.26
41180	St. Louis, MO-IL	2,698,687	71.31	3.40	10.77	4.46	32.90	17.53	0.71	1.54
44700	Stockton, CA	563,598	5.41	0.28	1.26	0.46	0.03	2.91	0.07	0.40
45060	Syracuse, NY	650,154	6.78	0.49	0.70	1.18	0.66	3.36	0.11	0.29
45300	Tampa-St. Petersburg-Clearwater, FL	2,395,997	40.95	2.67	2.31	0.31	21.64	12.26	0.46	1.31
45780	Toledo, OH	659,188	15.39	0.58	5.51	1.41	3.74	3.57	0.14	0.45
46060	Tucson, AZ	843,746	6.99	0.27	0.57	0.57	1.16	3.77	0.24	0.40
46140	Tulsa, OK	859,532	24.91	0.81	5.36	1.14	11.03	5.73	0.30	0.53
47260	Virginia Beach-Norfolk-Newport News, VA-NC	1,576,370	23.65	1.05	5.36	1.56	7.91	6.73	0.29	0.74
47900	Washington-Arlington-Alexandria, DC-VA-MD	4,796,183	61.54	3.95	3.42	6.22	21.39	23.40	0.87	2.29
48620	Wichita, KS	571,166	8.48	0.49	3.21	0.88	0.52	2.75	0.17	0.46
49340	Worcester, MA	750,963	11.27	1.00	2.20	1.95	1.68	3.98	0.12	0.34
49660	Youngstown-Warren-Boardman, OH-PA	602,964	7.77	0.52	1.22	1.26	1.25	3.18	0.08	0.26

Table A2 Summary of sector-based GHG emissions for the 100 most populated metropolitan areas in the United States for the year 2011. This data corresponds to the 2011a data discussed in Chapter 2. The estimates for the residential and commercial sectors were found by multiplying 2002 per capita values by 2011 population values. The emission estimates are reported million short tons of CO_2e

MSA Code	MSA Title	Industry	Electr. Gen.	Waste	On-Road Transpo.	Residential	Commercial	Total
17140	Akron, OH	0.20	0.10	0.01	3.94	1.63	0.65	6.53
16700	Albany-Schenectady-Troy, NY	1.46	4.43	0.10	4.02	1.87	0.93	12.81
16180	Albuquerque, NM	0.61	0.14	0.12	4.19	1.41	0.84	7.30
17900	Allentown-Bethlehem-Easton, PA-NJ	2.36	6.88	0.24	3.05	1.76	2.70	17.00
13020	Atlanta-Sandy Springs-Marietta, GA	0.84	33.13	1.38	25.95	6.60	4.08	71.98
13140	Augusta-Richmond County, GA-SC	2.97	1.15	0.19	2.70	0.51	0.28	7.80
19500	Austin-Round Rock-San Marcos, TX	2.01	5.59	0.61	7.93	0.95	1.23	18.32
11300	Bakersfield-Delano, CA	12.04	6.07	0.19	3.94	0.78	2.05	25.06
14540	Baltimore-Towson, MD	3.98	8.99	0.80	11.92	4.60	3.61	33.90
14060	Baton Rouge, LA	31.93	19.14	0.31	4.34	0.53	0.34	56.58
10180	Birmingham-Hoover, AL	11.65	38.03	0.84	7.40	1.07	0.84	59.84
13740	Boise City-Nampa, ID	0.43	0.00	0.11	2.09	0.96	0.67	4.25
14260	Boston-Cambridge-Quincy, MA-NH	1.05	10.97	1.26	16.42	12.67	5.42	47.78
12060	Bridgeport-Stamford-Norwalk, CT	0.08	1.64	0.27	3.31	2.33	1.18	8.82
16580	Buffalo-Niagara Falls, NY	0.44	5.36	0.39	3.82	2.62	0.95	13.59
18880	Charleston-North Charleston-Summerville, SC	5.52	14.65	0.22	2.88	0.41	0.38	24.05
15540	Charlotte-Gastonia-Rock Hill, NC-SC	0.96	6.73	0.60	13.25	1.92	1.41	24.87
19260	Chattanooga, TN-GA	0.63	0.00	0.27	3.04	0.44	0.60	4.98
13780	Chicago-Joliet-Naperville, IL-IN-WI	48.76	44.32	1.86	31.40	22.53	11.44	160.32
16860	Cincinnati-Middletown, OH-KY-IN	8.47	26.58	1.30	10.88	3.85	1.89	52.98
16940	Cleveland-Elyria-Mentor, OH	4.84	9.49	0.30	7.93	4.70	1.96	29.23
11700	Colorado Springs, CO	0.49	4.02	0.37	2.66	1.18	0.72	9.44
18700	Columbia, SC	0.99	5.13	0.17	3.87	0.49	0.45	11.10
16980	Columbus, OH	0.77	0.11	0.43	9.67	4.03	1.96	16.97

MSA Code	MSA Title	Industry	Electr. Gen.	Waste	On-Road Transpo.	Residential	Commercial	Total
19340	Dallas-Fort Worth-Arlington, TX	7.76	10.35	2.73	30.22	4.47	6.03	61.55
17020	Dayton, OH	0.98	0.15	0.10	4.68	1.66	0.82	8.40
11540	Denver-Aurora-Broomfield, CO	1.21	6.27	0.18	11.53	4.65	2.51	26.36
13460	Des Moines-West Des Moines, IA	0.55	0.15	0.11	1.80	1.13	0.95	4.69
14740	Detroit-Warren-Livonia, MI	9.00	8.90	2.46	17.24	10.99	4.15	52.73
19660	El Paso, TX	1.39	1.51	0.19	3.08	0.69	0.37	7.24
11260	Fresno, CA	0.90	0.34	0.13	3.74	0.91	0.56	6.56
14860	Grand Rapids-Wyoming, MI	0.12	10.37	0.35	4.27	1.73	0.92	17.76
15980	Greensboro-High Point, NC	0.40	0.53	0.42	3.49	0.83	0.43	6.10
19060	Greenville-Mauldin-Easley, SC	0.15	2.31	0.35	3.52	0.27	0.39	7.00
18020	Harrisburg-Carlisle, PA	0.63	0.04	0.19	2.33	1.13	0.68	5.00
12020	Hartford-West Hartford-East Hartford, CT	0.21	1.07	0.45	4.90	3.24	1.72	11.59
13380	Honolulu, HI	1.16	5.86	0.38	3.22	0.07	0.15	10.84
19380	Houston-Sugar Land-Baytown, TX	53.03	46.52	2.07	26.24	3.59	5.03	136.48
13820	Indianapolis-Carmel, IN	2.14	5.39	0.94	11.78	2.89	2.29	25.43
15500	Jackson, MS	2.61	0.55	0.15	4.16	0.40	0.21	8.08
12580	Jacksonville, FL	0.98	13.36	0.27	8.12	0.20	0.57	23.51
15380	Kansas City, MO-KS	1.22	26.89	0.90	8.64	3.77	2.46	43.87
19180	Knoxville, TN	1.56	7.46	0.19	4.84	0.62	0.42	15.08
12940	Lakeland-Winter Haven, FL	0.58	10.87	0.43	3.37	0.09	0.13	15.47
18140	Lancaster, PA	0.24	0.00	0.27	1.73	0.99	0.59	3.82
16220	Las Vegas-Paradise, NV	1.69	9.80	0.07	7.78	1.75	0.92	22.02
10420	Little Rock-North Little Rock-Conway, AR	0.36	0.43	0.39	3.92	0.85	0.87	6.82
10740	Los Angeles-Long Beach-Santa Ana, CA	19.46	5.46	2.68	51.97	10.61	2.30	92.48

Table A2 Continued. Summary of sector-based GHG emissions for the 100 most populated metropolitan areas in the United States for the year 2011. This data corresponds to the 2011a data discussed in Chapter 2. The estimates for the residential and commercial sectors were found by multiplying 2002 per capita values by 2011 population values. The emission estimates are reported million short tons of CO_2e

MSA Code	MSA Title	Industry	Electr. Gen.	Waste	On-Road Transpo.	Residential	Commercial	Total
13980	Louisville, KY-IN	8.09	20.17	0.27	5.58	2.00	1.17	37.28
20740	Madison, WI	0.37	7.80	0.05	2.94	1.12	1.28	13.58
19740	McAllen-Edinburg-Mission, TX	0.15	3.59	0.23	2.95	0.11	0.26	7.28
19140	Memphis, TN-MS-AR	2.14	6.85	0.38	6.73	1.55	0.77	18.42
12260	Miami-Fort Lauderdale-Pompano Beach, FL	1.07	13.12	1.84	25.02	0.81	1.26	43.12
20500	Milwaukee-Waukesha-West Allis, WI	0.47	12.63	0.24	5.77	3.18	2.65	24.95
15180	Minneapolis-St. Paul-Bloomington, MN-WI	5.60	19.22	0.51	15.93	7.00	8.04	56.30
11500	Modesto, CA	0.29	0.76	0.21	1.87	0.45	0.29	3.87
19100	Nashville-Davidson--Murfreesboro--Franklin, TN	0.72	7.33	0.32	9.48	1.51	1.00	20.36
12100	New Haven-Milford, CT	0.27	1.70	0.04	3.24	2.26	1.08	8.59
14020	New Orleans-Metairie-Kenner, LA	27.13	8.35	0.48	4.81	0.99	0.65	42.42
16300	New York-Northern New Jersey-Long Island, NY-NJ-PA	5.70	30.69	2.71	62.19	40.54	20.79	162.62
17460	Oklahoma City, OK	0.37	4.62	0.70	8.31	1.73	1.44	17.18
16020	Omaha-Council Bluffs, NE-IA	1.57	15.31	0.21	4.22	1.63	1.08	24.03
12540	Orlando-Kissimmee-Sanford, FL	0.31	15.51	1.00	11.62	0.31	0.48	29.22
11340	Oxnard-Thousand Oaks-Ventura, CA	0.59	0.17	0.28	3.46	0.82	0.50	5.81
12980	Palm Bay-Melbourne-Titusville, FL	0.00	0.23	0.24	3.34	0.08	0.13	4.01
17820	Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	12.07	11.81	2.10	19.06	12.39	7.38	64.82
10500	Phoenix-Mesa-Glendale, AZ	0.58	8.60	0.83	16.13	1.49	3.69	31.32
17860	Pittsburgh, PA	10.23	38.35	0.40	7.65	5.30	2.67	64.60
20940	Portland-South Portland-Biddeford, ME	0.25	1.10	0.16	2.24	1.72	0.69	6.15
17780	Portland-Vancouver-Hillsboro, OR-WA	1.68	0.95	0.13	7.73	1.85	1.67	14.02
18580	Providence-New Bedford-Fall River, RI-MA	0.19	7.25	0.21	5.99	4.26	2.25	20.14
15940	Raleigh-Cary, NC	0.12	0.00	0.23	5.80	1.12	0.82	8.09

MSA Code	MSA Title	Industry	Electr. Gen.	Waste	On-Road Transpo.	Residential	Commercial	Total
20220	Richmond, VA	2.40	11.01	0.74	5.90	1.49	1.14	22.68
10900	Riverside-San Bernardino-Ontario, CA	5.41	5.30	0.63	19.30	3.83	2.31	36.78
16620	Rochester, NY	1.31	0.13	0.57	4.44	2.12	0.95	9.52
11100	Sacramento--Arden-Arcade--Roseville, CA	0.28	2.01	0.41	8.93	2.09	7.12	20.85
19780	Salt Lake City, UT	2.95	0.25	0.36	5.02	3.04	0.36	11.98
19460	San Antonio-New Braunfels, TX	4.31	22.34	0.75	10.18	0.65	1.49	39.72
11020	San Diego-Carlsbad-San Marcos, CA	0.77	2.30	0.52	13.67	1.21	6.42	24.89
10780	San Francisco-Oakland-Fremont, CA	14.00	6.23	0.89	16.67	6.19	2.35	46.33
11180	San Jose-Sunnyvale-Santa Clara, CA	1.09	1.28	0.50	7.68	2.32	1.35	14.22
17980	Scranton--Wilkes-Barre, PA	0.64	0.03	0.21	2.01	1.37	0.66	4.93
20260	Seattle-Tacoma-Bellevue, WA	1.32	0.19	0.58	10.89	3.73	2.91	19.64
14500	Springfield, MA	0.26	1.07	0.15	2.57	2.00	0.95	7.00
15260	St. Louis, MO-IL	10.29	40.41	0.56	10.90	5.13	3.91	71.21
11460	Stockton, CA	0.30	0.49	0.40	3.01	0.63	0.38	5.20
16820	Syracuse, NY	0.37	1.74	0.23	2.81	1.33	0.55	7.02
12420	Tampa-St. Petersburg-Clearwater, FL	0.80	17.80	1.10	13.95	0.40	3.47	37.52
17300	Toledo, OH	4.97	3.75	0.12	3.33	1.53	0.63	14.34
10580	Tucson, AZ	0.63	0.82	0.05	4.55	0.73	0.35	7.13
17660	Tulsa, OK	5.51	11.84	0.50	5.98	1.38	0.98	26.20
20100	Virginia Beach-Norfolk-Newport News, VA-NC	0.42	4.35	0.44	6.44	1.84	1.24	14.72
12220	Washington-Arlington-Alexandria, DC-VA-MD-WV	1.14	14.24	1.40	21.89	8.15	5.18	52.01
13900	Wichita, KS	1.91	0.69	0.25	3.14	1.07	0.59	7.65
14460	Worcester, MA	0.34	4.05	0.28	4.03	2.30	1.17	12.17
17420	Youngstown-Warren-Boardman, OH-PA	3.16	0.21	0.19	3.07	0.00	0.00	6.64

Table A3 Summary of sector-based GHG emissions for the 100 most populated metropolitan areas in the United States for the year 2011. This data corresponds to the 2011b data discussed in Chapter 2. The estimates for the residential and commercial sectors were found by multiplying 2011 state-level per capita values by 2011 MSA population values. The emission estimates are reported million short tons of CO_2e

MSA Code	MSA Title	Industrial	Electr. Gen.	Waste	On-Road Transpo.	Residential	Commercial	Total
17140	Akron, OH	0.20	0.10	0.01	3.94	1.04	0.59	5.88
16700	Albany-Schenectady-Troy, NY	1.46	4.43	0.10	4.02	1.06	0.78	11.85
16180	Albuquerque, NM	0.61	0.14	0.12	4.19	0.89	0.65	6.59
17900	Allentown-Bethlehem-Easton, PA-NJ	2.36	6.88	0.24	3.05	0.85	0.55	13.94
13020	Atlanta-Sandy Springs-Marietta, GA	0.84	33.13	1.38	25.95	3.71	1.85	66.87
13140	Augusta-Richmond County, GA-SC	2.97	1.15	0.19	2.70	0.39	0.19	7.59
19500	Austin-Round Rock-San Marcos, TX	2.01	5.59	0.61	7.93	0.83	0.77	17.75
11300	Bakersfield-Delano, CA	12.04	6.07	0.19	3.94	0.69	0.33	23.27
14540	Baltimore-Towson, MD	3.98	8.99	0.80	11.92	2.19	1.90	29.77
14060	Baton Rouge, LA	31.93	19.14	0.31	4.34	0.42	0.27	56.40
10180	Birmingham-Hoover, AL	11.65	38.03	0.84	7.40	0.52	0.36	58.80
13740	Boise City-Nampa, ID	0.43	0.00	0.11	2.09	0.63	0.40	3.66
14260	Boston-Cambridge-Quincy, MA-NH	1.05	10.97	1.26	16.42	5.40	3.39	38.48
12060	Bridgeport-Stamford-Norwalk, CT	0.08	1.64	0.27	3.31	0.69	0.70	6.69
16580	Buffalo-Niagara Falls, NY	0.44	5.36	0.39	3.82	1.38	1.02	12.41
18880	Charleston-North Charleston-Summerville, S	5.52	14.65	0.22	2.88	0.23	0.19	23.70
15540	Charlotte-Gastonia-Rock Hill, NC-SC	0.96	6.73	0.60	13.25	0.69	0.56	22.79
19260	Chattanooga, TN-GA	0.63	0.00	0.27	3.04	0.34	0.26	4.54
13780	Chicago-Joliet-Naperville, IL-IN-WI	48.76	44.32	1.86	31.40	18.53	9.55	154.43
16860	Cincinnati-Middletown, OH-KY-IN	8.47	26.58	1.30	10.88	3.18	1.79	52.21
16940	Cleveland-Elyria-Mentor, OH	4.84	9.49	0.30	7.93	3.08	1.73	27.37
11700	Colorado Springs, CO	0.49	4.02	0.37	2.66	1.01	0.43	8.98
18700	Columbia, SC	0.99	5.13	0.17	3.87	0.27	0.22	10.65
16980	Columbus, OH	0.77	0.11	0.43	9.67	2.76	1.56	15.31

MSA Code	MSA Title	Industrial	Electr. Gen.	Waste	On-Road Transpo.	Residential	Commercial	Total
19340	Dallas-Fort Worth-Arlington, TX	7.76	10.35	2.73	30.22	3.05	2.81	56.92
17020	Dayton, OH	0.98	0.15	0.10	4.68	1.26	0.71	7.89
11540	Denver-Aurora-Broomfield, CO	1.21	6.27	0.18	11.53	3.97	1.70	24.86
13460	Des Moines-West Des Moines, IA	0.55	0.15	0.11	1.80	0.76	0.59	3.96
14740	Detroit-Warren-Livonia, MI	9.00	8.90	2.46	17.24	8.28	4.26	50.14
19660	El Paso, TX	1.39	1.51	0.19	3.08	0.38	0.35	6.91
11260	Fresno, CA	0.90	0.34	0.13	3.74	0.77	0.37	6.24
14860	Grand Rapids-Wyoming, MI	0.12	10.37	0.35	4.27	1.51	0.77	17.39
15980	Greensboro-High Point, NC	0.40	0.53	0.42	3.49	0.28	0.23	5.35
19060	Greenville-Mauldin-Easley, SC	0.15	2.31	0.35	3.52	0.22	0.18	6.74
18020	Harrisburg-Carlisle, PA	0.63	0.04	0.19	2.33	0.57	0.37	4.13
12020	Hartford-West Hartford-East Hartford, CT	0.21	1.07	0.45	4.90	0.91	0.91	8.45
13380	Honolulu, HI	1.16	5.86	0.38	3.22	0.02	0.07	10.72
19380	Houston-Sugar Land-Baytown, TX	53.03	46.52	2.07	26.24	2.84	2.62	133.32
13820	Indianapolis-Carmel, IN	2.14	5.39	0.94	11.78	2.16	1.24	23.66
15500	Jackson, MS	2.61	0.55	0.15	4.16	0.27	0.22	7.96
12580	Jacksonville, FL	0.98	13.36	0.27	8.12	0.07	0.23	23.04
15380	Kansas City, MO-KS	1.22	26.89	0.90	8.64	2.10	1.28	41.02
19180	Knoxville, TN	1.56	7.46	0.19	4.84	0.44	0.34	14.83
12940	Lakeland-Winter Haven, FL	0.58	10.87	0.43	3.37	0.03	0.10	15.38
18140	Lancaster, PA	0.24	0.00	0.27	1.73	0.54	0.35	3.13
16220	Las Vegas-Paradise, NV	1.69	9.80	0.07	7.78	1.76	1.34	22.44
10420	Little Rock-North Little Rock-Conway, AR	0.36	0.43	0.39	3.92	0.49	0.58	6.17
10740	Los Angeles-Long Beach-Santa Ana, CA	19.46	5.46	2.68	51.97	10.56	5.07	95.21

Table A3 Continued. Summary of sector-based GHG emissions for the 100 most populated metropolitan areas in the United States for the year 2011. This data corresponds to the 2011b data discussed in Chapter 2. The estimates for the residential and commercial sectors were found by multiplying 2011 state-level per capita values by 2011 MSA population values. The emission estimates are reported million short tons of CO_2e

MSA Code	MSA Title	Industrial	Electr. Gen.	Waste	On-Road Transpo.	Residential	Commercial	Total
13980	Louisville, KY-IN	8.09	20.17	0.27	5.58	0.90	0.62	35.62
20740	Madison, WI	0.37	7.80	0.05	2.94	0.78	0.53	12.49
19740	McAllen-Edinburg-Mission, TX	0.15	3.59	0.23	2.95	0.37	0.34	7.63
19140	Memphis, TN-MS-AR	2.14	6.85	0.38	6.73	0.83	0.65	17.58
12260	Miami-Fort Lauderdale-Pompano Beach, FL	1.07	13.12	1.84	25.02	0.29	0.96	42.30
20500	Milwaukee-Waukesha-West Allis, WI	0.47	12.63	0.24	5.77	2.12	1.43	22.67
15180	Minneapolis-St. Paul-Bloomington, MN-WI	5.60	19.22	0.51	15.93	4.66	3.52	49.43
11500	Modesto, CA	0.29	0.76	0.21	1.87	0.42	0.20	3.76
19100	Nashville-Davidson--Murfreesboro--Franklin, TN	0.72	7.33	0.32	9.48	1.02	0.79	19.66
12100	New Haven-Milford, CT	0.27	1.70	0.04	3.24	0.65	0.65	6.55
14020	New Orleans-Metairie-Kenner, LA	27.13	8.35	0.48	4.81	0.62	0.40	41.80
16300	New York-Northern New Jersey-Long Island, NY-NJ-PA	5.70	30.69	2.71	62.19	23.08	17.06	141.43
17460	Oklahoma City, OK	0.37	4.62	0.70	8.31	1.24	0.82	16.06
16020	Omaha-Council Bluffs, NE-IA	1.57	15.31	0.21	4.22	1.13	0.92	23.36
12540	Orlando-Kissimmee-Sanford, FL	0.31	15.51	1.00	11.62	0.11	0.37	28.92
11340	Oxnard-Thousand Oaks-Ventura, CA	0.59	0.17	0.28	3.46	0.68	0.33	5.50
12980	Palm Bay-Melbourne-Titusville, FL	0.00	0.23	0.24	3.34	0.03	0.09	3.92
17820	Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	12.07	11.81	2.10	19.06	6.19	3.98	55.22
10500	Phoenix-Mesa-Glendale, AZ	0.58	8.60	0.83	16.13	1.52	1.29	28.96
17860	Pittsburgh, PA	10.23	38.35	0.40	7.65	2.44	1.57	60.64
20940	Portland-South Portland-Biddeford, ME	0.25	1.10	0.16	2.24	0.03	0.15	3.93
17780	Portland-Vancouver-Hillsboro, OR-WA	1.68	0.95	0.13	7.73	1.63	1.06	13.20
18580	Providence-New Bedford-Fall River, RI-MA	0.19	7.25	0.21	5.99	1.54	0.99	16.16
15940	Raleigh-Cary, NC	0.12	0.00	0.23	5.80	0.45	0.36	6.95

MSA Code	MSA Title	Industrial	Electr. Gen.	Waste	On-Road Transpo.	Residential	Commercial	Total
20220	Richmond, VA	2.40	11.01	0.74	5.90	0.75	0.60	21.40
10900	Riverside-San Bernardino-Ontario, CA	5.41	5.30	0.63	19.30	3.51	1.69	35.84
16620	Rochester, NY	1.31	0.13	0.57	4.44	1.28	0.95	8.68
11100	Sacramento--Arden-Arcade--Roseville, CA	0.28	2.01	0.41	8.93	1.78	0.85	14.25
19780	Salt Lake City, UT	2.95	0.25	0.36	5.02	1.71	0.99	11.27
19460	San Antonio-New Braunfels, TX	4.31	22.34	0.75	10.18	1.03	0.95	39.55
11020	San Diego-Carlsbad-San Marcos, CA	0.77	2.30	0.52	13.67	2.56	1.23	21.05
10780	San Francisco-Oakland-Fremont, CA	14.00	6.23	0.89	16.67	3.58	1.72	43.09
11180	San Jose-Sunnyvale-Santa Clara, CA	1.09	1.28	0.50	7.68	1.52	0.73	12.80
17980	Scranton--Wilkes-Barre, PA	0.64	0.03	0.21	2.01	0.58	0.37	3.85
20260	Seattle-Tacoma-Bellevue, WA	1.32	0.19	0.58	10.89	2.63	1.74	17.35
14500	Springfield, MA	0.26	1.07	0.15	2.57	0.82	0.51	5.37
15260	St. Louis, MO-IL	10.29	40.41	0.56	10.90	2.88	1.75	66.80
11460	Stockton, CA	0.30	0.49	0.40	3.01	0.57	0.27	5.03
16820	Syracuse, NY	0.37	1.74	0.23	2.81	0.80	0.59	6.55
12420	Tampa-St. Petersburg-Clearwater, FL	0.80	17.80	1.10	13.95	0.15	0.48	34.27
17300	Toledo, OH	4.97	3.75	0.12	3.33	0.97	0.55	13.69
10580	Tucson, AZ	0.63	0.82	0.05	4.55	0.35	0.30	6.70
17660	Tulsa, OK	5.51	11.84	0.50	5.98	0.92	0.61	25.36
20100	Virginia Beach-Norfolk-Newport News, VA-NC	0.42	4.35	0.44	6.44	0.99	0.80	13.43
12220	Washington-Arlington-Alexandria, DC-VA-MD-WV	1.14	14.24	1.40	21.89	6.86	9.35	54.89
13900	Wichita, KS	1.91	0.69	0.25	3.14	0.86	0.42	7.27
14460	Worcester, MA	0.34	4.05	0.28	4.03	0.94	0.59	10.23
17420	Youngstown-Warren-Boardman, OH-PA	3.16	0.21	0.19	3.07	0.84	0.47	7.95

A2: Percent Change in Emissions between 2002 and 2011

Figure A2. illustrates that percent change in total GHG emissions for all MSAs analyzed. The uncertainty bars indicated upper and lower bound estimates based on the two different methods used to estimate emissions from residential and commercial buildings for the year 2011.

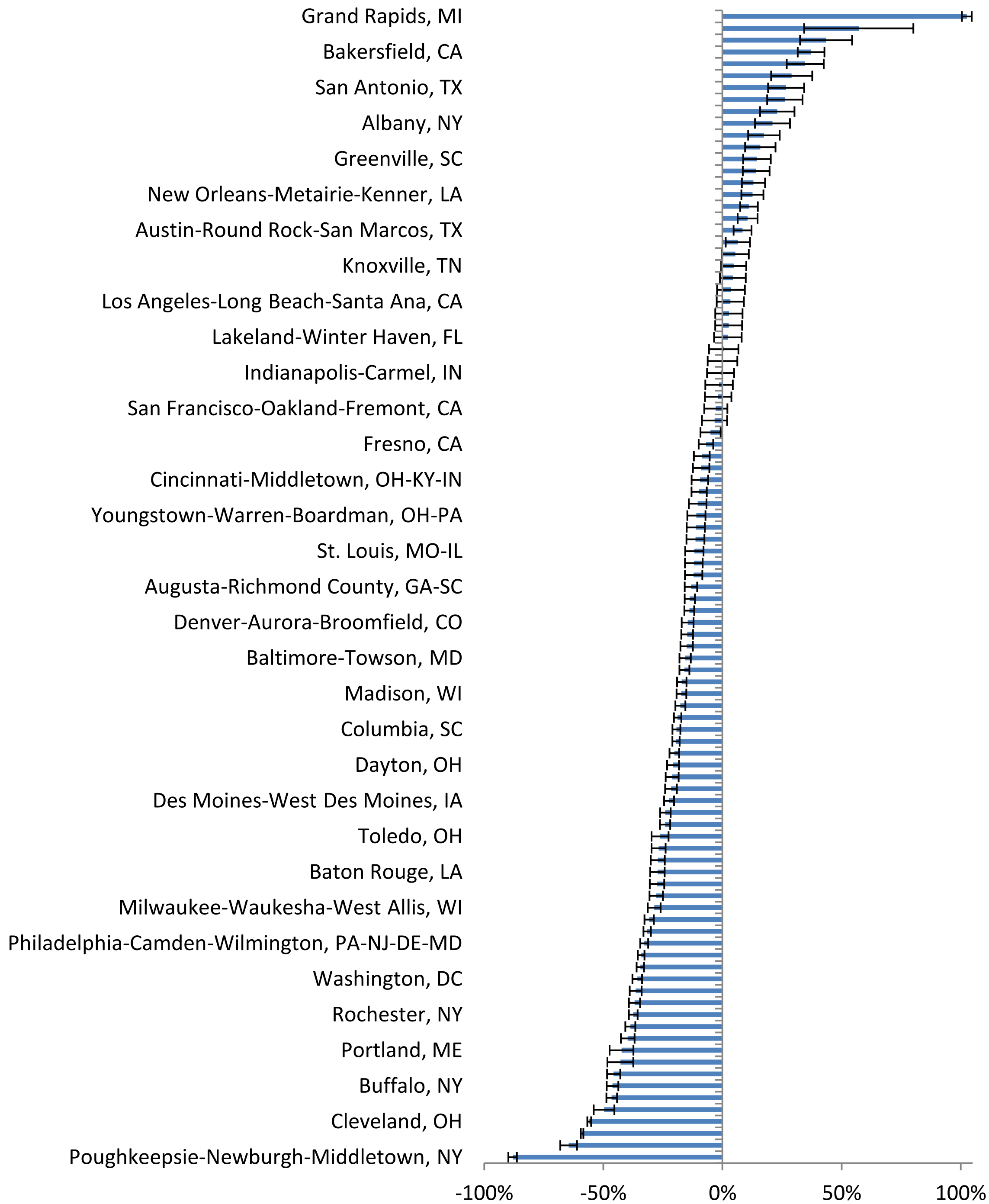

Figure A2 Percent change in total GHG emissions from 2002 to 2011 for the 100 largest metropolitan areas in the United States.

APPENDIX B: SUPPORTING INFORMATION FOR CHAPTER 3

B1: Summary of Communities with GHG Reduction Targets

Table B1 provides a summary of the various GHG reduction targets currently in place in communities across the United States. The table includes the base year and target emission reductions and years for the short-term, medium-term, and long-term. For example, Annapolis, MD has a medium term target of reducing emissions to 50% below 2006 values by the year 2025.

Table B1 Summary of the GHG reduction targets currently in place in various U.S. communities. Replicated from (ICLEI USA, 2015[A])

Community	Base Year	SHORT-TERM TARGET Decrease	Year	MEDIUM-TERM TARGET Decrease	Year	LONG-TERM TARGET Decrease	Year
Albany, CA✱	2004	25%	2020				
Albemarle County, VA✦✱	2007	24%	2020			80%	2050
Albuquerque, NM✦✱	2000	20%	2012	30%	2020	80%	2050
American Canyon, CA✱	2005	15%	2020	15%	2020		
Amherst, MA✦✱	1997	35%	2009	67%	2020		
Annapolis, MD✦✱	2006	25%	2012	50%	2025	100%	2050
Ann Arbor, MI✱	2000	25%	2025			90%	2050
Antioch, CA✱	BAU Forecast	25%	2020				
Arcata, CA✦✱	2005	20%	2010	40%	2020		
Aspen, CO✦✱	2004	30%	2020			80%	2050
Atlanta, GA✦	2009	20%	2020	40%	2030	80%	2050
Austin, TX✱	2007					Net Zero	2050
Baltimore, MD✱	2010	15%	2020				
Bedford, NY✱	2004	20%	2020				
Bellingham, WA✦✱	2000	7%	2012	28%	2020		
Benicia, CA✱	2000	10%	2020				
Berkeley, CA✦✱	2000	33%	2020			80%	2050
Boston, MA✦✱	2005	25%	2020			80%	2050
Boulder, CO✱	1990	7%	2012	10%	2020	80%	2050
Brattleboro, VT✦✱	2000	10%	2010	20%	2020		
Brookline, MA✦✱	1995	20%	2010	33%	2020		
Broward County, FL	2005	17%	2020			82%	2050

Table B1 Continued. Summary of the GHG reduction targets currently in place in various U.S. communities. Replicated from (ICLEI USA, 2015[A])

Community	Base Year	SHORT-TERM TARGET Decrease	Year	MEDIUM-TERM TARGET Decrease	Year	LONG-TERM TARGET Decrease	Year
Burlington, VT*	2007	20%	2020			80%	2050
Calistoga, CA*	2005	15%	2020	15%	2020		
Cambridge, MA+*	1990	20%	2010	30%	2020		
Carbondale, CO+*	2004	25%	2012	50%	2020		
Charleston, SC+*	1994	10%	2002	30%	2020		
Charlottesville, VA*	2000			10%	2035		
Chattanooga, TN+*	1990	7%	2012	20%	2020		
Chevy Chase, MD*	1990	7%	2012				
Chicago, IL+*	1990	25%	2020			80%	2050
Chula Vista, CA+*	1990	20%	2010	30%	2020		
Cincinnati, OH+*	2006	40%	2028			84%	2050
Cleveland, OH+*	2010	16%	2020	40%	2030	80%	2050
Collier County, FL*	2007	10%	2020	20%	2030	50%	2050
Columbia, MO*	2000	7%	2012	12%	2020		
Columbus, OH	2013	20%	2020				
Dallas, TX+*	2005	30%	2020	30%	2020		
Denver, CO*	1990	0	2020				
Des Moines, IA*	2008	15%	2015				
East Palo Alto, CA	2005	15%	2020				
Edina, MN	NA					80%	2050
El Cerrito, CA	2005	15%	2020	30%	2035		
Emeryville, CA+*	2004	25%	2020				
Eugene, OR+*	1990	10%	2020	50%	2030	75%	2050
Evanston, IL+	2005	13%	2012	20%	2016		
Falmouth, MA*	2001	10%	2020	10%	2020		
Falmouth, ME+*	2007	24%	2020			80%	2050
Fitchburg, WI*	1998	7%	2012	11%	2020		
Flagstaff, AZ*	1990	7%	2012	10%	2020		
Fort Collins, CO*	2005	20%	2020			80%	2050
Foster City, CA	2014	10%	2018				
Fremont, CA+*	2005	25%	2020				
Galloway, NJ+*	2007	24%	2020			80%	2050
Grand Rapids, MI	1990	1%	Annual				
Hamden, CT*	2001	10%	2015	14%	2020		
Hamilton Township, NJ	2008	20%	2020				
Hartford, CT*	2001	10%	2011	19%	2020		
Haverford, PA+*	2005	30%	2020	30%	2020		
Hawthorne, CA	2005	15%	2020				
Hayward, CA*	2005	12%	2020			82%	2050

Table B1 Continued. Summary of the GHG reduction targets currently in place in various U.S. communities. Replicated from (ICLEI USA, 2015[A])

		SHORT-TERM TARGET		MEDIUM-TERM TARGET		LONG-TERM TARGET	
Community	Base Year	Decrease	Year	Decrease	Year	Decrease	Year
Homer, AK*	2000	12%	2012	20%	2020		
Janesville, WI	2005					75%	2050
Kansas City, MO+*	2005	4%	2010	15%	2015	30%	2020
Keene, NH*	1995	10%	2015	13%	2020		
Key West, FL+*	2005	15%	2015	23%	2020		
Kirkland, WA*	2005	10%	2012	20%	2020	80%	2050
Knoxville, TN*	2005	20%	2020				
La Plata County, CO+*	2005	30%	2020				
Lawrence, KS+*	2002	30%	2020	50%	2030	80%	2050
Lexington, MA	2010	20%	2040				
Los Angeles, CA+*	1990	26%	2020	35%	2030		
Madison, WI+*	1990	20%	2010	30%	2020		
Manhattan Beach, CA	2005	7%	2020				
Marin County, CA*	1990	15%	2020	15%	2020		
Martinez, CA	2005	15%	2020				
Medford, MA*	1998	10%	2010	18	2020		
Miami, FL*	2006	20%	2020				
Miami-Dade County, FL	2005	10%	2015	20%	2020	80%	2050
Middlebury, VT*	2002	10%	2012	18%	2020		
Minneapolis, MN+*	2006	15%	2015	30%	2025	80%	2050
Mission, KS*	2005	20%	2020	20%	2020		
Montgomery County, MD+*	2005	80%	2050	27%	2020		
Montgomery County, PA*	2004	4%	2012	15%	2017	32%	2025
Napa County, CA*	2005	15%	2020	15%	2020		
Napa, CA*	2005	15%	2020	15%	2020		
Nashville, TN*	2005	20%	2020				
New Haven, CT*	1999	10%	2020	10%	2020		
New York, NY+	1990	30%	2030	80%	2050		
Newton, MA*	1998	7%	2010	13%	2020		
North Little Rock, AR	2008	10%	2015				
Northampton, MA+*	2000	8%	2010	25%	2017		
Northfield, MN+*	2005	15%	2013	50%	2028	100%	2033
Novato, CA*	2005	15%	2020	15%	2020		
Oak Park, IL+	2007	30%	2020				
Oakland, CA+*	2005	36%	2020			80%	2050
Olympia, WA+*	2005	50%	2020	70%	2035	80%	2050
Palo Alto, CA*	2005	5%	2012	15%	2020		
Park City, UT*	2005	15%	2020				
Philadelphia, PA+*	1990	10%	2010	20%	2015		

Table B1 Continued. Summary of the GHG reduction targets currently in place in various U.S. communities. Replicated from (ICLEI USA, 2015[A])

Community	Base Year	SHORT-TERM TARGET Decrease	Year	MEDIUM-TERM TARGET Decrease	Year	LONG-TERM TARGET Decrease	Year
Piedmont, CA	2005	15%	2020				
Pinecrest, FL*	2010	7%	2020				
Pittsburg, CA*	2005	15%	2020				
Pittsburgh, PA*	2003	20%	2023				
Portland, OR+*	1990	10%	2010	40%	2030	80%	2050
Richmond, VA+	2008	30%	2025				
Riverside, CA+*	2007	26%	2020	49%	2035	80%	2050
Roanoke County, VA+*	2007	30%	2020				
Roanoke, VA*	2005	10%	2015	15%	2020		
Sacramento County, CA*	2008	15%	2020				
Sacramento, CA+*	2005	15%	2020	38%	2030	83%	2050
Saint Helena, CA*	2005	15%	2020				
San Diego, CA*	2010	15%	2020	49%	2035		
San Francisco, CA+*	1990	25%	2017	40%	2025	80%	2050
San Luis Obispo, CA*	2005	15%	2020				
San Rafael, CA+*	2005	25%	2020				
San Ramon, CA	2008	15%	2020				
Santa Cruz County, CA	2009	21%	2020	43%	2035	64%	2050
Santa Cruz, CA+*	1990	30%	2020			80%	2050
Santa Monica, CA*	1990	15%	2015				
Seattle, WA+*	1990	30%	2020	58%	2030	100%	2050
Snohomish County, WA*	2000	20%	2020				
Sonoma County+	1990	25%	2015			80%	2050
Spokane, WA*	2005			30%	2030		
St. Louis, MO*	1990	7%	2012				
Stamford, CT+*	1998	20%	2018	22%	2020		
Sunnyvale, CA	2008	15%	2013				
Tacoma, WA+*	1990	15%	2012	40%	2020	80%	2050
Tucson, AZ	1990	7%	2012				
Upper Dublin, PA*	2007	10%	2017	13%	2020		
Washington, DC+*	2006			50%	2032		
Westchester County, NY+*	2005	20%	2015			80%	2050
Whatcom County, WA*	2001	10%	2012	17%	2020		
Williamstown, MA*	2000	10%	2010	20%	2020		
Worcester, MA+*	2002	11%	2010	25%	2020		
Yountville, CA*	2005	15%	2020				

B2: Elaboration on Scope 3 Emissions

Scope 3 emissions refer to indirect emissions (excluding the electricity, steam, or heat consumption – which are classified as Scope 2 emissions) associated with an activity or the use/purchase of a good or service. Examples include transportation of a good/product throughout the supply chain, extraction and processing of raw materials, etc (Greenhouse Gas Protocol, 2012).

B3: Summary of the Metropolitan Areas Included in the Analysis in Chapter 3

Table B2. Summary of Communities and MSAs included in analysis

MSA	Community
Atlanta-Sandy Springs-Marietta, GA	Atlanta, GA
Austin-Round Rock-San Marcos, TX	Austin, TX
Baltimore-Towson, MD	Annapolis, MD Baltimore, MD
Boston-Cambridge-Quincy, MA-NH	Boston, MA Brookline, MA Cambridge, MA Lexington, MA Medford. MA Newton, MA
Bridgeport-Stamford-Norwalk, CT	Stamford, CT
Charleston-North Charleston-Summerville, SC	Charleston, SC
Chattanooga, TN-GA	Chattanooga, TN
Chicago-Joliet-Naperville, IL-IN-WI	Chicago, IL Evanston, IL Oak Park, IL

Table B2 Continued. Summary of Communities and MSAs included in analysis

MSA	Community
Cincinnati-Middletown, OH-KY-IN	Cincinnati, OH
Cleveland-Elyria-Mentor, OH	Cleveland, OH
Columbus, OH	Columbus, OH
Dallas-Fort Worth-Arlington, TX	Dallas, TX
Denver-Aurora-Broomfield, CO	Denver, CO
Des Moines-West Des Moines, IA	Des Moines, IA
Grand Rapids-Wyoming, MI	Grand Rapids, MI
Hartford-West Hartford-East Hartford, CT	Hartford, CT
Kansas City, MO-KS	Kansas City, MO
Knoxville, TN	Knoxville, TN
Little Rock-North Little Rock-Conway, AR	North Little Rock, AR
Los Angeles-Long Beach-Santa Ana, CA	Hawthorne, CA Los Angeles, CA Manhattan Beach, CA Santa Monica, CA

Table B2 Continued. Summary of Communities and MSAs included in analysis

MSA	Community
Madison, WI	Fitchburg, WI Madison, WI
Miami-Fort Lauderdale-Pompano Beach, FL	Broward County, FL Miami, FL Miami-Dade County, FL Pinecrest, FL
Minneapolis-St. Paul-Bloomington, MN-WI	Edina, MN Minneapolis, MN
Nashville-Davidson--Murfreesboro--Franklin, TN	Nashville, TN
New Haven-Milford, CT	Hamden, CT New Haven, CT
New York-Northern New Jersey-Long Island, NY-NJ-PA	Bedford, NY New York City, NY Westchester County, NY
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	Haverford, PA Montgomery County, PA Philadelphia, PA Upper Dublin, PA
Pittsburgh, PA	Pittsburgh, PA
Portland-Vancouver-Hillsboro, OR-WA	Portland, OR
Richmond, VA	Richmond, VA
Riverside-San Bernardino-Ontario, CA	Riverside, CA

Table B2 Continued. Summary of Communities and MSAs included in analysis

MSA	Community
Sacramento--Arden-Arcade--Roseville, CA	Sacramento, CA Sacramento County, CA
San Diego-Carlsbad-San Marcos, CA	Chula Vista, CA San Diego, CA
San Francisco-Oakland-Fremont, CA	Albany, CA Antioch, CA Berkeley, CA East Palo Alto, CA El Cerrito, CA Emeryville, CA Foster City, CA Fremont, CA Hayward, CA Marin County, CA Martinez, CA Novato, CA Oakland, CA Piedmont, CA Pittsburg, CA San Francisco, CA San Rafael, CA San Ramon, CA
San Jose-Sunnyvale-Santa Clara, CA	Palo Alto, CA Sunnyvale, CA
Seattle-Tacoma-Bellevue, WA	Kirkland, WA Seattle, WA Snohomish County, WA Tacoma, WA
Springfield, MA	Amherst, MA Northampton, MA
St. Louis, MO-IL	St. Louis, MO
Tucson, AZ	Tucson, AZ
Washington-Arlington-Alexandria, DC-VA-MD-WV	Washington, DC
Worcester, MA	Worcester, MA

APPENDIX C: SUPPORTING INFORMATION FOR CHAPTER 4

C1. Maps of Electricity Service Areas

Figures C.1 and C.2 illustrate the boundaries for which the baseline electricity demand vs. temperature values were analyzed. The regions analyzed here are circled in red.

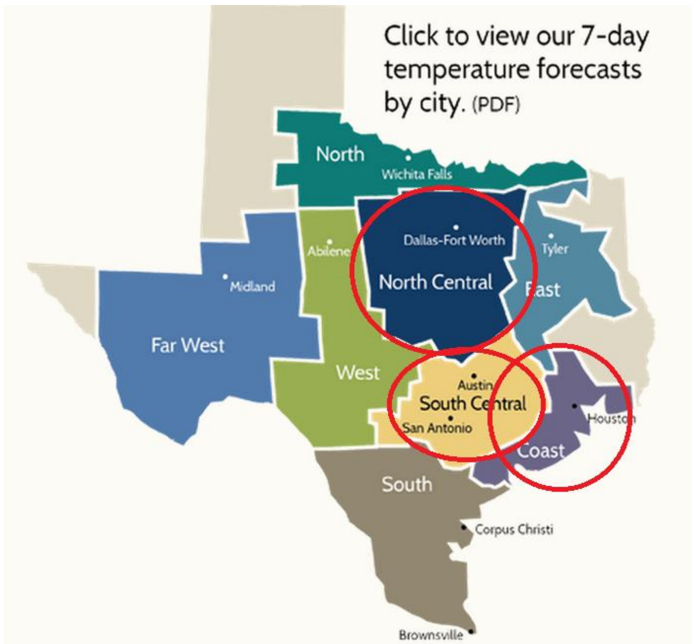

Figure C17Map of regions in ERCOT (Texas) for which baseline electricity usage data were used

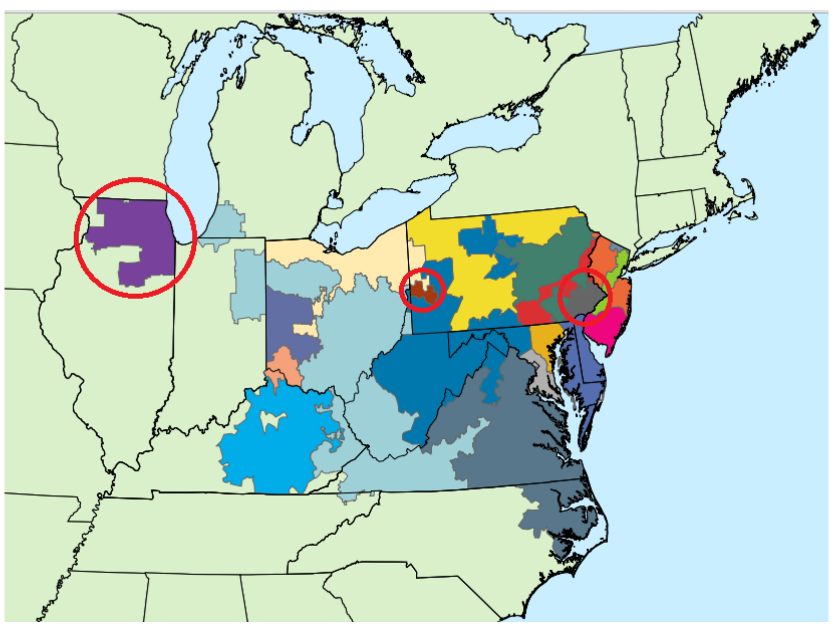

Figure C2   Map of regions in PJM for which baseline electricity usage data were used

C2. Maps of Climate Projection Regions

Figures C.3 through C.7 illustrate the regions for which projected temperature data were generated from the climate models. These regions are meant to correspond closely with the electricity service areas illustrated in Figures C.1 and C.2.

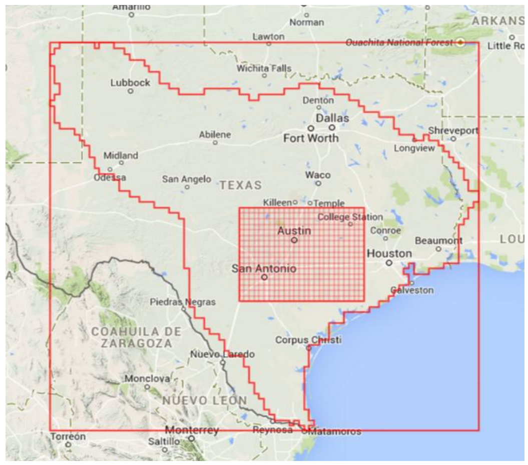

Figure C3 Map of region used to generate temperature projections for the San Antonio and Austin metropolitan areas

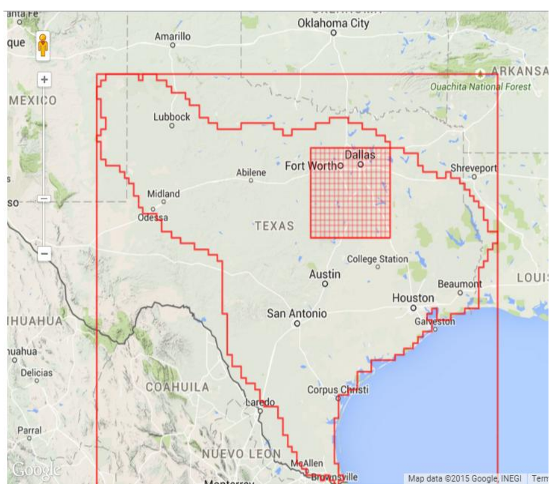

Figure C4 Map of region used to generate temperature projections for the Dallas/Fort Worth metropolitan area

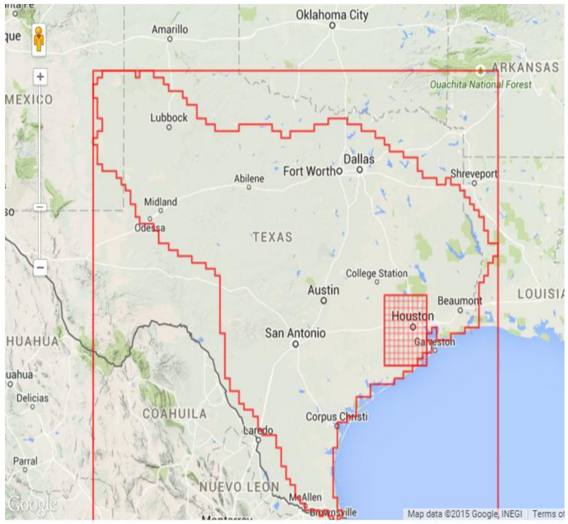

Figure C5 Map of region used to generate temperature projections for the Houston metropolitan area

Figure C6 Map of region used to generate temperature projections for the Chicago metropolitan area

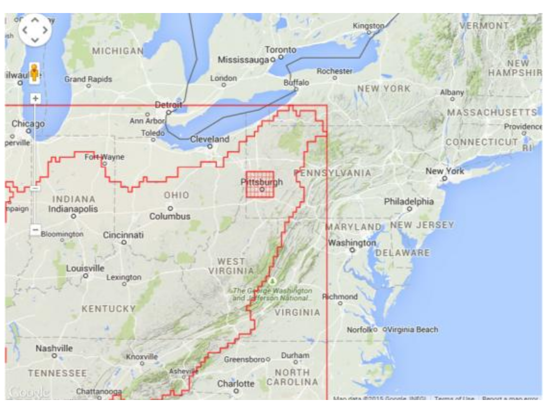

Figure C7 Map of region used to generate temperature projections for the Pittsburgh metropolitan area

C3. Additional Description of Temperature Projections and Range of Possible Values

Figure C.8 compares the average annual historical and projected temperatures for the areas of interest over a ten year period. The historical values are presented in green and represent the years 1990 to 1999. The projected values are presented in blue (climate model 1) and red (climate model 2) and represent the years 2025-2035.

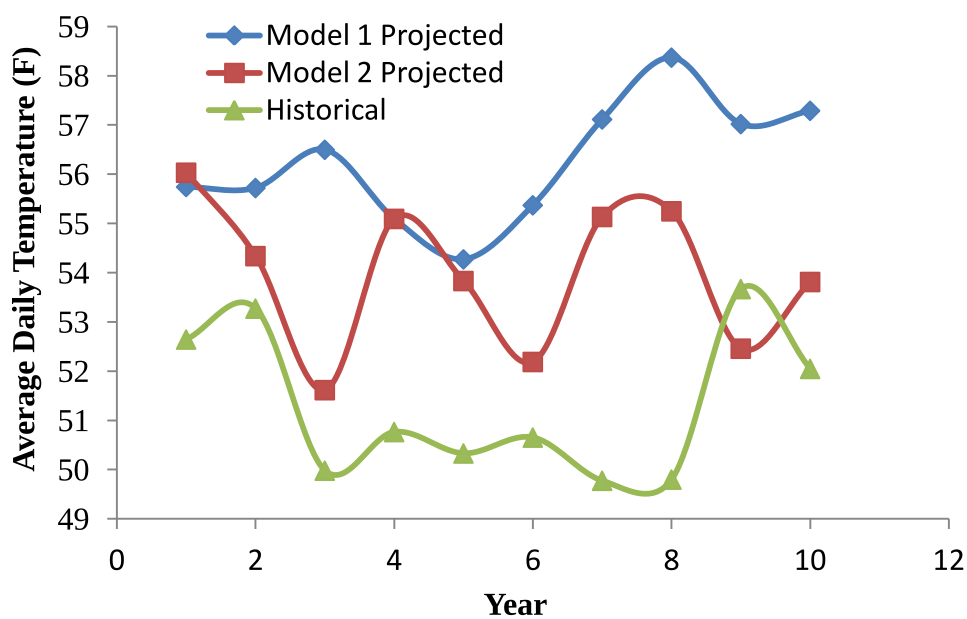

Figure C8 Average annual historical and projected temperatures for

Figure C.8 illustrates a few things: 1) the projected annual temperatures are generally expected to be higher than historical temperatures, 2) neither of the climate models predict monotonically increasing temperatures, and 3) compared to climate model 2, climate model 1 appears to have a more pronounced increasing trend over the decade.

Figure C.9 helps illustrate the potential range of uncertainty associated with the temperature projections produced by the climate models. In addition to showing the average (purple) historical (solid line) and projected (dotted line) temperature values, this figure also shows the maximum (red) and minimum (blue) temperatures predicted by the climate model. For each day of the year, we selected the highest and lowest temperature projections across models and years. More specifically, we had 20 temperature estimates for each day of the year (2 climate models x 10 years of projections). From these 20 data points, we used the absolute maximum for each day to form upper bound estimates and the absolute minimum for each day to form the lower bound estimates.

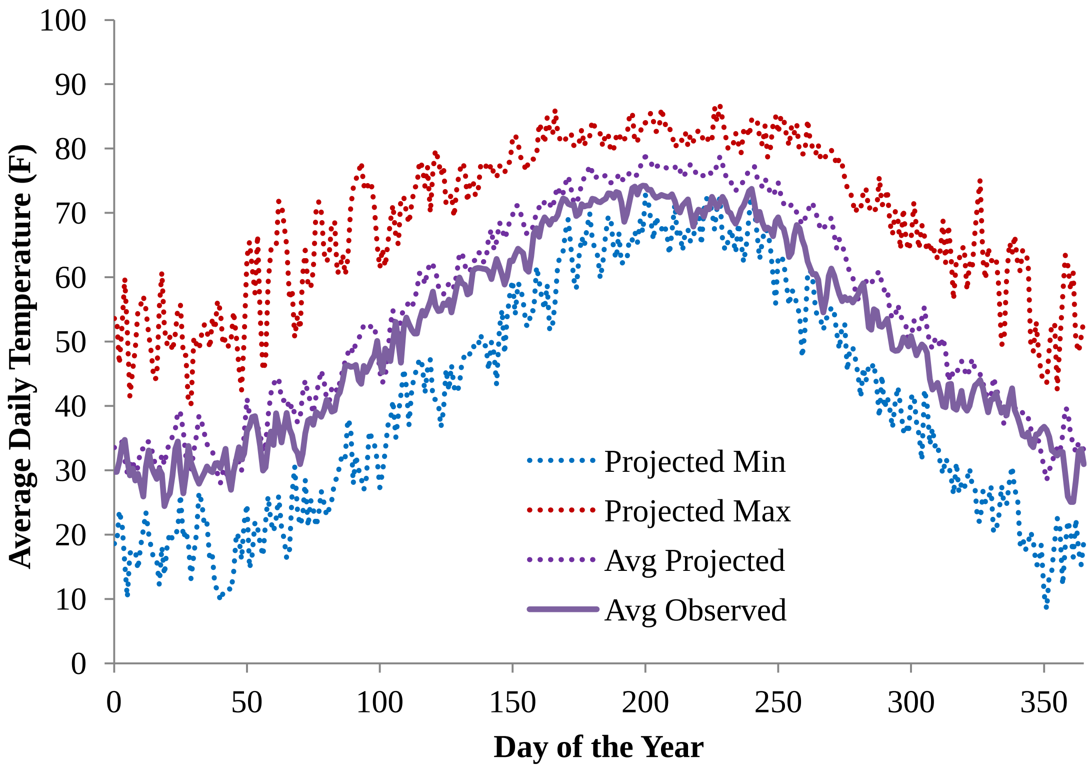

Figure C9 Average daily historical and projected temperature values included upper bound and lower bound estimates for the projected temperature values

Figure C9 helps illustrate a couple key points: 1) The average projected temperatures are generally expected to be higher than the historical average temperatures – especially in the summer months, and 2) The upper bound projections are substantially higher than the average historical values, while the lower bound projections are actually lower than the average historical values.

C4. Analysis of Accuracy of Regression Results

Figure C.10 compares projected daily electricity generation values to actual daily generation values for the Houston metropolitan area for the years 2010, 2011, 2013, and 2014. The projected values were estimated using the regression results presented in Table 1 of the main text. The actual electricity generation values were gathered from ERCOT (ERCOT, 2015) and the average daily temperature values for the time periods of interested were gathered from NOAA (NOAA, 2015).

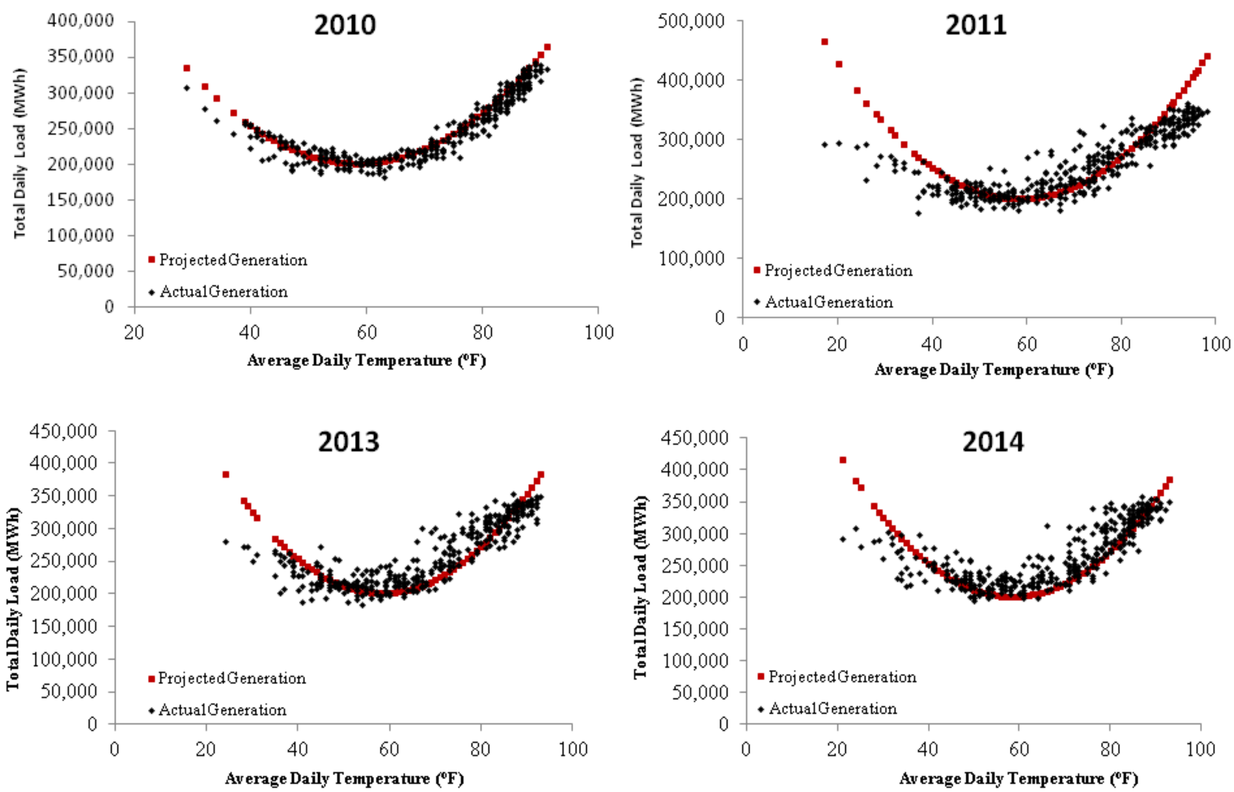

Figure C10 Comparison of projected daily electricity generation (using regression results from year 2012) to actual daily generation values for the Houston metropolitan area for the years 2010, 2011, 2013, and 2014).