Developing New Methods for Analyzing Urban Energy Use in Buildings:

Historic Turnover, Spatial Patterns, and Future Forecasting

by

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ABSTRACT

Energy use within urban building stocks is continuing to increase globally as populations expand and access to electricity improves. This projected increase in demand could require deployment of new generation capacity, but there is potential to offset some of this demand through modification of the buildings themselves. Building stocks are quasi-permanent infrastructures which have enduring influence on urban energy consumption, and research is needed to understand: 1) how development patterns constrain energy use decisions and 2) how cities can achieve energy and environmental goals given the constraints of the stock. This requires a thorough evaluation of both the growth of the stock and as well as the spatial distribution of use throughout the city. In this dissertation, a case study in Los Angeles County, California (LAC) is used to quantify urban growth, forecast future energy use under climate change, and to make recommendations for mitigating energy consumption increases. A reproducible methodological framework is included for application to other urban areas.

In LAC, residential electricity demand could increase as much as 55-68% between 2020 and 2060, and building technology lock-in has constricted the options for mitigating energy demand, as major changes to the building stock itself are not possible, as only a small portion of the stock is turned over every year. Aggressive and timely efficiency upgrades to residential appliances and building thermal shells can significantly offset the projected increases, potentially avoiding installation of new generation capacity, but regulations on new construction will likely be ineffectual due to the long residence time of the stock (60+ years and increasing). These findings can be extrapolated to other U.S. cities where the majority of urban expansion has already occurred, such as the older cities on the eastern coast. U.S. population is projected to increase 40% by 2060, with growth occurring in the warmer

southern and western regions. In these growing cities, improving new construction buildings can help offset electricity demand increases before the city reaches the lock-in phase.

DEDICATION

I dedicate this dissertation to my husband Dan, and our soon-to-be-born baby. Completing this would not have been possible without Dan's continual love, support, and sacrifice to get me through to the end.

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CHAPTER 1

INTRODUCTION

1.1 Buildings and Cities

Energy use within urban building stocks is continuing to increase globally as populations expand and access to electricity improves (U.S. Energy Information Administration 2013c). This projected increase in demand will likely require deployment of many new generation sources, but there is potential to offset some of this demand through modification of the buildings themselves. Building stocks are quasi-permanent infrastructures which have enduring influence on urban energy consumption, and research is needed to understand: 1) how development patterns constrain energy use decisions and 2) how cities can achieve energy and environmental goals given the constraints of the stock. Often, buildings stocks are decades or centuries old, so information is needed on how they can be adapted through replacement or upgrades so that they maintain flexible functionality for current and future energy demands. This requires a thorough evaluation of both the growth of the stock and as well as the spatial distribution of use throughout the city. In this dissertation, I use a case study in Los Angeles, California to quantify urban growth, forecast future energy use under climate change, and to make recommendations for mitigating energy consumption increases.

Globally, many urban areas across the globe continue to grow, but there is scant research on the mechanisms of building stock growth or the implications of different growth patterns. I define building stock growth as the incremental process by which a city expands or shrinks both in building count and spatial boundaries. Cumulative construction choices on building types, material composition, technologies, and location might preclude or permit

certain development paths for the city, such as reducing transportation-related air emissions (Marshall 2008). As buildings can remain within a stock for decades or centuries, constructing a new building within a city therefore implies a certain level of continuous resource commitment in order to support the on-going activities of the building, such as energy for heating or cooling the space or transportation to and from other parts of the city. In areas of the world that are still rapidly developing, understanding patterns of building stock growth will be important for better designing cities, and new construction creates opportunities for the implementation of higher efficiency technologies, such as by moving directly to zero-energy or passive buildings.

In contrast, areas that have already realized the majority of their urban growth will have the challenge of modifying existing building stock. Many cities in developed countries face an opposite problem in that the infrastructure is already "locked-in" and massive changes or new construction are not feasible. Previous studies have explored carbon and technology lock-in, which is how systems are fixed to certain development paths based on the historic interaction of institutions and technologies (Unruh 2000; Berkhout 2002), and the building stock undergoes a similar process as it grows and matures. In many cities in developed countries, lock-in has already occurred, meaning that new periods of rapid building construction are unlikely. In these cases, I need effective techniques to adapt the building stock both for changing needs (e.g. multi-generational living in the United States, (Shin 2002)) and for lowering energy and resource consumption. Understanding the mechanisms through which lock-in occurs and how to break this path dependence, when necessary, will be important for transitioning existing building stock to lower energy consumption regimes.

As cities continue to grow and utilize resources, I need to critically consider how future inhabitants will utilize energy. Access to energy in buildings correlates strongly with improved standards of living through the realms of health, education, and access to information (Joyeux and Ripple 2007), and maintaining or creating energy access in buildings across the globe should be prioritized. Buildings currently consume ~40% of energy world-wide (United Nations Environment Programme 2015), and obtaining higher levels of energy access would increase this demand and create the need for new sources of energy production. Furthermore, under climate change, larger percentages of the world's population will live in warmer climates and this could increase the energy demand for cooling building spaces (Sailor and Pavlova 2003; Davis and Gertler 2015). To reduce total energy demand, per capita conservation and efficiency are both potential resources for managing future energy demand (National Academy of Sciences 2010). Energy conservation refers to changing behaviors to those which utilize less energy, but don't necessarily provide the same function (e.g. increasing the thermoset temperature in the summer), whereas energy efficiency refers to maintaining the same functionality of the system, but for less energy input per desired output (e.g. holding the thermoset temperature constant, but installing a higher efficiency air conditioner). Research is needed to develop forecasts of how the building stock and energy consumption will jointly change over the next century in order to develop strategies for meeting the increased demand.

1.2 Objectives

In this dissertation, I investigate the previously discussed issues of city growth, spatial analysis, and energy forecasting. Specifically, I have the following objectives:

I. Characterize turnover of an urban building stock over time including material requirements

II. Create new geographies for urban energy assessment with more homogenous energy consumption

III. Forecast urban energy consumption under changing climatic and technological conditions

IV. Identify pathways for mitigating climate-related increases in energy consumption in buildings

My dissertation includes three studies which focus on understanding building stock deployment over time in a city, developing new methods for spatial modeling of current building energy use, and spatially-detailed forecasting of building energy use under climate change scenarios.

1.3 Case Study: Los Angeles County

Throughout the dissertation, I use Los Angeles County, California (LAC) as the primary case study for exploring issues of urban growth and urban form. I utilize the county level as data are readily available at this geography, and it captures the majority of the Los Angeles Metropolitan Statistical Area. LAC is the largest county in the U.S., and it is home to nearly 1 out of every 30 Americans. Decisions made involving quality of life and environmental outcomes for LAC, therefore, will not only serve as an example for transforming cities, but could influence total U.S. air emission and environmental impacts. Furthermore, the state of California has demonstrated significant political will towards mitigating negative consequences of building energy use and moving towards sustainable living, so there is potential for application of my research findings in informing urban policy.

1.4 Dissertation Organization

This dissertation contains three main chapters, each focused on a different aspect of building infrastructure growth, use, and adaptation.

Chapter 2: Growth of Urban Building Stocks (Objective: I)

Building stocks constitute enduring components of urban infrastructure systems, but little research exists on their residence time or changing environmental impacts. Using Los Angeles County, California as a case study, I develop a framework for assessing the changes in city building stocks over time (i.e. construction and demolition rates), the residence time of buildings and their materials, and the associated embedded environmental impacts. In Los Angeles, previous land use decisions prove not easily reversible, and past building stock investments may continue to constrain the energy performance of buildings. The average age of the building stock has increased steadily since 1920, and more rapidly after the post-WWII construction surge in the 1950s. Buildings will likely endure for 60 years or longer, making infrastructure in this city a quasi-permanent investment. The long residence time, combined with the physical limitations on outward growth, suggest that the Los Angeles building stock is unlikely to have substantial spatial expansion in the future. Once a building is constructed and added to the building stock, that building becomes a continuous sink of material, monetary, and energetic resources, resulting in environmental impacts. The long residence time of structures implies a commitment to use and maintain the infrastructure, potentially creating barriers to an urban area's ability to improve energy efficiency. The immotility of buildings, coupled with future environmental goals, indicates that urban areas will be best positioned by instituting strategies that ensure reductions in life-cycle (construction, use, and demolition) environmental impacts.

Chapter 3: Clustering Buildings for Improved Energy Analysis (Objectives: II)

Within residential electricity consumption there exists significant variability from home-to-home due to the differences in building thermal properties, appliances, and

inhabitant behavior. I define these variables as the "socio-technical" characteristics of the building stock. Electricity analyses at sub-city scales that use predefined geographies, such census tracts, might artificially split areas with homogenous socio-technical characteristics leading to analyses that don't effectively contrast the drivers of energy use. The objective of this sub-study is to use the spatial relationships between demographics, building types, and electricity consumption to form new geographies with less variability for use in residential energy assessment. Using Los Angeles and New York City as case studies, I compare the differences in variability of energy use within predefined geographies (e.g. census tract) and geographies defined by clustering on socio-technical characteristics. I find that using socio-technical clustering, regardless of the chosen subset of variables, reduces the variability over pre-defined geopolitical boundaries with high statistical significance ($p << 0.0001$). By defining geospatial regions of energy analysis, I reduce intra-regional variability by 13% in Los Angeles and 29% in New York, thereby improving opportunities for prediction and forecasting. This is the first study to examine the role of spatial boundaries in urban energy assessment. The creation of socio-technical geographies for building electricity assessment creates opportunities for improving predictions and forecasts for future sub- and cross-city energy studies.

Chapter 4: Forecasting Residential Electricity Use 2020-2060 Under Climate Change (Objectives III & IV)

Climate change could significantly alter consumer demand for energy in buildings. Climate change may affect local climates, altering heating and cooling loads of buildings. Warming climates could lead to the increased saturation of cooling technologies (Sailor and Pavlova 2003; Davis and Gertler 2015) thereby increasing electricity consumption. Here I present an assessment of changing residential electricity and natural gas demand in Los

Angeles County, California (LAC) under multiple climate change models, and I investigate the potential for energy efficient technologies to offset increased demand. Using an 84 building prototypes, I develop a spatially and temporally resolute energy forecast by scaling energy consumption simulations of the prototypes to all of LAC. With temperature increases, I find that without policy intervention, residential electricity demand in LAC could increase as much as 34 - 92% between 2020 and 2060. However, aggressive policy intervention aimed at upgrading heating and cooling systems as well as other appliances within homes can decrease this demand increase to 5%, potentially avoiding the installation of new generation capacity. I therefore recommend aggressive energy efficiency measures to mitigate projected increases in LAC's electricity consumption.

Chapter 5: Conclusion and Synthesis

In this chapter, I discuss the knowledge gaps which I have bridged with this dissertation research in the context of the current literature, and I identify the next steps for advancing the study of urban buildings and energy.

1.5 References

Berkhout, Frans. 2002. "Technological Regimes, Path Dependency and the Environment." *Global Environmental Change* 12 (1): 1–4. doi:10.1016/S0959-3780(01)00025-5.

Davis, Lucas W., and Paul J. Gertler. 2015. "Contribution of Air Conditioning Adoption to Future Energy Use under Global Warming." *Proceedings of the National Academy of Sciences* 112 (19): 5962–67. doi:10.1073/pnas.1423558112.

Joyeux, Roselyne, and Ronald D. Ripple. 2007. "Household Energy Consumption versus Income and Relative Standard of Living: A Panel Approach." *Energy Policy* 35 (1): 50–60. doi:10.1016/j.enpol.2005.10.012.

Marshall, Julian D. 2008. "Energy-Efficient Urban Form." *Environmental Science & Technology*

42 (9): 3133–37. doi:10.1021/es087047l.

National Academy of Sciences. 2010. *Real Prospects for Energy Efficiency in the United States*. Washington, D.C.: National Academies Press. doi:10.17226/12621.

Sailor, David J., and A.A. Pavlova. 2003. "Air Conditioning Market Saturation and Long-Term Response of Residential Cooling Energy Demand to Climate Change." *Energy* 28 (9): 941–51. doi:10.1016/S0360-5442(03)00033-1.

Shin, Stephanie. 2002. "Planning for a Multi-Generational Future : Policies, Regulations, and Designs for Multi-Generational Housing in the United States." Massachussets Institute of Technology. http://hdl.handle.net/1721.1/73825.

U.S. Energy Information Administration. 2013. "International Energy Outlook 2013." http://www.eia.gov/forecasts/archive/ieo13/ieo_tables.cfm.

United Nations Environment Programme. 2015. "Sustainable Buildings and Climate Initiative." http://www.unep.org/sbci/AboutSBCI/Background.asp.

Unruh, Gregory C. 2000. "Understanding Carbon Lock-In." *Energy Policy* 28 (12): 817–30. doi:10.1016/S0301-4215(00)00070-7.

CHAPTER 2

THE GROWTH OF URBAN BUILDING INFRASTRUCTURE, ITS UNINTENDED LOCK-IN, AND EMBEDDED ENVIRONMENTAL EFFECTS

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2.1 Introduction

New methods are needed to understand the drivers and patterns of infrastructure construction and the associated environmental investment in urban areas. Lock-in effects (i.e., committing ourselves to a pathway of infrastructure use and environmental impacts that is difficult to diverge from) and the long-term ramifications of urban growth are poorly understood, yet cities continue to deploy infrastructure without a rigorous understanding of how these systems may affect long-term sustainability goals. Urban infrastructures, such as buildings, have both local and remote environmental impacts from the materials and energy consumed during construction, maintenance, operation, and eventual demolition (Chester and Horvath 2009). The initial infrastructure investments during construction should be weighed against the potential tradeoffs in the use of the infrastructure over its lifetime, but the connection between "embedded" resources and "emergent" behaviors (i.e., the use of the infrastructure) lacks definition and quantification. Embedded energy and emissions are those from the extraction of primary resources, their processing into construction materials,

transportation to the construction site, and the construction of the building. Embedded impacts are those resulting from anthropogenic activities, and the sequestration of biogenic materials (e.g. carbon in wood) is not included. Henceforth, embedded environmental effects will refer to the embedded materials, energy, and emissions from constructing the Los Angeles building stock.

There are many studies quantifying embedded emissions of specific buildings, small neighborhoods, or comparing between building types (e.g. Lippke et al. 2004; Ochsendorf et al. 2011; Ochoa Franco 2004), but no studies were identified which quantified this embedded component across an entire metropolitan area. Masanet, Stadel, and Gursel (2012) provide an in-depth overview of building life-cycle assessment (LCA) studies to date. LCA is a methodology for estimating the cradle-to-grave impacts of products, services, activities, or processes, including embedded emissions. Most of the LCA studies identified focus on emissions of an individual building (Gustavsson, Joelsson, and Sathre 2010; Lippke et al. 2004; Salazar and Meil 2009) while some focused on comparing material choices (i.e. steel vs wood) in building construction (Guggemos and Horvath 2005; Petersen and Solberg 2005; Upton et al. 2008). These studies provide results too limited in scope to apply to an entire metropolitan area, given the heterogeneity of building functions, sizes and construction materials, but do establish robust methods for quantifying embedded emissions. A subset of studies use 2-3 types of building types to compare neighborhoods in different areas of a city, with the intent of studying secondary changes from densification (Frijia, Guhathakurta, and Williams 2012; Norman, MacLean, and Kennedy 2006; Kimball et al. 2013; Chester et al. 2013). These studies, while valuable for assessing the upstream impacts of neighborhood design and redevelopment, do not provide a comprehensive framework for contextualizing the impacts of building systems across an entire metropolitan area and how these impacts

change over time. Two identified studies quantified embedded impacts on a larger spatial scale. Power (2008) examines whether constructing new buildings or retrofitting older buildings is preferable from an environmental standpoint for the United Kingdom. Mohareb and Kennedy (2012) assess the carbon storage in the infrastructure materials of 2005 Toronto, among other sinks of carbon sequestration, to study the potential for further increasing urban carbon capture. For urban sustainability goals, embedded impacts should be studied on a regional scale to provide a systematic understanding of the effects of growth and decay in urban systems.

2.1.1 New Methods for Embedded Building Assessment

Here, a methodology is developed for assessing how buildings have been deployed and deconstructed over the lifetime of a city and the environmental ramifications of infrastructure design choices. To develop the methodology, a key challenge is the assessment of transient building turnover rates. As a city develops, buildings are constructed and later demolished, and the net effect of this growth and decay is the infrastructure that exists today. Assessing growth and decay is unique as no study to-date was found which quantified regional building turnover over an extended period of time. Tanikawa and Hashimoto (2009) estimate the embedded materials in the material stocks of sub-metro areas in Japan and the U.K. to predict where waste will be when infrastructure is demolished. They also project demolition rates into the future based previous demolition patterns, as observed from aerial images, but do not assess an entire metro area or the impacts of building stock. A second advancement of this research is quantifying embedded impacts of buildings across an entire urban area. This allows for realistic accounting of the variability in environmental performance based on differences in building structure, and how embedded impacts change

over time. A case study is developed to test the methodology, focusing on buildings in Los Angeles County, California, USA.

2.1.2 Building Infrastructure in Los Angeles

Los Angeles County is chosen as a case study because i) the city is young (having experienced most of its growth between 1930 and 1960), but ii) mature enough to have been in use for multiple generations, and iii) has historical infrastructure data from before when major investments commenced (Whittemore 2012b). While the Los Angeles urban area includes 5 counties (Los Angeles, Orange, San Bernardino, Riverside, and Ventura), this article focuses on Los Angeles County, specifically, given that data are often reported based on this geopolitical boundary. Approximately half of the five-county area residents reside within Los Angeles County, and that ratio is projected to remain roughly the same through 2060 (Department of Finance 2013). Throughout the article Los Angeles County will be referred to as *Los Angeles*.

In addition to the relatively young age, Los Angeles is a rich case study because of the large population, extensive infrastructure over a large area, and significant political interest in mitigating environmental impacts (State of California 2003; State of California 2008; City of Los Angeles 2007). In 2010, Los Angeles had 9.8 million residents (U.S. Census Bureau, 2010), which means that approximately 1 out of every 30 American citizens resided in the county, and the population is on track to increase by 18% to 11.6 million by 2060 (Department of Finance 2013). Historical growth was facilitated by extensive investment in infrastructure (Federal Highway Administration 2014) and has led to the densest roadway network in the U.S. (Sorensen 2009). Extensive water conveyance has resulted in the state expending large amounts of electricity on water provision (Snow 2008),

and sprawling development has decentralized jobs and activities and made public transit investment difficult (Garreau 1991).

2.2 Methodology

The environmental impacts of urbanization processes are partially predicated on how infrastructure has been deployed, and building embedded impact assessment should therefore be based on long-term growth models. As such, a framework is developed for analyzing the construction and demolition of urban building stock and identifying the corresponding embedded materials, energy use, and greenhouse gas (GHG) emissions changes over time. First, the development of an urban growth model to estimate turnover rates of city building stocks is described. Subsequently, prototypical building models are presented for three representative time periods of growth to estimate embedded effects. In doing so, a spatially and temporally specified embedded impact analysis is created, capturing the start of urbanization in Los Angeles (approximately 1900) to present day.

2.2.1 Turnover Modeling

A methodology was developed for estimating turnover rates based on emerging big data. The Los Angeles County Assessor database provides a record of the current day building stock, including initial construction year, but excludes previously demolished buildings (since this information is not relevant for tax purposes). The main data source on former buildings is the U.S. Decadal Census, which captured the number of residential dwelling units in Los Angeles during each decade and approximates the vintage (i.e. year of construction) distribution. A growth model is developed to estimate demolition by vintage (specified as 10-year age bins). No historical records were identified which gave similar information for commercial or industrial buildings, so the turnover analysis is performed

initially only for residential dwelling units and then the rates are applied to non-residential buildings. Although differences in turnover rates likely exist between building classifications, residential turnover rates were applied to other building classifications due to the dearth of data on commercial and industrial buildings. Differences are also likely to exist between types of residential buildings, but the resolution of data from the census is not high enough to ascertain the distinct patterns. I explore the uncertainty in and sensitivity of results to this assumption later.

A doubly-constrained growth factor model was used to converge on a matrix-based solution of estimates of building turnover (Table 1). This approach is traditionally used in trip generation modeling to estimate the number of trips between travel zones (Mathew and Krishna Rao 2006), but has been modified here to represent buildings entering or leaving a building stock. Each cell in the matrix represents the new additions or subtractions of dwelling units by vintage in a given year. The diagonal of the matrix is always positive and captures the construction of new dwelling units. The upper triangle of the matrix is always negative, because once a vintage is constructed, it can either maintain the stock or decline. Fundamentally, the model uses US Census estimates of housing growth and the current building stock (from the American Community Survey) to converge on a solution that describes the number of dwelling units from each vintage that exist in each time period.

Table 1: Residential Dwelling Unit Estimation Matrix

		Changes in Dwelling Units by Year							
		Pre-1900	1901-1910	1911-1920	..	y_d	..	2000-2007	**2008 Totals**
Initial Construction Year	Pre-1900	$\boldsymbol{C_{1900}}$	$-D_{1900,1910}$	$-D_{1900,1920}$	..	$-D_{1900,d}$	..	$-D_{1900,2008}$	R_{1900}
	1901-1910	0	$\boldsymbol{C_{1910}}$	$-D_{1910,1920}$	...	$-D_{1910,d}$	..	$-D_{1910,2008}$	R_{1910}
	1911-1920	0	0	$\boldsymbol{C_{1920}}$	..	$-D_{1920,d}$	..	$-D_{1920,2008}$	R_{1920}
	…	…	…	…	..	**...**	..	…	**…**
	b_v	0	0	0	..	$\boldsymbol{C_v}$	..	$-D_{v,2008}$	R_v
	…	…	…	…	..	…	..	…	**…**
	2000-2008	0	0	0	..	0	..	$\boldsymbol{C_{2008}}$	R_{2008}
Change in Units		ΔS_{1900}	$\Delta S_{1901-1910}$	$\Delta S_{1911-1921}$	..	ΔS_d	..	$\Delta S_{2001-2008}$	$\sum_v \boldsymbol{R_v} = \sum_d \boldsymbol{\Delta S_d}$

The variables in the matrix are defined as follows:

C_v: Number of dwelling units constructed of vintage *v*

$D_{v,d}$: Number of dwelling units constructed of vintage *v* demolished in decade *d*

ΔS_d: The change in the total dwelling units in the stock in decade *d*

R_v: Number of dwelling units of vintage decade *v* remaining in the 2008 stock

b_v: A given vintage

y_d: A decade of assessment

There are three conditions used to solve the matrix (Table 1).

1) Construction (C) is always positive, and demolition (D) is always negative. Each cell represents an addition or subtraction to the housing stock based on year and building vintage
2) The sum of each column in the matrix must equate to the change in the total number of units observed in the census each decade. More specifically, the total additions and subtractions to the stock in a given year must equal the expected net change in the stock:

$$\Delta S_d = C_d + \sum_v D_{v,d}$$

3) The sum across the columns must equal the disaggregated housing stock of 2009.

$$R_v = C_v + \sum_v D_{v,d}$$

This matrix is doubly constrained based on the decadal change in building stock (ΔS_d) from the U.S. Decadal Census and the 2008 building stock from the American Community Survey (R_v) (U.S. Census Bureau, 2008).

Construction of dwelling units, represented as C_d on the diagonal of the matrix, is obtained from the U.S. Decadal Census for all decades 1940 and later, and are modified based on a i) constraints from the total number of buildings surviving to 2008 and the reported change in stock for the decade and ii) capping the decadal stock turnover at 10%. When possible, the construction modifications were maintained within the official published standard error accompanying the census estimates. Holding construction constant during matrix iterations is necessary so that only negative (demolition) intermediate results are modified, thus avoiding sign changes that would violate Condition 1. U.S. Census estimation of dwelling units begins in 1940, so pre-1940 construction results are estimated by assuming an increasing net demolition rate over time to 1940 levels (i.e., incrementing the total percent of the building stock demolished each decade by 0.5% starting with 1900-1909 until 1940). This assumes that as the city aged it turned over buildings at a higher rate. For an in-depth discussion on construction estimates, see Appendix A.

Initial weights for demolition are projected using the vintage breakdowns available in the U.S. Census. With the initial weights occupying the demolition cells, the program is iterated by first taking the ratio of the expected row demolition sum ($R_v - C_v$) over the

matrix row sum ($\sum_v D_{v,d}$). This ratio is equivalent to the Furness balancing factor in trip generation. All demolition values in the row are then multiplied by this ratio. The same procedure is used for the columns with the expected and actual column sums ($\Delta S_d - C_d$ and $\sum_v D_{v,d}$, respectively). Iterations continue until the total error between expected and actual demolition sums is minimized.

Once the model converges to a solution with a small difference between expected and actual values (<5,000 dwelling units), the rates of dwelling unit turnover by vintage are then applied to commercial and industrial buildings, obtained from the assessor database. The assessor dataset likely misses illegal dwelling units by miscategorizing them as either non-residential or lower density. The number of previously demolished buildings of all classifications is calculated using the rates from the dwelling unit turnover model. For the turnover of all categories, the size of the building is assumed to be the average of that vintage and category which exist in 2008. This potentially favors certain types of buildings (perhaps larger, more spacious homes, for example).

Applying residential turnover rates to commercial and industrial buildings introduces uncertainty into the turnover model and a sensitivity analysis was performed to explore how significantly results are affected by this assumption. In the most aggressive scenario, where turnover rates are doubled, meaning that more commercial and industrial buildings were initially constructed, there is approximately a 5% increase in the initial floor area constructed across all decades. The assumption does not significantly impact the final results. For more detail on the commercial and industrial turnover rate sensitivity and uncertainty assessments, see Appendix A.

2.2.2 Prototypes

A prototyping approach was developed for quantifying embedded energy use and GHG emissions by subdividing the urban building stock by use (residential, commercial, and industrial) categories and by construction time period. Fourteen base prototypes were created (4 residential, 8 commercial, 2 industrial) and then differentiated temporally based on three major eras of construction (for a total of 42 prototypes). Prototyping is a common approach in electricity consumption analysis (Howard et al. 2012; Huang et al. 1991; Hashem Akbari et al. 1993; Heiple and Sailor 2008) but has not been applied to quantifying regional infrastructure impacts. Prototypes were developed based on the count and total area of unique use and building codes in the 2008 Los Angeles Assessor database (Los Angeles County Assessor Office 2009). Single family homes comprise the majority of buildings in Los Angeles, both by count (~1.9 million homes or 64% of buildings) and by area (~244 million m^2 or 41% of total floor area). Single family homes were therefore subdivided into three sub-categories based on the era of construction, each with unique material inventories to capture changes in material choice over time. Commercial and industrial buildings are more heterogeneous in both material choice and size compared to residential buildings due to the diverse functions of commercial buildings, and consequently they are segmented into eight commercial and two industrial prototype categories. The prototypes and their composition in Los Angeles are shown in Table 2.

Table 2: Prototype Categories

Code	*Type*	*Square Footage*	*Percentage (SqFt)*	*Count*	*Percentage (Count)*
R1.2	Single Family 1950-1990	1,482,104,812	23%	960,722	32%
R3	Small Multifamily	977,802,420	15%	450,482	15%
I1	Light Industrial	786,012,611	12%	53,426	2%
R1.1	Single Family Pre-1950	763,194,906	12%	831,749	28%
R2	Large Multifamily	549,079,743	9%	115,278	4%
R1.3	Single Family Post-1990	354,970,687	6%	131,784	4%
C3	Neighborhood Store	352,581,397	6%	92,099	3%
R4	Condominium	351,492,166	6%	311,450	11%
C5	High-Rise Office	321,433,022	5%	20,109	1%
I2	Heavy Industrial	119,060,476	2%	4,311	0%
C2	Department Store	111,741,194	2%	3,387	0%
C1	Hotel	66,177,802	1%	3,606	0%
C7	Church	49,947,604	1%	9,179	0%
C8	School	38,017,226	1%	4,603	0%
C6	Hospital	35,144,993	1%	1,162	0%
C4	Low-Rise Office	32,845,029	1%	6,317	0%

2.2.2.1 Building Materials

Residential building material inventories are based on building-era information from the assessor's office. For residential buildings, the state of California publishes a handbook used by assessors' offices throughout the state to assess home values. This provides standardized classification information and sample material inventories (California State Board of Equalization 2010; Los Angeles County Assessor Office 2009). The assessor

database "Quality Class Code" is used in combination with the CSBE (2010) sample material inventories for three time periods of construction: pre-1950, 1950-1990, and post-1990. These three categories were chosen as the main time periods of assessment because of this additional detail in CSBE (2010). Quantities of materials were selected based on the average size for each building observed in the assessor database. The commercial and industrial prototype material inventories were estimated from RSMeans (2009). This is not a location-specific source like that for residential buildings, but it is the best-available approach since CSBE (2010) does not provide material classification guidelines for commercial and industrial structures. In California, design of buildings for seismic activities increases the amount of structural materials such as steel and concrete. To accommodate this, all structural material quantities were scaled by a factor of 1.2 for all buildings post-1970 in accordance with structural design standards (American Society of Civil Engineers 2013). Since most construction is pre-1970, this has a less than 5% impact on the total material quantities across the county.

2.2.2.2 Embedded Impacts

Embedded energy use and GHG emissions for each of the sixteen categories were estimated based on three time categories for each construction vintage. Current building construction materials and practices are first estimated and then adjustments are made for 1950-1990 buildings and pre-1950 buildings based on temporal efficiency improvements in the manufacture of construction materials. Material takeoffs for each prototype are provided in Appendix A. Embedded energy use and GHG emissions were modeled with the Athena Building Impact Estimator using radiative forcing factors of 25 for CH_4 and 298 for N_2O based on 100 year radiative forcing (Athena Sustainable Materials Institute 2012;

Intergovernmental Panel on Climate Change 2001). Results associated with the manufacturing and construction phases were included while maintenance and end-of-life are considered to be beyond the scope of this study.

2.2.2.3 Time Modification of Environmental Impacts

Major construction material industries have experienced improvements in production efficiencies that are incorporated into the temporal prototyping modeling. These efficiencies have presumably led to decreases in energy use and environmental impacts over time. For example, between 1958 and 1994, efficiencies in the steel industry resulted in a reduction in GHG emissions of 38% per unit mass produced (Worrell, Price, and Martin 2001). Similarly, the energy use associated with producing cement, a major component of concrete, dropped 30% between 1970 and 1997 (Martin, Worrell, and Price 1999). Athena models emissions associated with *current* manufacturing and construction processes, and does not account for the potentially greater emissions during the construction of a building in the past. To adjust for the higher emissions during earlier years of production, adjustment factors for steel, concrete and aluminum were compiled for the two earlier time periods (pre-1950 and 1950-1990). These three materials were selected due to their high contributions to the embedded emissions profile as well as the available literature on improvements in these industries (Worrell, Price, and Martin 2001; Martin, Worrell, and Price 1999; U.S. Department of Energy 2007b). Wood was excluded from the learning-curve assessment because of scarce literature on efficiency improvements and the relative maturity of the lumber industry. Energy efficiency penalties of 61%, 29%, and 152%, derived from the literature, were applied to pre-1950 buildings for steel, concrete, and aluminum respectively. The GHG penalties for this time period and these materials were 56%, 40% and 152%,

respectively. For buildings constructed between 1950 and 1990, energy penalties of 39%, 14% and 117% for steel, concrete, and aluminum were applied. For GHG emissions, these penalties were 25%, 20%, and 17%, respectively. These penalties were applied in proportion to the energy use or GHG emissions attributed to the production of each material in the prototypes. Changes in transportation, fuel mixes, or other supply chain factors are not included. This approach is likely conservative (underestimating historic emissions) by not accounting for changes in minor materials production or generally improving vehicle fuel economy (U.S. Environmental Protection Agency 2012).

2.2.3 From Building Prototypes to City-scale

The 42 prototype LCAs were normalized per unit area and multiplied by the area of each building in the Assessor database (Los Angeles County Assessor Office 2009). This provides embedded steel, wood, concrete, energy use, and GHG emissions profiles for each of the approximately 2.3 million buildings in Los Angeles. Embedded emissions are also quantified for previously demolished buildings based on the estimates of the turnover model. These turnover emissions are not spatially resolute, but provide a framework by which emissions change over time.

2.3 Results

2.3.1 A Changing Building Infrastructure

There is a similar and approximate linear decline for each building vintage, but over the past 20-30 years there has been a slowing of this trend, likely in response to land-use regulation and increasingly limited land (Figure 1). With the exception of the most recent 30 years, vintages are removed or replaced at approximately 8% per decade. The most recent 30 years have declined at approximately 2% per decade. The turnover rate of each vintage is

dependent upon the city-wide demolition rate that includes all vintages in a given decade (Figure 1). The city-wide demolition rate has been decreasing over the past 30 years, causing the slowing demolition rates from 1980 to onwards. These slowing turnover rates accompany a massive housing crisis, multiple policies limiting more intense land development, and a shortage of available land for spatial expansion (Whittemore 2012b; University of Southern California, Southern California Studies Center, and Brookings Center on Urban and Metropolitan Policy 2001a).

Once buildings are constructed, they become quasi-permanent infrastructure with 50% of buildings residing for 60 years or more. Prior to 1980, Los Angeles had experienced growth predicated on an abundance of undeveloped land and population-supporting resources, such as water and sewage capacity (University of Southern California, Southern California Studies Center, and Brookings Center on Urban and Metropolitan Policy 2001a). Had this trend continued, the median age of most vintages would be approximately 60 years, with almost all of the vintage disappearing in 120 years. This means that under unlimited growth and the accompanying higher turnover rates, portions of building vintages and their embedded impacts will persist for over a century. Under situations of growth limitation, as Los Angeles is currently experiencing (University of Southern California, Southern California Studies Center, and Brookings Center on Urban and Metropolitan Policy 2001a), turnover rates slow significantly, and buildings can remain even longer. These findings underscore the importance of designing buildings and urban form for long-term use as the stock will continue to be used for multiple generations under changing political, economic, and cultural conditions.

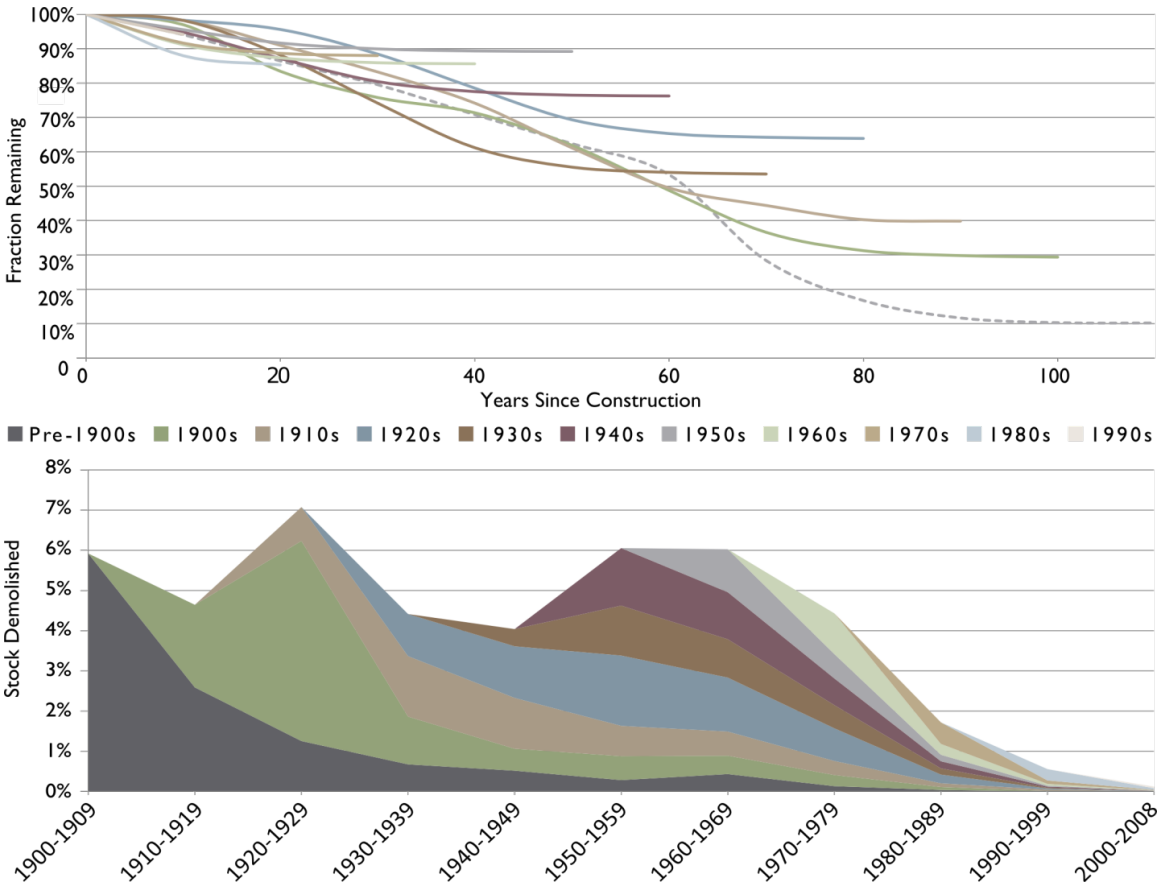


Figure 1: Building Turnover Rates The fraction of buildings remaining since initial construction (top), by vintage and the total stock demolished with percent contribution by vintage (bottom). Under unconstrained growth (until ~1970), demolition follows a generally linear trend which was ultimately disrupted by major restrictions on high-density and commercial development in the 1980s. This pattern is seen in both the turnover trends and the percent of stock demolished. Pre-1900s are represented as a dashed line as this category includes approximately 10 decades of buildings.

Barring substantial changes to land-use policy in Los Angeles, the existing housing stock will likely be fixed for a considerable part of the 21st century, and the challenge will be providing for a growing population with aging building structures. In the Los Angeles metropolitan area, nearly two-thirds of the land is owned by the federal government, and the majority of land available for development is in the high desert which has a harsh climate, fragile ecosystems, and is remote from the existing urban core. Removing areas with the most fragile ecosystems, approximately 5% (165,609 acres) are available for development

(Landis 2000). Land unavailability in combination with increasing land values has resulted in the majority of post-1980 population growth occurring within the existing urban core, but at a much slower construction rate than previously observed (University of Southern California, Southern California Studies Center, and Brookings Center on Urban and Metropolitan Policy 2001a). Between 1990 and 2010, one dwelling unit was added for every 3.4 new residents, whereas between 1950 and 1960 one dwelling unit was added for every 2.7 new residents (U.S. Census Bureau, 1950, 1960). Turnover of old buildings is also slow with less than 2% of the stock being demolished between 2000-2008 compared to 8% during the 1960s and 1970s. Dwelling units have become increasingly crowded with more people per unit and less space per person (Figure 2). Unless new areas are opened for development, existing structures will likely need to be modified, as many have already been illegally (Chavez and Quinn 1987),to accommodate the increasing population.

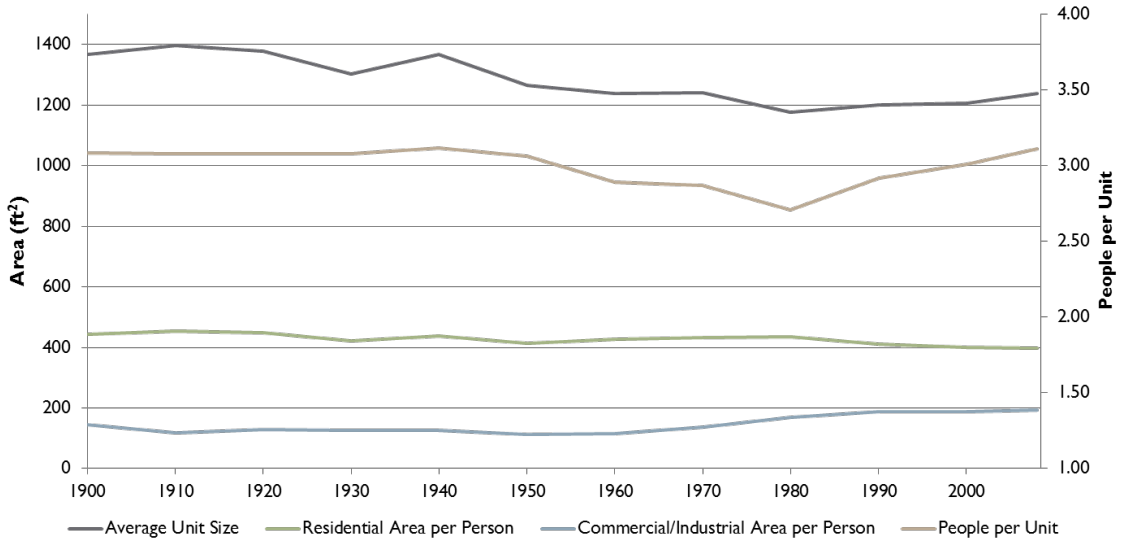


Figure 2: Use of the Building Stock 1900-2008. The figure shows the change in building floor area per resident of Los Angeles, subdivided by residential and commercial/industrial building uses. Both indicators have grown since 1900 with commercial/industrial having a rapid increase, doubling within the last 50 years, but both indicators now seem to be trending towards less space per person. Some of the dynamics of this change are explained by the average size of buildings and the changes in use. Although dwelling units, on average

are getting larger (new construction in 2008 is double the size of 1940 construction), there are now more people per dwelling unit than was observed 40 years ago.

2.3.2 Stock Growth and Patterns of Use

In the past, Los Angeles has accommodated additional population growth by sprawling outwards to provide large areas of land for new inhabitants, but this spatial growth is now being halted (Figure 3). Physically, there are few available undeveloped areas in Los Angeles or the surrounding four counties (Orange, Ventura, San Bernardino, and Riverside) due to the natural barriers of the mountains and the ocean, and the available land that does exist is either in the harsh and remote high desert or are governmentally protected areas (University of Southern California, Southern California Studies Center, and Brookings Center on Urban and Metropolitan Policy 2001a). Interdependent infrastructure, in particular roadway supply, is also constrained, with 94% of peak vehicle travel and 62% of roadway lane-kilometers experiencing congestion (Texas Transportation Institute 2011). Los Angeles also faces the constraints of dwindling water supplies and deteriorating infrastructure (American Society of Civil Engineers 2012). A video has been developed showing the historic spatial growth of the Los Angeles building infrastructure which can be found at: www.urbantransitions.org/losangelesgrowth.

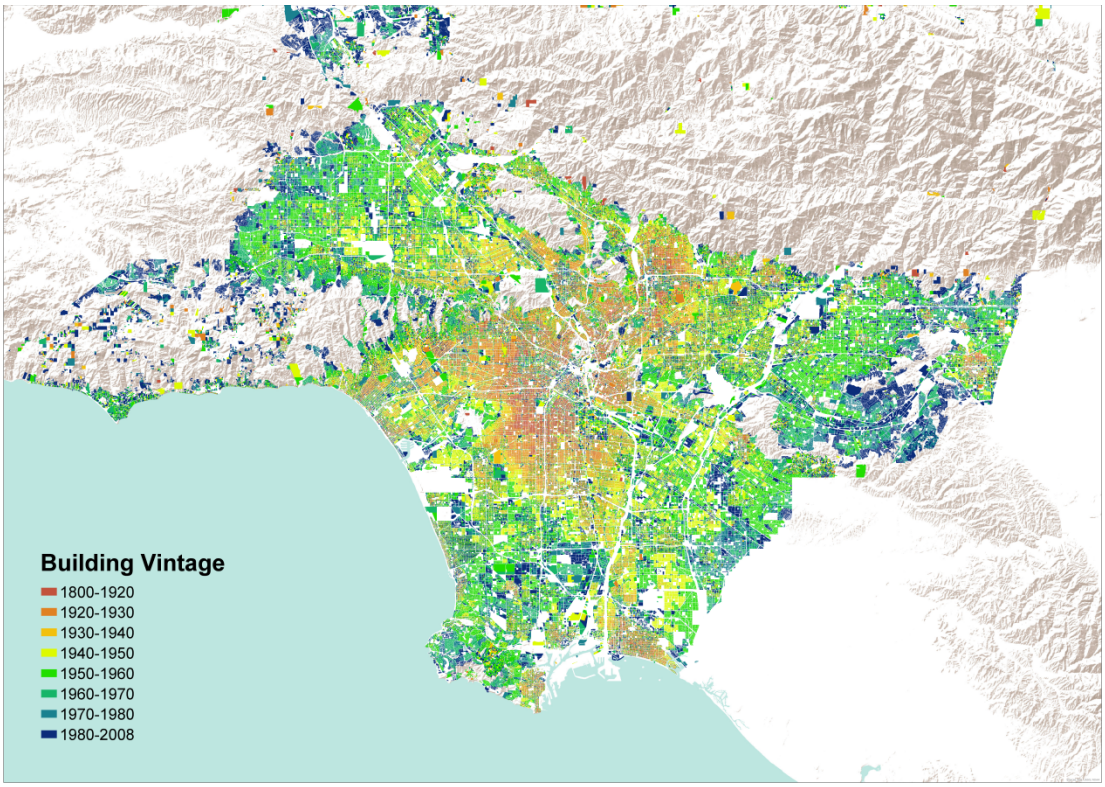


Figure 3: Historic Growth Development of Los Angeles County. The majority of growth occurring in the middle of the twentieth century is visualized (orange, yellow, and green) and growth has largely emanated from the historical downtown area.

Population change alone is not an accurate predictor of building growth, as regulation, zoning, and resource availability directly impact construction and demolition rates. All four phases of growth as described by Whittemore (2012) are visible in construction patterns as are major historic events (Figure 4). Early growth starts around 1905, but slows with the beginning of World War I in 1914 and drops more dramatically upon U.S. entry to the war in 1917. Upon the advent of Los Angeles zoning in 1921, large increases in residential construction occurred (particularly multi-family dwelling units) which follows the expected trend of "over-zoning", or increasing the dwelling density beyond the social interest, during this period (Whittemore 2012b). A dip in construction occurs upon the stock market crash in 1929 and the following Great Depression, but single family home construction increases after the passing of FHA incentives in 1934. World War II in 1941

noticeably decreases all building construction although population during this period continues to increase causing the expected wartime housing shortage. After the war, single family homes were constructed on a massive scale, but by the early 1960s single family construction subsided and multi-family construction began to increase. During the 1970s, population increased more rapidly than new dwelling unit construction causing the cost of housing to increase and creating a shortage. This trend continues until the late 1980s when Los Angeles was forced by the California state courts to comply with their general plan, forcing massive downzoning, and moving lots to lower density. This froze multifamily construction in many municipalities throughout the county although over time small steps have been taken, such as creative side-stepping of 1986's Proposition U which limits commercial density, to open more areas to multifamily structure development (Whittemore 2012a).

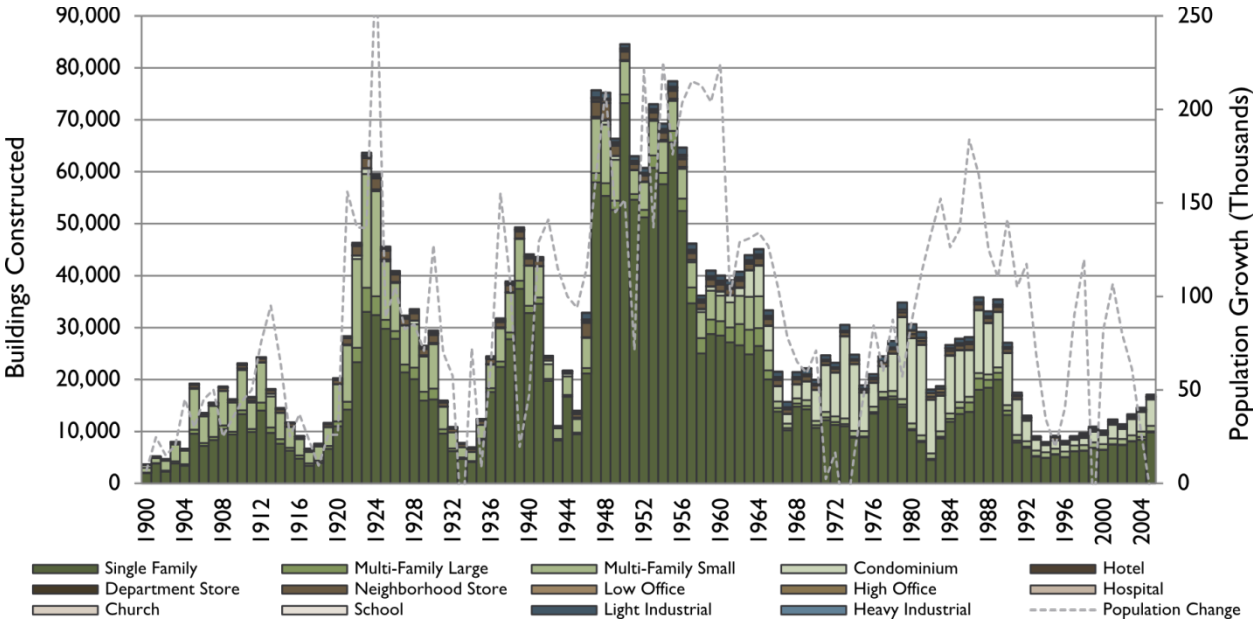


Figure 4: Building Construction Trends and Population Changes. Growth in Los Angeles has not been evenly distributed, temporally or spatially. Changes in new building construction show some parallels with population growth, but they are not perfectly correlated which means other factors such as older building turnover or changes in urban inhabitant preferences contribute to new building growth. The chart shows new building

construction across all zoning types as extrapolation from new dwelling unit construction rate estimation in the U.S. Decennial Census. The figures is for the 2008 building stock (Los Angeles County Assessor Office 2009).

2.4 Embedded Materials and Impacts

Embedded materials and environmental impacts from buildings are not uniformly distributed across Los Angeles, and there are clear relationships between the building purpose, materials, and subsequent environmental impacts. Construction of residential, commercial, and industrial buildings utilizes distinct material profiles which create geospatial patterns in material embedding that are linked to zoning. Core materials (concrete, steel, and wood), energy use, and GHG emissions are aggregated by census block, shown in Figure 5. For concrete and steel, the most intensive 20% of the census block groups contain over 50% of the total steel and concrete. Wood is more evenly distributed across the urban area with the most intensive 20% contributing just over 30% of the total embedded wood. Larger quantities of concrete and steel are used in the construction of commercial and industrial buildings, and also in multi-story residential units. Under the original urban planning zoning philosophy employed in Los Angeles (and also throughout the US) during the 1920s, commercial buildings were to be clustered at intersections, multi-family buildings placed along arterial roadways, industrial buildings segregated away from residences, and low-density single family homes dispersed on smaller local roads (Whittemore 2012b). As such, concrete and steel tend to be concentrated in the Wilshire to Downtown to East Los Angeles corridors, the oldest and often most mixed-use areas of the city. Zoning practices have changed throughout Los Angeles history resulting in a segregation of building uses. The more even dispersion of embedded wood throughout the city reflects the dominating share of single family homes amongst all buildings. Furthermore, single family zoning in Los Angeles has often been accompanied by a minimum lot size, leading to the low-density even

dispersion of wood witnessed throughout areas zoned single family residential. These differences in intensity are indicative of the variations in material choice between building types (residential, commercial, industrial) as well as historic zoning practices that have affected building density.

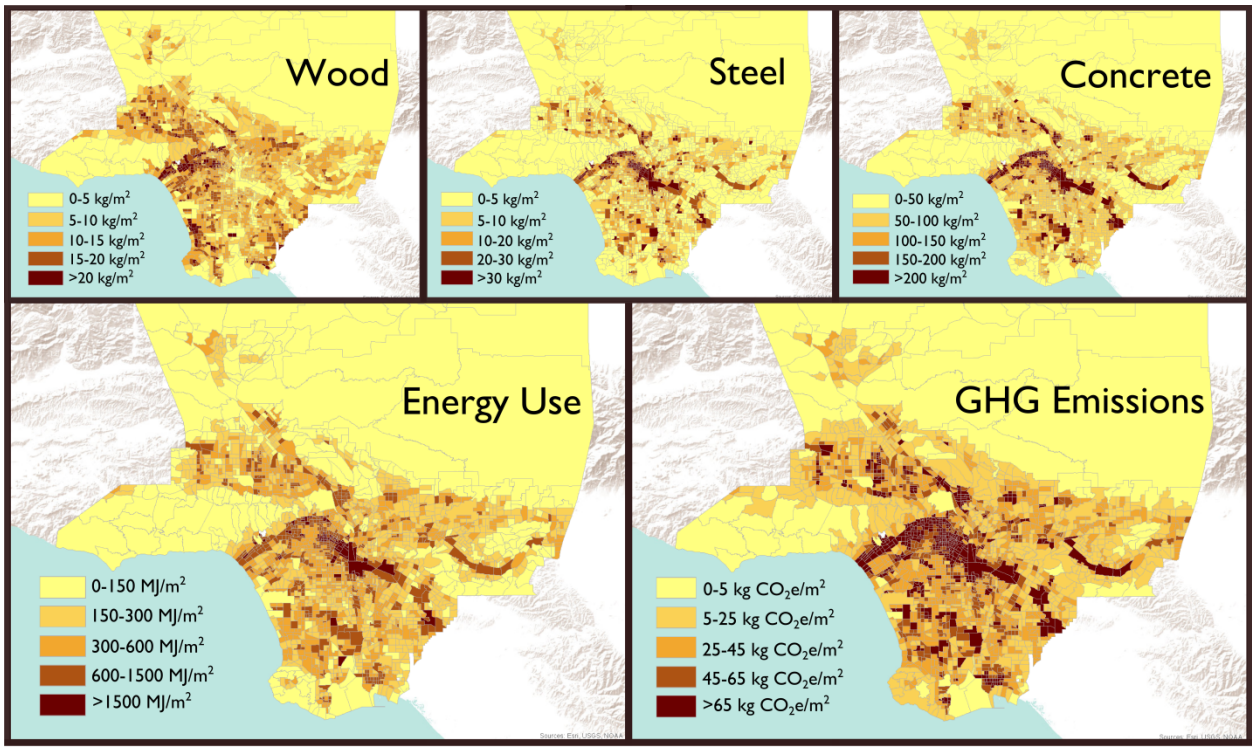


Figure 5: Embedded Materials and Environmental Impacts. The location of building materials is dependent upon building density and building types in an area. The darker the color, the more materials and impacts are embedded per land area. The locations of material embedding correspond to the areas of highest energy and CO_{2eq} investment in the infrastructure.

2.4.1 Embedded Environmental Impacts

Incremental decisions over the history of Los Angeles have led to the current mixture of buildings and the associated embedded materials, energy use, and GHG emissions intensities of the contemporary building stock. Pre-1970s buildings comprise over 64% of the housing stock, and contribute over 56% of embedded GHG emissions (Figure 6). Newer building vintages have an overall lower embedded impact per building area than

older due to efficiency improvements in material manufacturing. Post-1990s commercial buildings have approximately 30% less embedded GHG emissions per unit area than buildings built before 1950 The relatively lower contribution of older vintages to the total embedded GHG emissions is due to the differences in the building types (commercial, residential, and industrial) initially constructed. Commercial and industrial buildings tend to be newer than residential buildings and also more intense locations of embedded GHG emissions. In the uncertainty assessment of commercial and industrial turnover rates, the most aggressive scenario increased the GHG emissions from initial building construction by 8.5%. The full results of this assessment are in Appendix A.

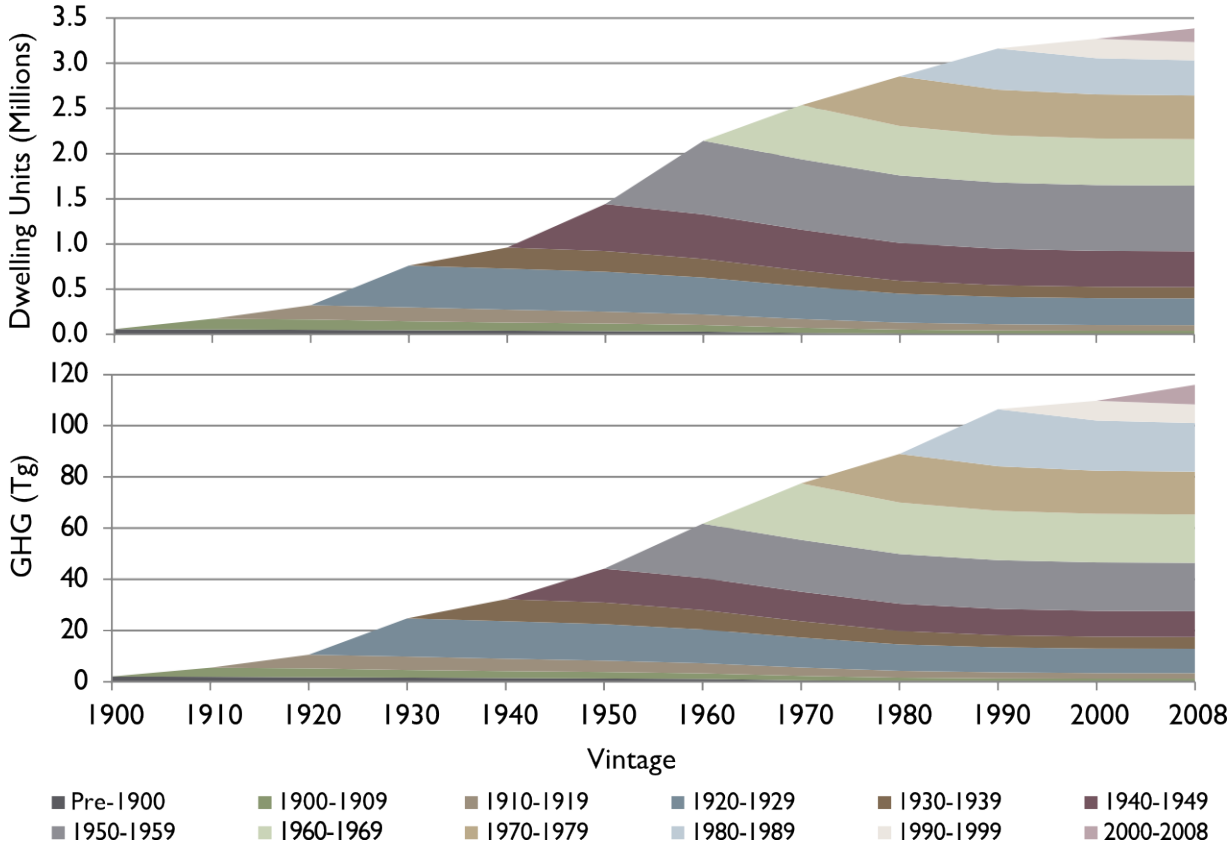


Figure 6: Cumulative Embedded GHG of Los Angeles 1900-present. The contributions of each building vintage to the total building stock are shown by decade by decade. More modern building vintages have a higher initial embedded footprint, and

contribute disproportionately more to the present day stock. This is a function of the increasing size of new construction, especially for commercial and industrial buildings. For both the dwelling unit count and GHG emissions embedded footprint, the cumulative charts indicate that building construction is "peaking", and is unlikely to continue at previously observed rates.

2.5 Discussion and Conclusions

The results of the turnover model indicate that the building stock of Los Angeles has largely become "locked-in", as shown in Figure 1, meaning that periods of extensive building construction are unlikely, and the benefits of upgrading the infrastructure to meet energy and environmental goals may be limited. This lock-in phenomenon has been recognized in other infrastructure systems, most notably transportation (Cantarelli et al. 2010; Coleman 2010), and some of this discourse has included land-use (Barter 2004). Lock-in implies that the infrastructure is path-dependent: certain potential futures have been excluded based on past decisions. Large-scale turnover of the building stock is possible, but is likely prohibitive because of the massive monetary and resource investments that are necessary to make transitions occur. Furthermore, the building stock is highly interdependent on many other supporting infrastructure systems such as electricity, gas, sewer, water, emergency response, transportation, and communications, all of which would need substantial modifications if large sections of building stock were changed. As such, Los Angeles should plan for the long-term upkeep of structures that were deployed largely between 1940 and 1970 and energy efficiency improvements that preferentially target portions of the building stock based on long expected lifetimes.

Supply chains necessary to support the construction and use of urban infrastructure can be far-reaching, often spanning continents, and consequently the environmental impacts of Los Angeles building construction may occur in political jurisdictions remote from the metro area. Tracing the exact locations of emissions is difficult given that data on material

supply chains are not readily geospatially specified (Reap et al. 2008). This might be particularly relevant in historic supply chain analysis where the data may no longer exist. The quantification of energy consumption and GHG emissions, which are considered global, and other emissions not addressed here could have consequences on human and environmental health beyond Los Angeles' border. These location-specific impacts further complicate environmental decision making since those impacted by an emission (for example: human respiratory impacts from particulate emissions during material processing) might be remote from the decision-maker, thus externalizing the cost from the triggering region.

The retrofitting of buildings has been excluded from this study due to both a lack of data on renovation activities as well as their uncertain impact on the embedded emissions profile of the building stock. When a building is renovated, some materials are removed from the building and others are added, potentially improving the energy efficiency of the structure. While this increases the life cycle emissions of the individual building, it does not necessarily increase the embedded emissions profile of the urban building stock. The embedded energy and GHG emissions of the new materials incorporated into a building could be higher, lower, or on par with the embedded emissions of the removed materials. This issue is further complicated by the efficiency improvements over time in producing materials (i.e. 1950s steel has more embedded energy than 1990s steel). It is unclear if building retrofitting significantly contributes to the total embedded emissions profile of the building stock.

The energy use and GHG emissions investment in the building stock of Los Angeles is significant compared to annual emissions from the city, but relatively small compared to the use over the lifetime of the building. In a 2010 Regional GHG Inventory, Los Angeles was reported to emit ~99 Tg per year from activities within the county (electricity

consumption, industrial activity, transportation, agriculture, etc.)(ICF International 2013). These emissions are only those that occur within the geopolitical boundary and would be even larger if supply chain activities from remote regions (i.e. manufacture of consumer goods for Los Angeles consumption in a foreign country) were included in the inventory. This helps to contextualize the large quantity of GHG embedded in the 2008 standing building stock (~120 Tg) which is the same order of magnitude as a full year of present-day GHG emissions. While the embedded emissions have accumulated over a century (Figure 6), the contribution of these emissions is not negligible in the building life-cycle (Masanet, Stadel, and Gursel 2012) and is typically allocated to the activities of other sectors, and not assessed concurrently in energy and environmental goals. Comparing embedded energy to typical household energy use reveals the significance to which resources are invested for infrastructure services. Using the reported energy costs from Los Angeles homes in the American Housing Survey and the average residential electricity prices (~$0.18/kWh) in 2011, average embedded energy use for a dwelling unit (~252 GJ) is equivalent to approximately 3.8 years of energy consumption (electricity and natural gas) during the use phase. Assuming a building remains in the stock 60 or more years as suggested by the turnover model, the embedded energy use could be less than 5% of the energy consumed over the life of a building. This is within the range identified in the literature synthesis by Sartori and Hestnes (2007). The low fraction of life-cycle energy use could mean that there are opportunities for lowering use phase energy by making more upfront investments (e.g., insulation, material use with improved thermal properties, efficient lighting) during construction. Additional material investments during the retrofitting of buildings could also yield some of these lifetime savings.

Los Angeles has reached a critical juncture of building use and as policymakers develop strategies to meet greenhouse gas reduction and environmental goals, new insights into urbanization processes will be critical. The building stock of the region is locked-in, leaving little room for new inhabitants unless densification of housing occurs. The challenge now is how Los Angeles should try to adapt its rapidly aging, immotile building infrastructure to provide a high quality of life for all current and future inhabitants.

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2.7 References

Akbari, Hashem, J Eto, S Konopacki, Asim Afzal, K Heinemeier, and Leo Rainer. 1993. "Integrated Estimation of Commercial Sector End-Use Load Shapes and Energy Use Intensities in the PG&E Service Area, LBL-34263."

American Society of Civil Engineers. 2012. "Report Card for Los Angeles County Infrastructure." http://www.ascemlab.org/pdf/2012-ASCE-Report Card-Revised-10-2-2012-REVISED_FINAL_FOR THE WEBSITE.pdf.

———. 2013. *Minimum Design Loads for Buildings and Other Structures.*

Athena Sustainable Materials Institute. 2012. "Athena Impact Estimator for Buildings, Version 4.1.1412."

Barter, Paul. 2004. "Transport, Urban Structure and 'Lock-in' in the Kuala Lumpur Metropolitan Area." *International Development Planning Review* 26 (1): 1–24. doi:10.3828/idpr.26.1.1.

California State Board of Equalization. 2010. "Assessors' Handbook, Section 531: Residential Building Costs."

Cantarelli, Chantal C, Bent Flyvbjerg, Bert van Wee, and Eric J E Molin. 2010. "Lock-in and Its Influence on the Project Performance of Large-Scale Transportation Infrastructure Projects: Investigating the Way in Which Lock-in Can Emerge and Affect Cost Overruns." *Environment and Planning B: Planning and Design* 37 (5): 792–807. doi:10.1068/b36017.

Chester, Mikhail V, and Arpad Horvath. 2009. "Environmental Assessment of Passenger Transportation Should Include Infrastructure and Supply Chains." *Environmental Research Letters* 4 (2): 024008. doi:10.1088/1748-9326/4/2/024008.

Chester, Mikhail V., Matthew J. Nahlik, Andrew M. Fraser, Mindy a. Kimball, and Venu M. Garikapati. 2013. "Integrating Life-Cycle Environmental and Economic Assessment with Transportation and Land Use Planning." *Environmental Science and Technology* 47 (21): 12020–28. doi:10.1021/es402985g.

City of Los Angeles. 2007. *Sustainability Practices in the City of Los Angeles.* . http://ens.lacity.org/mayor/villaraigosa/mayorvillaraigosa331283124_0718 2007.pdf. .

Coleman, Andrew. 2010. "Transport Infrastructure, Lock-Out and Urban Form: Highway Development in Auckland and the United States." *Policy Quarterly* 6 (4): 23–27.

Department of Finance. 2013. "New Population Projections: California To Surpass 50

Million in 2049," 2.

Federal Highway Administration. 2014. "Historic Statistics Series." https://www.fhwa.dot.gov/policy/ohpi/hss/hsspubsarc.cfm. .

Frijia, Stephane, Subhrajit Guhathakurta, and Eric Williams. 2012. "Functional Unit, Technological Dynamics, and Scaling Properties for the Life Cycle Energy of Residences." *Environmental Science & Technology* 46 (3): 1782–88. doi:10.1021/es202202q.

Garreau, J. 1991. *Edge City: Life on the New Frontier*. New York: Doubleday.

Guggemos, Angela Acree, and Arpad Horvath. 2005. "Comparison of Environmental Effects of Steel- and Concrete-Framed Buildings." *Journal of Infrastructure Systems* 11 (2): 93–101. doi:10.1061/(ASCE)1076-0342(2005)11:2(93).

Gustavsson, Leif, Anna Joelsson, and Roger Sathre. 2010. "Life Cycle Primary Energy Use and Carbon Emission of an Eight-Storey Wood-Framed Apartment Building." *Energy and Buildings* 42 (2): 230–42. doi:10.1016/j.enbuild.2009.08.018.

Heiple, Shem, and David J Sailor. 2008. "Using Building Energy Simulation and Geospatial Modeling Techniques to Determine High Resolution Building Sector Energy Consumption Profiles." *Energy and Buildings* 40 (8): 1426–36. doi:10.1016/j.enbuild.2008.01.005.

Howard, B, L Parshall, J Thompson, S Hammer, J Dickinson, and V Modi. 2012. "Spatial Distribution of Urban Building Energy Consumption by End Use." *Energy & Buildings* 45. Elsevier B.V.: 141–51. doi:10.1016/j.enbuild.2011.10.061.

Huang, Joe, Hashem Akbari, Leo Rainer, and Ron Ritschard. 1991. "481 Prototypical Commerical Buildings for 20 Urban Market Areas, LBL-29798." Berkeley, CA.

Intergovernmental Panel on Climate Change. 2001. *Climate Change 2001: The Scientific Basis*. New York: Cambridge University Press.

Kimball, M., Mikhail V. Chester, C. Gino, and J. Reyna. 2013. "Assessing the Potential for Reducing Life-Cycle Environmental Impacts through Transit-Oriented Development Infill along Existing Light Rail in Phoenix." *Journal of Planning Education and Research* 33 (4): 395–410. doi:10.1177/0739456X13507485.

Landis, JD. 2000. "Raising the Roof: California Housing Development Projections and Constraints, 1997-2020." *City*. Sacramento, CA. http://escholarship.org/uc/item/1391n947.pdf.

Lippke, Bruce By Bruce, Jim Wilson, John Perez-garcia, Jim Bowyer, and Jamie Meil. 2004. "CORRIM : Life-Cycle Environmental Performance of Renewable Building Materials." *Forest Products Journal* 54 (6): 8–19.

Los Angeles County Assessor Office. 2009. "Los Angeles County Database."

Martin, N., Ernst Worrell, and Lynn Price. 1999. "Energy Efficiency and Carbon Dioxide Emisions: Reduction Opportunities in the U.S. Cement Industry, LBNL-44182."

Masanet, Eric, Alexander Stadel, and Petek Gursel. 2012. "Life-Cycle Evaluation of Concrete Building Construction as a Strategy for Sustainable Cities, SN3119." Skokie, Illinois.

Mohareb, Eugene, and Christopher Kennedy. 2012. "Gross Direct and Embodied Carbon Sinks for Urban Inventories." *Journal of Industrial Ecology* 16 (3): 302–16. doi:10.1111/j.1530-9290.2011.00445.x.

Norman, Jonathan, Heather L. MacLean, and Christopher A Kennedy. 2006. "Comparing High and Low Residential Density: Life-Cycle Analysis of Energy Use and Greenhouse Gas Emissions." *Journal of Urban Planning and Development* 132 (1): 10–21. doi:10.1061/(ASCE)0733-9488(2006)132:1(10).

Ochoa Franco, Luis A. 2004. "Life Cycle Assessment of Residential Buildings." Carnegie Mellon University.

Ochsendorf, John, Leslie Keith Norford, Dorothy Brown, Hannah Durschlag, Sophia Lisbeth Hsu, Andrea Love, Nicholas Santero, Omar Swei, Amanda Webb, and Margaret Wildnauer. 2011. "Methods, Impacts, and Opportunities in the Concrete Building Life Cycle." *Research Report R11-01, Concrete and Sustainability Hub, Department of Civil and Environmental Engineering, Massachusetts Institute of Technology*, Research Report, , no. August. Concrete Sustainability Hub, Department of Civil and Environmental Engineering, Massachusetts Institute of Technology: 119. http://www.greenconcrete.info/downloads/MITBuildingsLCAreport.pdf.

Petersen, Ann Kristin, and Birger Solberg. 2005. "Environmental and Economic Impacts of Substitution between Wood Products and Alternative Materials: A Review of Micro-Level Analyses from Norway and Sweden." *Forest Policy and Economics* 7 (3): 249–59. doi:10.1016/S1389-9341(03)00063-7.

Power, Anne. 2008. "Does Demolition or Refurbishment of Old and Inefficient Homes Help to Increase Our Environmental, Social and Economic Viability?" *Energy Policy* 36 (12): 4487–4501. doi:10.1016/j.enpol.2008.09.022.

Reap, John, Felipe Roman, Scott Duncan, and Bert Bras. 2008. "A Survey of Unresolved Problems in Life Cycle Assessment." *The International Journal of Life Cycle Assessment* 13 (5): 374–88. doi:10.1007/s11367-008-0009-9.

RSMeans. 2009. *2008 Square Foot Costs: Residential, Commercial, Industrial, Institutional.* 15th ed. Kingston, MA: RSMeans Company.

Salazar, James, and Jamie Meil. 2009. "Prospects for Carbon-Neutral Housing: The Influence of Greater Wood Use on the Carbon Footprint of a Single-Family

Residence." *Journal of Cleaner Production* 17 (17): 1563–71. doi:10.1016/j.jclepro.2009.06.006.

Sartori, I., and A.G. Hestnes. 2007. "Energy Use in the Life Cycle of Conventional and Low-Energy Buildings: A Review Article." *Energy and Buildings* 39 (3): 249–57. doi:10.1016/j.enbuild.2006.07.001.

Snow, Lester A. 2008. "Managing An Uncertain Future: Climate Change Adaptation Strategies for California's Water." *State of California Department of Water Resources*.

Sorensen, Paul. 2009. "Moving Los Angeles." *Access* 35: 16–24.

State of California. 2003. *Assembly Bill 1866*. http://www.leginfo.ca.gov/pub/05-06/bill/asm/ab_0001-0050/ab_32_bill_20060927_chaptered.pdf.

———. 2008. *Sustainable Communities and Climate Protection Act*. California State Senate. http://www.leginfo.ca.gov/pub/07-08/bill/sen/sb_0351-0400/sb_375_bill_20080930_chaptered.pdf.

Tanikawa, Hiroki, and Seiji Hashimoto. 2009. "Urban Stock over Time: Spatial Material Stock Analysis Using 4d-GIS." *Building Research & Information* 37 (5-6): 483–502. doi:10.1080/09613210903169394.

Texas Transportation Institute. 2011. "Urban Area Summary: Los Angeles." http://d2dtl5nnlpfr0r.cloudfront.net/tti.tamu.edu/documents/ums/congestion-data/losan.pdf.

U.S. Census Bureau. n.d. "Social Explorer Tables." www.socialexplorer.com.

U.S. Department of Energy. 2007. "U . S . Energy Requirements for Aluminum Production," 150. http://www1.eere.energy.gov/industry/aluminum/pdfs/al_theoretical.pdf.

U.S. Environmental Protection Agency. 2012. "Light-Duty Automotive Technology, Carbon

Dioxide Emissions, and Fuel Economy Trends: 1975 Through 2011."

University of Southern California, Southern California Studies Center, and Brookings Center on Urban and Metropolitan Policy. 2001. "Sprawl Hits the Wall, Confronting the Realitities of Metropolitan Los Angeles." In *The Atlas of Southern California*, 1–57. http://scholar.google.com/scholar?hl=en&btnG=Search&q=intitle:Sprawl+hits+the+wall,+confronting+the+realitities+of+metropolitan+Los+Angeles#0.

Upton, Brad, Reid Miner, Mike Spinney, and Linda S. Heath. 2008. "The Greenhouse Gas and Energy Impacts of Using Wood instead of Alternatives in Residential Construction in the United States." *Biomass and Bioenergy* 32 (1): 1–10. doi:10.1016/j.biombioe.2007.07.001.

Whittemore, Andrew H. 2012a. "Requiem for a Growth Machine: Homeowner Preeminence in 1980s Los Angeles." *Journal of Planning History* 11 (2): 124–40. doi:10.1177/1538513211417344.

———. 2012b. "Zoning Los Angeles: A Brief History of Four Regimes." *Planning Perspectives* 27 (3): 393–415. doi:10.1080/02665433.2012.681140.

Worrell, Ernst, Lynn Price, and Nathan Martin. 2001. "Energy Efficiency and Carbon Dioxide Emissions Reduction Opportunities in the US Iron and Steel Sector." *Energy* 26 (5): 513–36. doi:10.1016/S0360-5442(01)00017-2.

CHAPTER 3

DEFINING GEOGRAPHICAL BOUNDARIES WITH SOCIAL AND TECHNICAL VARIABLES TO IMPROVE URBAN ENERGY ASSESSMENTS

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Nomenclature

CBG	U.S. Census Block Groups
CT	U.S. Census Tracts
NYC	New York City
LA	Los Angeles
LADWP	Los Angeles Department of Water and Power
ACS	American Community Survey
RASS	Residential Appliance Saturation Survey
RECS	Residential Energy Consumption Survey
HoH	Head of Household
HH	Household

3.1 Introduction

Residential building energy use is a major driver of urban energy use, yet there remains relatively poor information at neighborhood scales across cities of the drivers of this energy consumption. In 2014, residential buildings consumed 21.7% of total energy use in

the U.S. (U.S. Energy Information Administration 2013b), nearly 60% of which was electricity (U.S. Energy Information Administration 2013a). Understanding how and where homes within cities use energy will become even more critical as electricity demand in U.S. homes has increased 34% over the last three decades despite efficiency improvements (U.S. Department of Energy 2008). Improving understanding of how energy is used in homes across cities will require analysis of large geographical regions with sufficient detail to support informed decision-making. In this article, I assess whether the use of newly defined sub-city geographies for building energy use based on social and technical variables yields more meaningful predictive capacity than predefined (and often geopolitical, such as census tracts) regions.

3.1.1 Energy and Spatial-Scale

To date there are few rigorous city-wide assessments of building energy use. This research defines four characteristics of a rigorous study of building energy use: 1) wide geographical coverage (e.g. an entire city), 2) a large sample size or universal coverage of the area, 3) spatial detail at an intermediate scale so that different areas of energy consumption in different areas of the city can be identified, and 4) validation with large-scale reporting of actual energy use. Few studies meet all four of these criteria. Many building electricity analyses focus on the individual building level. For example, Chan investigates the optimal height for installing balconies on residential buildings in order to maximize the solar shading benefits (Chan 2015), and Pan et al. examine green building design options to improve two office buildings in Shanghai, China (Pan, Yin, and Huang 2008). However, extrapolating from a single building to predict a larger area may fail to capture the variability between different types of buildings and different habits of users. Another group of studies investigate city-level or national patterns with minimal spatial resolution. Tso and Guan

perform a multilevel regression on a residential energy survey that maintains regional (i.e. 1-4 U.S. states) resolution, but without sub-urban detail (Tso and Guan 2014). Larivière and Lafrance develop a statistical model that relates city-wide variables such as density, weather, and demographics to electricity use in Canada (Larivière and Lafrance 1999). Howard et al. 2012 model energy use across New York City at fine spatial resolutions by applying end-use intensities to building type and floor area (Howard et al. 2012). Although their data are modeled and not metered, this type of detailed geospatial analysis could be an important framework for capturing macro patterns while retaining building-level detail. Anderson et al. find that building-level and urban-level energy studies tend to be confined within their respective scales with little overlap, but argue that an integrated framework is necessary to achieve policy goals within the building sector (J. E. Anderson, Wulfhorst, and Lang 2015). In building energy assessment, working at a meso-scale is necessary to capture both wide geographical coverage and spatial detail.

City-wide energy analyses need meso-scale spatial detail to understand how consumption varies among different users and areas of a city, but efforts modeling at this scale do not meet the four criteria outlined in the previous section. In this article, "meso" is defined as smaller than urban or census tract, but larger than an individual household or city block. It can be thought of as a neighborhood, or group of neighborhoods with similar characteristics. Furthermore, the choice of the meso-geography needs to be based upon characteristics relevant to energy consumption. Building energy use is spatially correlated due to micro-climates from urban form (Ratti, Baker, and Steemers 2005) and also through relationships in building design, year of construction, and type of inhabitants. There have been some efforts to model urban energy-use at the sub-city level, but nearly all of these efforts are simulation-based from a handful of building types. For example, Shimoda et al.

simulate energy consumption in Osaka City using archetypal use patterns (Shimoda et al. 2004), and Jones et al. model residential energy used based on characteristics of the building stock (Jones, Patterson, and Lannon 2007). In a similar way, Stephan and Stephan study the life cycle energy use of residential buildings in Lebanon based off of a single case study (Stephan and Stephan 2014). Building energy studies to date that do include meso-levels of geography tend to default to geopolitical boundaries such as the census tract, without any justification for the choice of spatial boundaries. Caputo et al. analyze energy policy strategies in the building sector at the neighborhood scale in Milan, Italy, but aggregate the study to the Italian National Census Tract level (Caputo, Costa, and Ferrari 2013). Heiple and Sailor develop a bottom up model for residential and commercial buildings in Houston, Texas, and aggregate the parcel-level data into 1.33 kilometer grid cells (Heiple and Sailor 2008). There are no other studies found that investigate the impact of meso-geographies on intra-regional heterogeneity in building energy use. There is a need not only to study energy use at the meso-scale, but also to develop methods for aggregating data to these intermediate geographies. To fill this gap, the objective of this study is to use the spatial relationships between demographics, building types, and electricity consumption to form new geographies with less variability for use in residential energy assessment. This is the first study to quantify the impact of spatial boundary selection on energy use homogeneity. In this article, the terms "homogeneity" and "heterogeneity" are used to discuss the similarity or dissimilarity of data points within a region (e.g. demographic data or energy consumption).

3.1.2 Redefining Energy Assessment Geographies

In this study, meso-level spatial boundaries are created for energy assessment based upon the social and technical characteristics of residential units. Social characteristics are defined as the demographic profile of the households, and the technical characteristics are

defined as the building shell properties along with appliance prevalence and use. This approach has the advantage of capturing both the geographic and socio-technical definitions of "neighborhoods", and energy analysis geographies should include not just what kinds of buildings are there, but also what kinds of people use those buildings. Using pre-defined geographies is potentially problematic as it might split areas of relatively homogeneous electricity use thereby making predictions less accurate. Literature on zone choice exists in the social sciences for identifying spatial correlations in demographic data or assessing boundary changes over time. For example, Rey and Sastré-Gutiérrez (2010) compare different regionalization schemes in assessing regional inequality in Mexico (Rey and Sastré-Gutiérrez 2010). The definition of appropriate geographical boundaries is an integral component to large-scale energy analysis, but there is no identified literature discussing the significance of zone choice on energy assessments.

3.1.3 Case Studies

To explore the significance of geography definitions to the prediction of electricity use, two case studies are developed for the residential building stocks of two United States cities: Los Angeles (LA), California, and New York City (NYC), New York. Residential stocks are chosen because the function of (and to some extent activities within) residential buildings is largely homogenous, unlike for commercial or industrial buildings.

For LA and NYC, geographies built using endogenous socio-technical characteristics are compared to geopolitical (i.e. census tract) geographies to examine which has more homogenous electricity consumption. The correlation between social and technical characteristics of homes and electricity consumption is tested, and as is whether the use of these characteristics in clustering can reduce the variance in electricity predictions. This

hypothesis is tested in two cities with unique building stock, density, consumption profiles, and climates.

3.2 Methodology

Electricity, social, and technical data are prepared at the census block group (CBG) level, and a max-p clustering algorithm is used to explore the significance of geography in electricity analysis. It is hypothesized that clustering on social and technical variables using a max-p clustering algorithm will reduce heterogeneity of electricity use between residential buildings within each cluster over using pre-defined geographical boundaries. The clustering algorithm is used to aggregate CBGs into larger areas by creating spatially-contiguous areas with minimum difference within a set of pre-defined variables. The goal is to identify the clustering formulations which lead to the most homogeneous regions with respect to electricity consumption. For each city, there are nine sets of variables used for clustering:

1. Electricity use alone. This provides the most homogenous regions possible within a given data set since electricity use is the variable of interest.
2. Technical variables on building characteristics and appliance prevalence.
3. Social variables on the demographics of the inhabitants
4. A combination of all social and technical variables
5. A subset of the 10 most significant social and technical variables
6. A subset of the 6 most significant social and technical variables
7. All social and technical variables with weights representing the significance of each variable to total energy use
8. The subset of the 10 most significant social and technical variables with weights representing the significance of each variable to total energy use

9. The subset of the 6 most significant social and technical variables with weights representing the significance of each variable to total energy use

These clustering formulations inform the types of variable subsets that might be significant to forming new energy analysis geographies for each city. Figure 7 gives an overview of the methods.

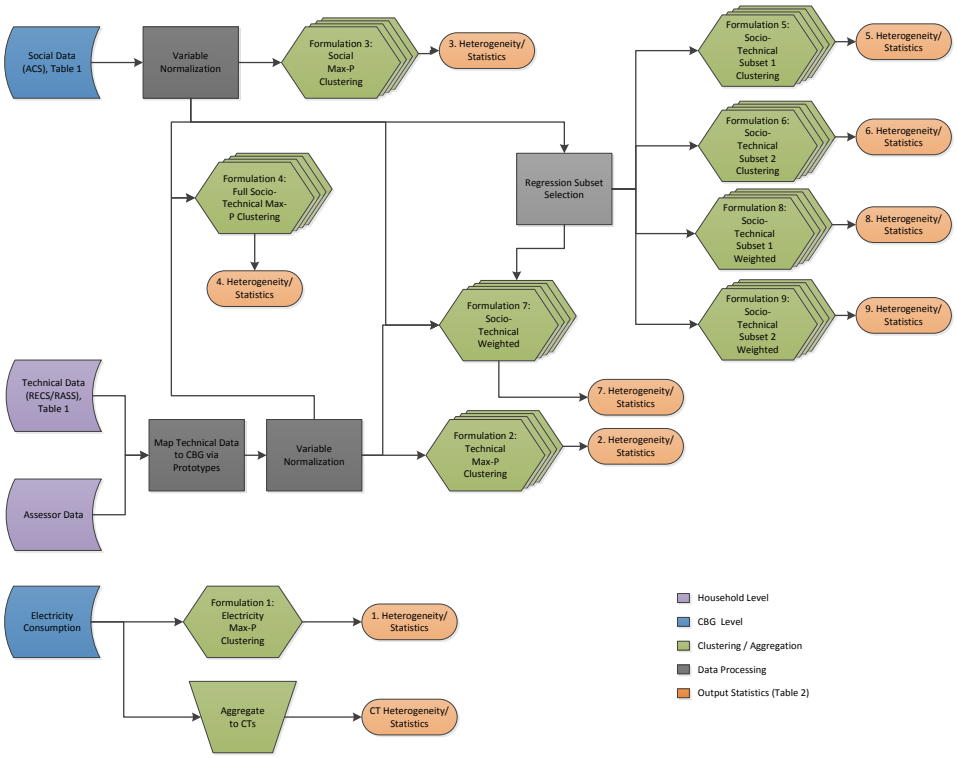


Figure 7: Process Overview. Visual summary of methodological steps.

3.2.1 Geospatial Electricity Demand

CBG electricity data are obtained for both cities, and census and appliance surveys are used to calculate social and technical variables for each CBG. Household-level electricity data are rarely available for large areas and are more frequently obtained at an intermediate geography such as CBG or zip-code. Likewise, social data are generally at a meso-geography, for example census tract, and not the household level. For this reason, CBG data is used to

test the hypothesis, although similar principles could be used to cluster at the household level if data are available.

For the case studies, the study scope includes only electricity use and not natural gas consumption for several reasons. For the NYC case study, there are estimates of both electricity and fuel (including natural gas and other heating fuels), but there is only electricity data for LA. The hypothesis is therefore tested on electricity data, although this methodology is likely as applicable for analyzing total home energy use. In the Appendix, there is a case study for NYC comparing how clustering results differ between electricity versus total home energy use.

For LA, total annual residential electricity consumption is obtained for fiscal year 2011-2012 from the LADWP service area, aggregated by CBG [19]. LADWP is the electricity provider for approximately 40% of the residential accounts in Los Angeles County, which is 2503 CBGs and 1,305,759 residential accounts. The LADWP service territory covers 1,157 km^2.

The NYC Mayor's Office of Long-Range Planning and Sustainability provides electricity data at the zip-code level for year 2009, but these data are not resolute enough to formulate questions on geography. Howard et al. 2012 developed a regression model for annual consumption using zip-code data which predicts electricity and fuel use at the tax-lot (a geography typically containing 1-2 buildings) by using building use code and year of construction as predictors (Howard et al. 2012). The predictive results of this study generally fall within 20% of the actual data. For this study the residential subset from the Howard model is used to test the clustering hypotheses, covering all of NYC, 587 km^2.

For NYC, electricity and fuel use on each tax-lot is allocated between residential and non-residential purposes with the factors provided in Howard et al. 2012. The number of

residential units on each tax lot is used as an approximation of the number of electricity accounts, although this might not always be the case (e.g. an entire building is metered under a single account). In this study, the household is the basic unit of energy use, and residential units stand as a reasonable approximation for household count. Once residential electricity and fuel consumption is partitioned at the tax-lot level, these values are aggregated to the CBG. For NYC, data is included from all five boroughs, which encompasses 6497 CBGs and approximately 3.8 million electricity accounts (Figure 8).

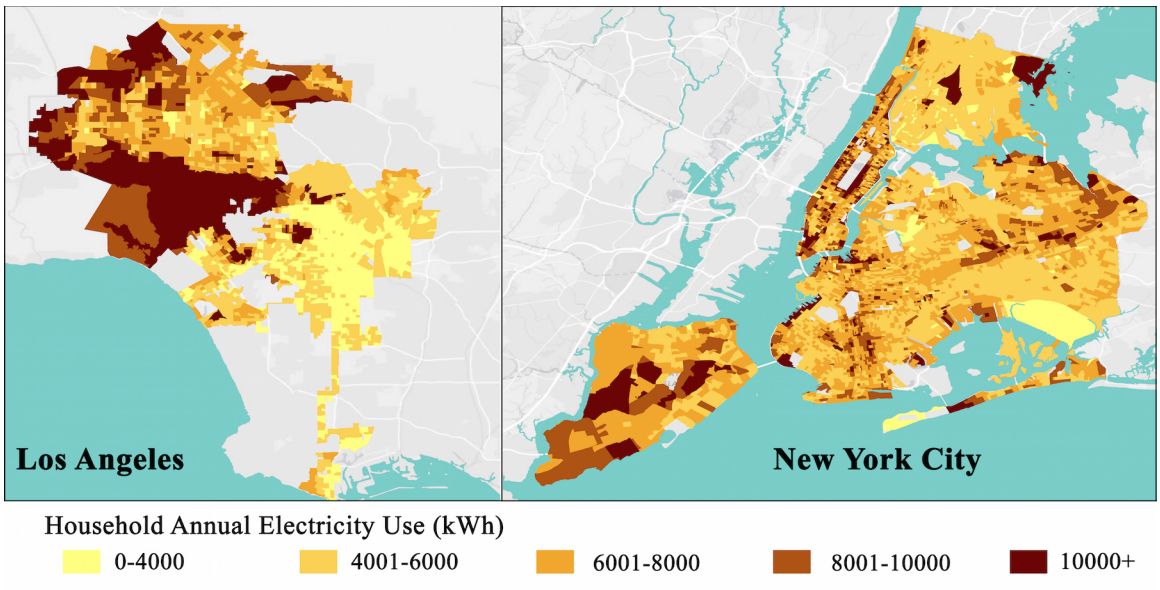


Figure 8: Household Electricity Use in LA and NYC. Annual household electricity use in LA and NYC by CBG. Overall, NYC has higher electricity consumption and more variance between areas.

3.2.2 Socio-Technical Data

For LA and NYC, social and technical profiles are compiled for every CBG in each city. The American Community Survey (ACS), conducted annually by the U.S. Census Bureau, provides a rich array of demographic variables, including many which previous studies showed to be influential to electricity consumption (U.S. Census Bureau 2012). ACS provides these data at the CBG level and combines five years of estimates. For this study,

the 2008-2012 ACS data are used in both LA and NYC. Additionally, in both cities, governmental agencies have residential energy consumption surveys, including information on building stock characteristics and appliance prevalence. However, these surveys lack information on the spatial distribution of these technical characteristics.

Technical properties of buildings are assumed to be correlated to 1) the building classification (single family detached, multifamily high-rise, etc.) and 2) the year of construction, and a prototyping approach is employed to map survey data to geographies. For LA, a subset of data for the LADWP service area is pulled from the 2009 California Residential Appliance Saturation Survey (RASS) which is developed by the California Energy Commission (California Energy Commission 2009). RASS micro-data are household-level, and the LADWP subset includes approximately 2697 survey responses. In NYC, the 2009 Residential Energy Consumption Survey (RECS), conducted nation-wide by the U.S. Energy Information Administration (EIA), is used (U.S. Energy Information Administration 2005). Both the RASS and RECS datasets provide household-level survey data on a variety of socio-technical characteristics relevant to electricity consumption as well as the quantities of electricity, natural gas, and other fuels used in the home.

Household-level data from RECS are filtered to obtain a subsample that is NYC-specific. In RECS as in RASS, the EIA provides household-level micro-data, but for most of the country these data are only given by geographic region (e.g. "West South Central Census Division" which includes Arkansas, Louisiana, Texas, and Oklahoma). Each time RECS is administered, the micro-data provided additional geographical resolution for several of the largest U.S. states such as Texas and California. This is the case for New York state as well. The RECS micro-data is further filtered to obtain only households in NYC by using two other criteria: climate zone and urban/rural classification. Most of New York state falls into

the "Very Cold/Cold" Building America Collapsed Climate Region (U.S. Department of Energy 2009a), however the five counties of NYC and three surrounding suburban counties are "Mixed-Humid". Data from the three surrounding suburban counties are removed by including only urban data points. Thus the 475 household-level data points for NYC are obtained using the boundaries of the climate zones and urban/rural classification.

3.2.3 Variable Selection and Assignment

Nine social variables and twelve technical variables from the RASS, RECS, and ACS datasets are selected which are significant to residential electricity use based on previous studies (Table 3). I selected RASS and RECS variables that were as similar as possible to allow for an equivalent comparison between the two regions. RASS and RECS variables that are as similar as possible are selected to allow for an equivalent comparison between the two regions. Slight differences exist between the variable definition of the RASS and RECS datasets; these differences are discussed in Appendix B.

Table 3: Socio-Technical Variable Subset for Max-p Clustering The variables were selected based on their availability in the survey data and their significance in previous literature. I provide the variable, name, description, and source as well as the studies that have identified these characteristics as significant.

Variable Name	*Type*	*Description*	*Literature*
Age	Social	Head of household (HoH) age	1-5
Family Composition	Social	Household (HH) is a family unit	2,3,6,7
Gender	Social	HoH is female	3,4
HH Size	Social	Number of members in HH	2-5, 7-33
Education Level	Social	HoH has only a HS degree or less	7
HH Income	Social	HH Income	1-4, 7-11
Ethnicity	Social	HoH is non-white	2, 3
Rental Unit	Social	HH in rental unit	2, 5, 7, 11
Employment	Social	HoH is unemployed	2
Air Conditioning	Technical	Unit has air conditioning	2, 8, 9, 11, 12
Insulation	Technical	HoH reports "adequate" insulation	3, 5, 7, 13-15
Construction Year	Technical	Building year of construction	3, 4, 11, 16
Windows	Technical	Unit has double-paned windows	5, 8, 13-15
Electric Heat	Technical	Unit has electric heat	1, 5, 7, 12
Exterior Siding	Technical	Unit has wooden or vinyl siding	13, 15
Natural Gas Use	Technical	Cubic feet/therms of natural gas use	3
Refrigerators	Technical	Number of refrigerators in unit	2, 5, 9, 12
Computers	Technical	Number of computers in unit	12
Televisions	Technical	Number of TVs in unit	5, 9, 12
Pool	Technical	Unit has a pool	5, 7, 9
Floor Area	Technical	Unit size	3-5, 7, 8

3.2.3.1 Literature Key

1 Larivière and Lafrance 1999
2 Davis 2010
3 Brounen, Kok, and Quigley 2012
4 Brounen, Kok, and Quigley 2013
5 Kavousian, Rajagopal, and Fischer 2013
6 Fritzsche 1981
7 Gillingham, Newell, and Palmer 2009
8 Longstreth and Topliff 1990
9 Reiss and White 2005
10 K. P. Anderson 1973
11 Tso and Yau 2007
12 Choi, Cho, and Kim 2012
13 Dall'O', Galante, and Pasetti 2012
14 Jakob 2006

15 Florides et al. 2002
16 Costa and Kahn 2011

Technical data are assigned to each CBG based upon the age and type of the residential building stock within each area. From the micro-data available in the RASS and RECS dataset, thirty-two prototypes are developed for LA and eighteen prototypes for NYC. NYC has fewer prototypes because there are fewer sample points in the dataset, and categories had to be collapsed to have a representative sample for each prototype. The full list of these prototypes and their sample sizes is provided in Appendix B. For every prototype category a technical profile of the characteristics listed in Table 3 is calculated.

Every building in LA and every tax lot in NYC is assigned a prototype category based upon the building use code and year of initial construction. In LA, the 2009 County tax assessor's database is used for building-level classification (Los Angeles County Assessor Office 2009), and in NYC the PLUTO database is used (New York City Department of City Planning 2009). From these two data sources, the number of buildings of each prototype category located in each CBG is known for the case study regions. From these, technical profiles are assigned based upon the weighted average of the properties of the prototypes in each CBG. This gives a unique technical profile for every CBG in each city.

3.2.4 Clustering Formulation

The max-p regions clustering algorithm, a geospatial assessment approach that relies upon the properties of existing small regions to endogenously determine the number of clusters, is used in developing new geographies. This algorithm was developed specifically for defining geographical boundaries for quantitative analysis (Duque, Anselin, and Rey 2012). Applications of the algorithm to-date include assessing changes in neighborhood boundaries across time (Rey et al. 2011) and studying inter-regional equity (Rey and Sastré-

Gutiérrez 2010). The algorithm aggregates *n* geographic areas into the maximum number of regions *p* such that:

1. All regions are spatially connected
2. The value of a predefined attribute for each region must be greater than or equal to a predefined value
3. Each area A_i must be assigned to a single region R_k
4. Each region R_k must have at least one area A_i (Duque, Anselin, and Rey 2012)

Setting an appropriate predefined threshold value (Item 2) is an important condition for the solutions of this algorithm. Other more traditional clustering approaches include setting the number of clusters a priori. For this approach, the threshold is set to provide a similar number of residential accounts as a census tract, but since this algorithm does not provide a deterministic solution, there is some variability in the clusters the algorithm forms. This variability is explored in the results and discussion. The predefined threshold value is the number of electricity accounts; the minimum number of electricity customers in each solution is therefore specified.

3.2.5 Max-P Clustering Algorithm

A mathematical overview of the max-p clustering algorithm is provided, adapted from Duque et al. 2012 for this specific problem:

Step 1: Define Set of Areas for Los Angeles County (Census Block Groups)

$$A = \{A_1, A_2, \dots, A_n\}$$

$$n = |A|$$

Step 2: Define attributes of each census block group, and the set of attributes

A_{iy}, denotes attribute y of area A_i where $y \in Y = \{1,2, \dots, m\}$ with $m \geq 1$

Step 3: Define the dissimilarity between census block groups

$d: AxA \rightarrow \boldsymbol{R}^{+} \cup \{0\}$ is the dissimilarity based on Y such that $d_{ij} \equiv d(d_i, d_j)$ satisfies

$$d_{ij} \geq 0, d_{ij} = d_{ij}, \text{and } d_{ij} = 0 \text{ for } i, j = 1,2, \dots, n$$

Condition: All areas must be touching and form a single region

$W = (V, E)$ denotes contiguity graph so that $v_i \in V$ corresponds to areas $A_i \in A$ and edges $\{v_i, v_j\} \in E$ if and only if A_i and A_j share a boarder. W must be connected graph

Step 4: Defining all feasible partitions

$P_p = \{R_1, R_2, \dots, R_p\}$ partition of areas A into p regions with $1 \leq p \leq n$ such that:

$|R_k| > 0$ for $k = 1,2, \dots, p$ (each area must contain at least one area A_i)

$R_k \cap R_{k'} = \emptyset$ for $k, k' = 1,2, \dots, p \ \wedge k \neq k'$ (there is no overlap between areas)

$\cup_{k=1}^{p} R_k = A$ (adding all areas R_1 through R_p will give the full area A)

The sum of the attribute of interest, l_i for each area A_i within R_k must be greater than the defined threshold, and the threshold must be defined as to be less than the sum of l_i for all areas A_i

$$\sum_{A_i \in R_k} l_i \geq threshold \begin{cases} \text{for } k = 1,2, \dots, p, \text{and} \\ threshold \ \in \boldsymbol{R}^{+} \cup \{0\} | 0 \leq threshold \leq \sum_{A_i \in A} l_i \end{cases}$$

$W(R_k)$ is connected for $k = 1,2, \dots, p$

Let $\boldsymbol{\Pi}$ denote the set of all feasible partitions of A

Evaluation Criterion for a Feasible Partition $P_p \in \Pi$

Heterogeneity of region k with $R_k \in P_p$ (summation of dissimilarity between all areas in R_k):

$$h(R_k) = \sum_{ij: A_i, A_j \in R_k, i \leq j} d_{ij}$$

Total heterogeneity of partition $P_p \in \Pi$

$$H(P_p) = \sum_{k=1}^{p} h(R_k)$$

Max-p-regions problem: maximizes the number of regions in the partition and maximizes the heterogeneity between the regions.

$$Determine\ P_p^* \in \Pi\ such\ that\ \left|P_p^*\right| = \max\left(\left|P_p\right|: P_p \in \Pi\right), \text{and}$$

$$\nexists P_p \in \Pi: \left|P_p\right| = |P_p^*| \wedge H(P_p) < H(P_p^*)$$

A summary of the variables included in the formulation are given below (Table 4).

Table 4: Variable Definitions

Variable	*Definition*
n	Number of areas in Set A
A	Set of areas A_1 through A_n
A_{iy}	Denotes attribute y in area A_i
l_i	Spatially extensive attribute of area A_i
d	Dissimilarity between the areas
P_p	A set of partitions of A into R
R_k	A grouping of areas A
Π	Set of all feasible partitions of A
$h(R_k)$	Heterogeneity of R_k
$H(P_p)$	Heterogeneity of a partition P_p

3.2.6 Algorithm Implementation

Clustering on electricity data alone provides a lower bound on the heterogeneity of electricity consumption that naturally exists in the dataset. The same threshold value is used for all nine formulations, so they are comparable in size. The electricity data are not normalized for clustering, because it is the only variable used for the "Electricity" formulation, and it will not change the results.

Next, clusters are formed on the social and technical variables independently, and then subsequently the full set of socio-technical characteristics. For these formulations, each

of the socio-technical variables are normalized to fall between 0 and 1 to avoid any bias in the model towards variables based on the difference in magnitude. For example, "Income" is of the 10^4 order whereas "Female" is of the 10^{-1} magnitude. The algorithm is run 100 iterations per formulation to capture a statistically significant "average" result and to catalogue the variability which exists within the max-p regions solutions for each formulation. The algorithm intentionally does not have a seed, so every run yields slightly different results.

To explore the clustering capabilities on a subset of socio-technical variables, a regression model is run to develop weights based on variable influence to the variation in the electricity data. First regression model with all of the socio-technical parameters is developed and the variables with the highest predictive power are selected to use in clustering. The goal of the regression is to identify significant variables, not to develop a predictive model of electricity use, so regression-specific issues (e.g. multicollinearity, heteroskedasticity) are not corrected. Forward stepwise model building shows similar variable significance levels to running the regression model once with all variables present. Therefore, t-values from the full model are used as a measure of significance (see Appendix B). Once a subset of variables is selected and clustering performed, the variables are narrowed to a smaller subset using the same procedure. This yields three formulations of socio-technical subsets for each case study.

Additionally, the regression coefficients from each subset are used to explore the impact of weighting on the clustering results. The regression coefficients quantify the relative significance of the variables to the variation in electricity use. Including these in the clustering algorithm places more significant variables as higher weighted in the clustering process. For each of the three socio-technical subset models, the max-p algorithm is run

another 100 iterations, respectively, while weighting the normalized variables with the regression coefficients. Essentially, this increased the magnitude of significant variables while decreasing (relatively) the magnitude of less-significant variables.

To compare the clustering outputs of each of the nine clustering set-ups in both case studies, several benchmarks and measurements of homogeneity are developed. For the benchmarks, the clustering on only the electricity data provides a lower bound on the variability which exists in the data. As a point of comparison, all clustering statistics on the pre-defined census tracts (CT) are calculated for each city. Comparing variability to CTs indicates whether there is value in defining new geographies for electricity using socio-technical variables, or whether the existing geographical definitions have lower or comparable homogeneity.

3.3 Results

Using max-p regions clustering with socio-technical characteristics significantly reduces the heterogeneity of electricity consumption within regions compared to using pre-defined CT geography. The reduction is greater for NYC, which has more natural variability in the electricity data compared to LA, where there is a fairly narrow range of variance between households. Weighting the clustering variables based on relative significance does not yield more homogenous geographies in the two case studies; it does however lead to more consistent clustering results between iterations due to the additional constraint of the weights.

3.3.1 Residential Energy Overview

LA and NYC have distinct climates and building stock, which impact how each city uses electricity. These differences in climate, infrastructure, and demographics lead to different end use energy consumption profiles for LA and NYC. According to the 2009

RASS, the majority of energy use (~68%) in the LADWP service area is natural gas for space and water heating. The main driver of end-use electricity consumption is the miscellaneous category, which includes interior and exterior lighting as well as items not covered specifically in the energy consumption survey (Figure 9). The accompanying documentation for the RASS analysis states that they believe lighting to be the largest contributor to this category (California Energy Commission 2009). Next the main contributors are TV/electronics, refrigerators, and heating and cooling. The total energy devoted to heating and cooling in the LADWP area is approximately 36%. Pools (in the form of water circulation and heating) are also a non-negligible contributor to the energy consumption profile.

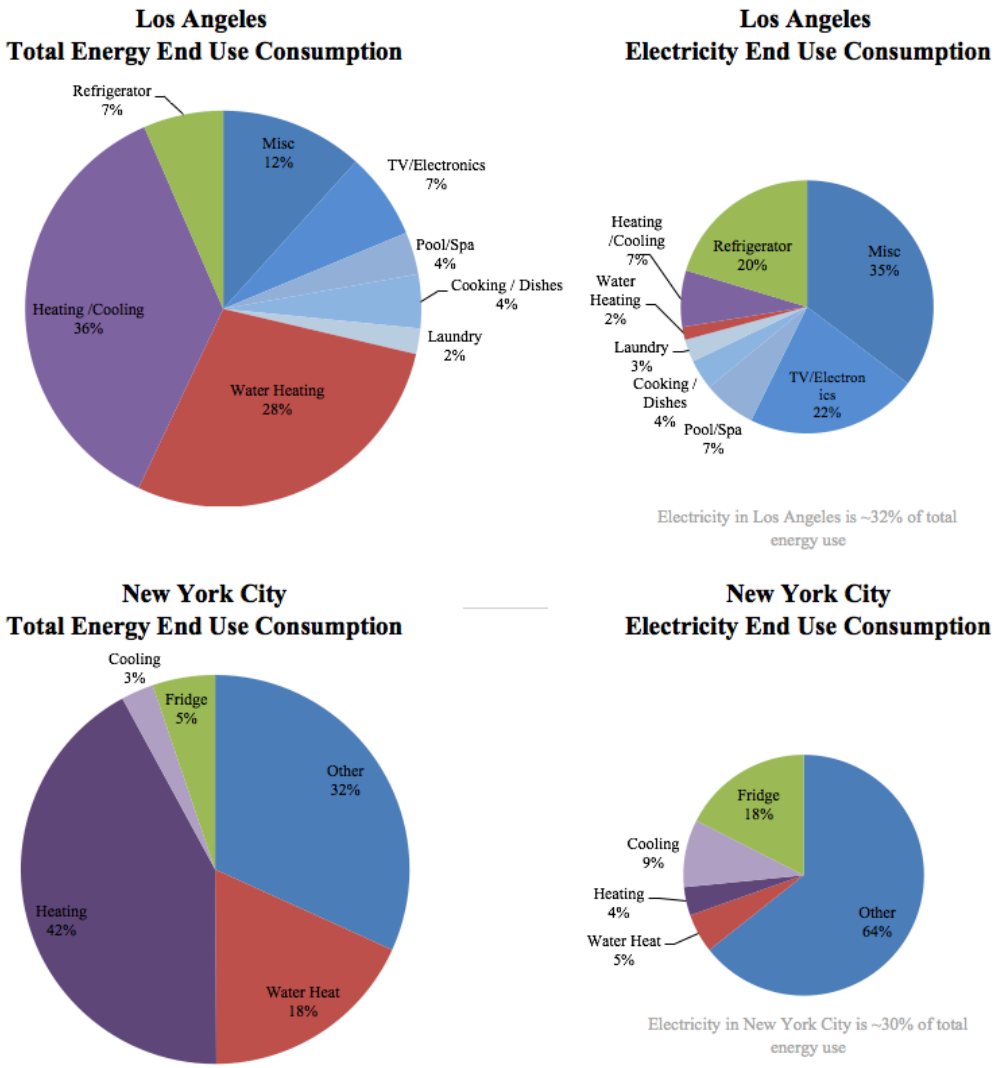


Figure 9: Residential End Use Consumption in LA and NYC. Based on the 2009 RASS and RECS Surveys, I break down residential end use consumption in the LADWP service area and NYC for both total energy use and electricity. In LA, most energy comes from electricity so the profiles are similar. In NYC, a large portion of energy comes from non-electric heating, so the profiles show substantial variation.

There are fewer categorical distinctions of end-uses of energy in RECS than are present in RASS. Within RECS, fewer end-use categories are provided than in RASS, so the leading electricity consumer is "Other". This category, presumably, includes consumers such as pools, electronics, small appliances, cooking, laundry, and lighting. Without more data it is difficult to make that distinction. The next largest consumers of electricity in NYC are

refrigerators, followed by heating and cooling. Although many categories are aggregated together in the RECS data, the profile of electricity use is quite similar to LA, since the majority of heating is non-electric (~70%) (U.S. Energy Information Administration 2005). This electricity consumption profile is likely to be quite different for areas with heavy (electric) cooling loads.

Total energy consumption shows a slightly different profile than electricity consumption in NYC. Of the non-electric energy sources such as natural gas, fuel oil, and wood, nearly 60% goes to space heating. This significantly influences the total energy profile, making space heating the number one end-use consumer of residential energy. This is again followed by the ambiguous "Other" category, and then water heat, which also uses a lot of non-electric energy. Comprehensive strategies for examining energy use in NYC should therefore consider all sources of energy use because of the heavy heating and cooling loads. There's a lot of potential for reduction in these areas.

3.3.2 Cluster Heterogeneity

Measures of variability are developed to compare the heterogeneity of different clustering formulations and iteratively run the algorithm to explore the variability within the clustering solution sets. Within each cluster, a weighted (by number of accounts) standard deviation of the average consumption of each CBG within the cluster is calculated. Based upon the standard deviation of each cluster, an average standard deviation for the entire study area is then calculated as a measure of the typical heterogeneity from that clustering run. Likewise, the standard deviation of the heterogeneity measure from each cluster can be measured. Because multiple clustering solutions exist under each max-p formulation, 100 iterations are then run and the heterogeneity measure and standard deviation of the heterogeneity measure across runs are averaged. These are referred to as the formulation

heterogeneity and the formulation standard deviation, respectively, for this article. The results for each formulation are summarized in Table 5. For each formulation, a t-test is performed to calculate the probability that the formulation heterogeneity is less than that of the CTs. In every single case, the p-value is much less than 0.0001, indicating a high level of certainty that this is the case.

Table 5: Average Formulation Heterogeneity and Formulation Standard Deviation. For each of the eight clustering formulations and the pre-defined CTs I calculate the measures of heterogeneity and standard deviation as defined in Section 3.2. The heterogeneity measure is based upon standard deviation within each cluster and represents average variation of annual electricity use (in kWh). I calculate the standard deviation of these variances across the city as well (also in kWh).

	Los Angeles				*New York City*			
	Heterogeneity (kWh)	St. Dev. (kWh)	t-statistic	p value	Heterogeneity (kWh)	St. Dev. (kWh)	t-statistic	p value
1. Electricity	437.2	13.1	-93.7	9E-99	694.1	8.1	-367.8	6E-158
2. Social	512.0	14.2	-34.0	9E-57	741.6	10.5	-238.3	1E-138
3. Technical	513.8	14.6	-31.9	4E-54	708.2	8.6	-330.5	9E-153
4. Socio-Technical Full	500.6	11.3	-53.0	9E-75	728.4	8.6	-308.0	1E-149
5. Socio-Technical Subset 1	495.0	15.2	-42.8	6E-66	725.3	7.9	-339.2	7E-154
6. Socio-Technical Subset 2	486.1	14.0	-52.9	1E-74	736.7	8.5	-302.0	7E-149
7. Socio-Technical Full, weights	496.3	12.8	-49.9	3E-72	726.4	9.9	-269.3	6E-144
8. Socio-Technical Sub1, weights	507.3	15.3	-34.7	2E-57	727.2	8.4	-316.1	8E-151
9. Socio-Technical Sub2, weights	505.5	13.1	-41.9	5E-65	733.7	8.6	-299.7	1E-148
Census Tracts (CTs)	560.5	-	-	-	992.8	-	-	-

3.3.3 Los Angeles Results

For LA, a theoretical minimum consumption is established based upon the electricity-only formulation. This formulation has a formulation heterogeneity of 437.2 kWh/household/year, which is approximately 7.9% of average annual household use in the LADWP service area. This number represents the natural variation which already exists within the CBGs when clustered to this threshold, and represents a pseudo "theoretical minimum" standard deviation which could be achieved through clustering. This is because the most effective way to obtain areas of homogenous electricity use would be to cluster on electricity use itself.

The formulation heterogeneity of the clustering results is compared to pre-defined CT geography to benchmark performance. For the CTs in the LADWP service area there is an average standard deviation of 560.5 kWh/ household/year, which is approximately 10.1 % of average annual household use. This higher variance in the CT geography indicates that clustering reduces heterogeneity. For LA there is not a large difference between the tract variability and the theoretical minimum of the electricity clustering, indicating little room for improvement over the existing geographical definition.

By including the formulation standard deviation, all of the social, technical, and socio-technical cluster formulations outperform the tract geography. In LA, the difference between the different subsets is not significant. The worst performing of the cluster formulations is the technical variables only with just a 0.8% (of average HH use) improvement over the CTs while the best performing is the socio-technical subset A1 without weights, which is the subset that includes just the top six significant socio-technical variables. Weighting the clustering parameters has little impact on the formulation heterogeneity, although it might slightly reduce the standard deviation of the Heterogeneity.

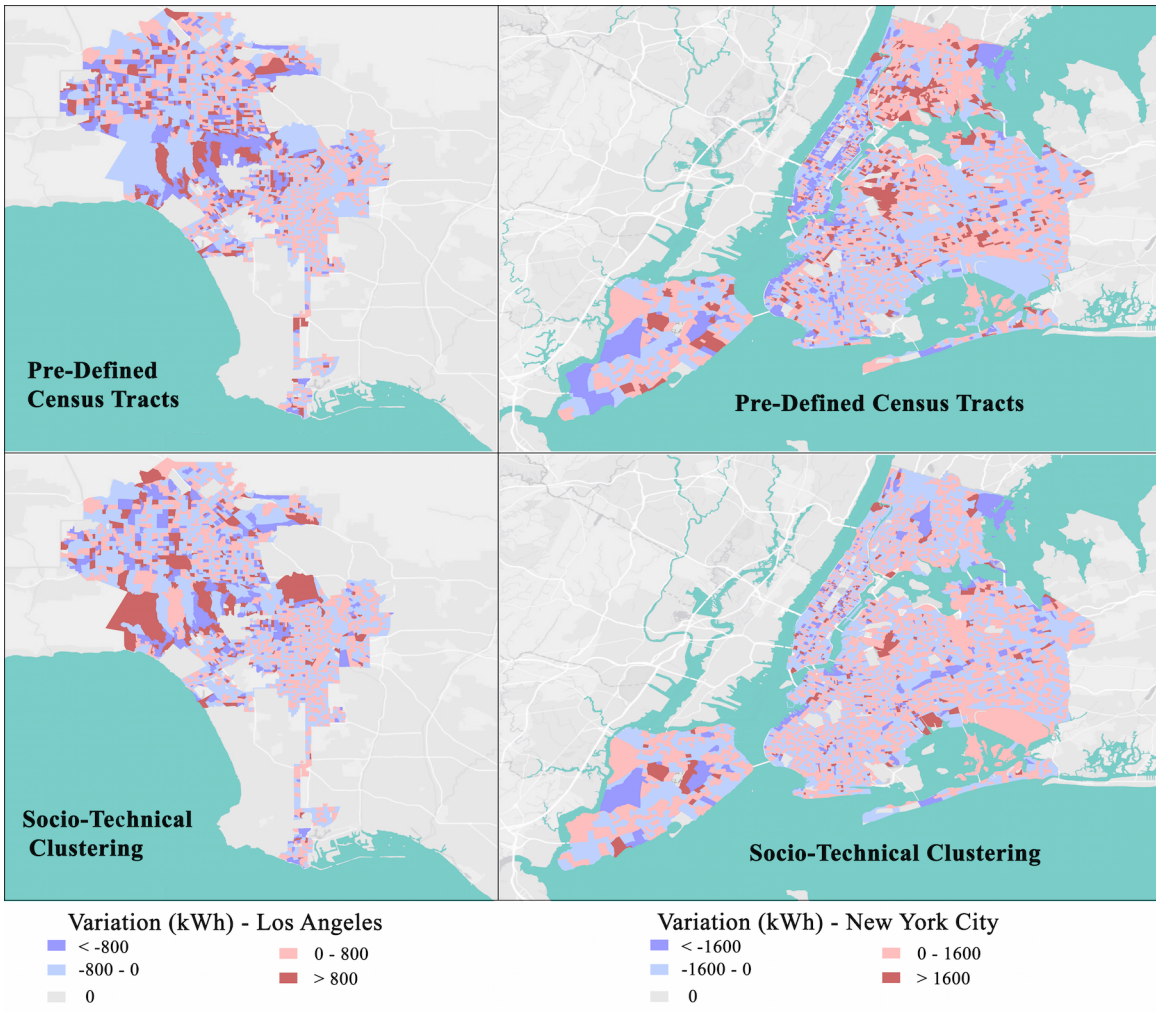


Figure 10: Spatial Distribution of CBG deviation from cluster average in LA. This choropleth map shows the difference between the CBG electricity use and the average cluster electricity use where I assign the CBG. Red represents an overestimation and blue represents an underestimation. I can tell that the socio-technical clustering has fewer CBGs with the extreme differences (bright red and blue) compared to the pre-defined CTs.

3.3.4 New York City Results

In NYC both the annual average use and the formulation standard deviations are greater than in LA, with the average residential unit consumption at 6,515 kWh per year, electricity clustering with a formulation standard deviation 694.1 kWh (10.7% of total). Formulation heterogeneity from the CTs is 992.8 kWh, or 15.2% of the average unit use.

This is a slightly larger range of potential improvement than exists for LA, where there is more homogeneity in the residential consumption profile overall.

As in LA, all of the clustering scenarios in NYC were less heterogeneous than the CT geography. The scenario which performed the best consistently was the purely technical clustering with the lowest overall average standard deviation of 708.2 kWh (10.9%). There is little difference between the formulation heterogeneity of the two larger subsets of socio-technical variables (~727 kWh), but the smallest subset actually performed slightly worse with a result of 733.7 kWh. The social clustering showed lower heterogeneity (741.6 kWh) than this smallest subset, but it is not statistically different than the second smallest clustering formulation. In NYC, I also formulation heterogeneity for total energy use (including fuel), and similarly find it is lowest for the technical clustering scenario, and that all clustering formulations improve over the pre-defined CTs (see Appendix B.5). Similar to the LA results, the weighting of the socio-technical clusters did little to reduce the average standard deviation but it did reduce the formulation standard deviation. Perhaps this is best considered a measure of the consistency of the max-p algorithm than a measure of the homogeneity of clusters.

3.3.5 Socio-Technical Subset Selection

For both stages of the regression selection, parameters that are significant at a 0.1 p-value are kept (see Appendix B). For LA and NYC, the significant variables vary substantially, but the presence of a pool and renting the unit are significant to the variation in the consumption of electricity between households in all four clustering sets. As discussed in the introduction, that does not mean that these are the two main drivers of total electricity consumption. In general, LA tended to have more social variables with statistical significance

whereas NYC had a higher amount of technical variables remaining in both subsets (see Appendix B).

3.3.6 CBGs Variance Distribution

In both cases, clustering creates lower average standard deviation within geographies, and consequentially, a lower difference between each of the CBGs and its cluster average electricity use. In LA when mapping the difference between the clustering formulation with the lowest heterogeneity I observe slight improvements in the deviation of the CBG from its respective cluster (Figure 10). In NYC, mapping the two sets yields obvious variations between the lowest heterogeneity formulation and the CT assignment, implying a substantial improvement in homogeneity of electricity use (Figure 10).

The difference between the two is more readily seen when the absolute values of the data are plotted against the cumulative percentage of data present (Figure 11). The area between curves represents the difference in the cumulative absolute value of error between the pre-defined CTs and the clustering approach. The greater this area between the curves, the more the algorithm improves over existing geography.

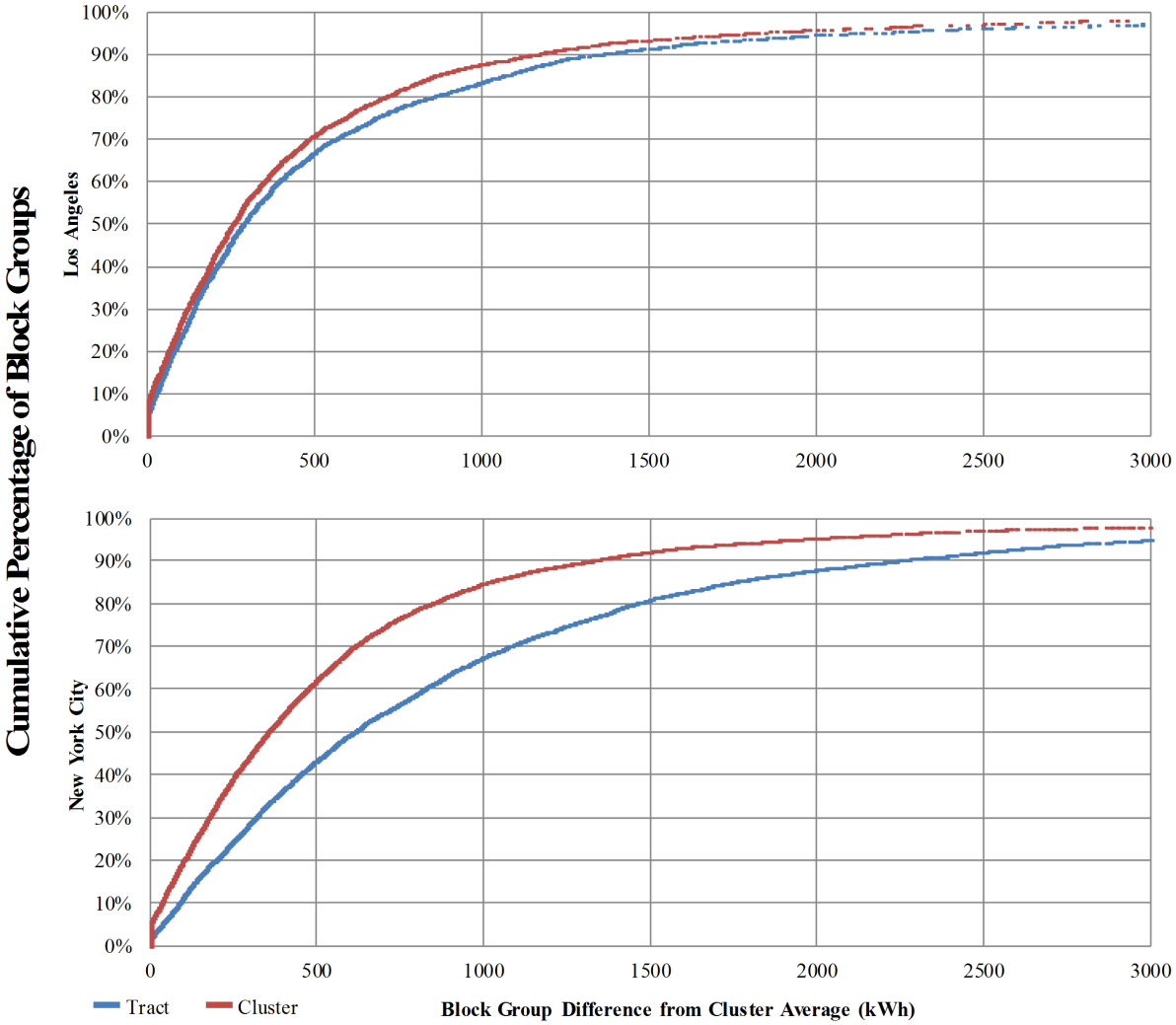


Figure 11: Cumulative Deviation of CBGs from Cluster Average in LA (left) and NYC (right). I compare the deviation of each CBG from the average of its cluster both from the CT assignment as well as the lowest variance Clustering Formulation in each city. Since the goal is to have all of the deviations as close to zero as possible, clustering formulations with a higher cumulative percentage at the lower difference in electricity use perform better.

There are several potential reasons why significant variables in LA include more social variables whereas NYC includes more technical variables. Primarily, LA and NYC have dramatically different heating and cooling loads. It is possible that the base load of electricity required to heat and cool homes is such a dominating amount that what drives the

difference in the results therefore is the choice-loads (televisions, pools). In LA, perhaps there is more choice in the amount of electricity used, so social factors play a larger role.

3.4 Discussion

The results show that regions defined using the socio-technical building characteristics have lower variance than pre-defined geopolitical boundaries, so a re-consideration of geospatial boundaries used in electricity forecasting is therefore recommended. Furthermore, the use of intelligent spatial aggregation could provide a framework for thinking about the spatial difference in building energy use. In urban-scale building energy analyses, redefining spatial boundaries based upon socio-technical characteristics to compile areas with more similar energy usage than pre-defined geopolitical boundaries provide should be considered. Previous studies show that electricity consumption in the home is correlated to both social and technical characteristics, and my work discovers that using a subset of these characteristics can significantly improve the intraregional homogeneity of energy consumption.

3.4.1 Patterns of building energy use

There are smarter ways to define analysis boundaries, even without a full understanding of the relative significance of specific socio-technical variables within a local context. The results show that all clustering formulations based on technical, social, or socio-technical variables create areas with more homogenous electricity usage than the pre-defined CTs. The U.S. Census Bureau originally defined geographical sub-boundaries based foremost on existing physical features (e.g. rivers) and political boundaries (e.g. county line), and secondarily based on the socio-economic status of the inhabitants. The intent of CTs is to remain consistent overtime so that comparative statistics can be calculated, thus with each

passing decade and as regions change, census boundaries correspond less to socio-economic status.

The max-p algorithm performs comparably with and without weighting the variables based on their correlation to electricity consumption, suggesting that merely identifying the appropriate variables for clustering is a more important step in defining geographies than understanding their relative importance. To select a solution, the max-p regions algorithm evaluates the difference of the total variance of all variables between regions. This implies that weighting should influence the chosen solution, as a higher weight (for a more significant variable) will increase the variance. Because the weights are based on regression coefficients, the magnitudes are potentially not great enough to significantly influence the variance, or possibly not correcting for positive and negative coefficients keeps this from appearing in the results. Another potential reason that this might not influence the clustering homogeneity of electricity use is the level of multicollinearity in the variables. If one variable is weighted more heavily at the expense of another variable to which it is significantly correlated (e.g. income and floor area), it is possible that the same total variance becomes expressed in the model regardless of weighting since both variables capture essentially the same information. As weighting seems to have no significance in either of the case studies, this suggests that understanding the nuances of variable significance in a specific location is not a hurdle to forming more meaningful geographies for energy analysis.

3.4.2 Improving Spatial Modeling

Building energy use cannot be isolated from its local context, and analyzing urban energy use at a meso-geography such as the "neighborhood" scale might be more appropriate than building-level or city-wide assessments. As it is defined for this article, the "neighborhood" level is a mesoscale geography that is more resolute than the CTs or clusters

in this study and would aggregate households. To manage growing energy demand in the face of restricted or uncertain supply, a system-level understanding of the patterns of energy use that occur across cities is needed, with enough detail to identify the varying amounts of energy being consumed by different types of people at different spatial locations. Furthermore, the practical steps that can be taken to improve existing building stocks need to be investigated, and stocks should be designed with flexibility to meet future, often uncertain, demands. The neighborhood level might be more appropriate than the household level for predicting electricity use as energy consumption depends heavily upon behavior, which can be highly influenced by the activities of others in the same area. Potentially these new neighborhoods, based on both social and technical characteristics, would be the basic unit for a new type of urban energy analysis.

3.4.3 Urban building energy systems

There is potential to improve urban building energy assessment in at least two areas based on the results of this study: 1) re-defining boundaries of meso-assessments and 2) formulating spatially-targeted policies for energy efficiency and conservation. Neighborhood/mesoscale geographies with socio-technical clustering in urban energy analysis can offer many advantages over existing aggregation methods. Foremost, this scale is necessary to provide sufficient detail for understanding patterns and decision-making. Furthermore, defining mesoscale neighborhoods that can be flexibly changed over time as behavior and use characteristics change will be necessary to monitor how different areas of the city use energy. There also can be advantages in designing studies. If a mesoscale neighborhood has relatively homogenous energy use (based upon clustering), this could aid in limiting data collection to a statistically significant sample from each area. Conversely, if a study starts with full household level data and wants to aggregate (for privacy or data-

condensing reasons), areas with similar energy consumption and socio-technical characteristics will be grouped together. Homogeneity beyond just energy use or a subset of the variables might be advantages in developing non-energy metrics as well. Clustering also lowers the intra-cluster variance over pre-defined geographies. Using a pre-defined geography will provide the appropriate *average* statistics for energy use, but it will create areas with higher levels of variance in forecasting, for example, by placing more outliers together. As building energy technologies continue to become more efficient and increasingly incorporated into building codes, energy conservation and efficiency efforts will be targeted at behavior and other high-energy emerging technologies, and energy clustering can inform a more efficient allocation of these policies. For example, computers and personal electronics have quickly become important contributors to the total residential building consumption profile, and this proportion continues to rise (Sanquist et al. 2012). Electric vehicles are another technology that might dramatically change home energy use profiles. Additionally, new appliances and disruptive technologies may change the way households use energy. Furthermore, having increased distributed and on-site energy generation will potentially change the way homeowners make decisions about energy use. In this light, conservation and efficiency policies, which often have a large economic cost associated, should be targeted at the areas of buildings and the types of people where they will have the most benefit. Through a redefinition of energy geographies, specific neighborhoods could be identified where, for example, building retrofits will have the largest savings in wintertime heating use. Clustering could provide a way to identify the hotspots of building energy use.

3.4.4 Technological Urban Systems

This study is the first where the max-p regions algorithm has been applied to technical rather than social variables, and there are potential applications for this framework

in other urban systems such as water usage, solar panel installation, and information and communication technology penetration. Like energy usage, the function of other urban systems depends on characteristics of the infrastructure and human activities, and using meso-geographies could inform robust studies on these services. For example, if a relationship existed between income, building construction year, and likelihood of solar panel installation at the home, these variables could be used in clustering to identify neighborhoods that are most (or least) likely to install solar panels in the near future. This might have implications for both local grid infrastructure as well as business forecasting.

3.4.5 Survey Design

There are also potential applications of using clustering of electricity use to design smarter surveys of building energy use. This study uses a prototype approach to approximate the building shell properties and appliance prevalence across two entire cities because of the lack of detailed spatial technical data, but to further understand urban-scale energy use, a more detailed profile of building technical data across cities is needed, at comparable or finer resolution as the social data from the US Census. Performing clustering on a city could be useful for identifying which areas could be considered homogenous and a statistically significant sample could then be collected from each of these regions on technical characteristics. Understanding the building stock as it exists, including how it constrains or permits decisions on energy use will be important for identifying future paths towards lower energy consumption.

3.5 Conclusions

In this article, it is shown that intra-zone variability of electricity use can be reduced by redefining spatial boundaries with the socio-technical characteristics of homes. This can be done by choosing social and technical variables that have been shown to have high

correlations to residential electricity use. A max-p clustering algorithm is used to endogenously determine the clusters in case studies in two US cities: Los Angeles and New York City. Multiple formulations are considered including only technical variables, only social variables, all social and technical variables, subsets of social and technical variables, as well as formulations weighted based on variable significance. To benchmark the performance of the clusters, the intra-cluster similarity of electricity use in homes is compared to a pre-defined geography commonly used in energy analysis: the US Census Tract. For both case studies, all clustering formulations have a statistically significant reduction in consumption variability compared to census tracts, suggesting that redefining boundaries even if the context-specific drivers (i.e the most important socio-technical variables) are uncertain will improve over existing geopolitical boundaries. This is significant, for multiple reasons. First, this study might provide the foundation of a new framework for urban energy assessment, based upon clustering, at a sub-urban scale. Even if the exact local relationship between socio-technical variables and energy variables is unknown, in these case studies it is shown that clustering can place homes with similar energy consumption profiles into the same geographies much better than using a pre-defined geography, with a high level of statistical significance. Additionally, there is some evidence to suggest that these intermediate geographies might be more appropriate for urban energy assessment than building-level or city-scale. Second, clustered energy assessment can directly inform spatially-targeted policies within a city by identifying "hotspots" of energy use. This level of nuanced understanding of how homes use energy within a city could lead to better economic allocation of local resources. Understanding spatial differences in energy use might also lead to better design of building technology surveys (i.e. thermal shells and appliances) that provide sub-urban detail. Finally, there are

potential applications of this algorithm to other urban technical and infrastructure systems beyond urban energy use. Altogether, the framework offers potential to help us rethink how we approach urban environmental, resource, and economic assessments.

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3.7 References

Anderson, John E., Gebhard Wulfhorst, and Werner Lang. 2015. "Energy Analysis of the Built environment—A Review and Outlook." *Renewable and Sustainable Energy Reviews* 44 (April). Elsevier: 149–58. doi:10.1016/j.rser.2014.12.027.

Anderson, Kent P. 1973. "Residential Demand for Electricity: Econometric Estimates for California and the United States." *The Journal of Business* 46 (4): 526. doi:10.1086/295576.

Brounen, Dirk, Nils Kok, and John M. Quigley. 2012. "Residential Energy Use and Conservation: Economics and Demographics." *European Economic Review* 56 (5). Elsevier: 931–45. doi:10.1016/j.euroecorev.2012.02.007.

———. 2013. "Energy Literacy, Awareness, and Conservation Behavior of Residential Households." *Energy Economics* 38 (July). Elsevier B.V.: 42–50. doi:10.1016/j.eneco.2013.02.008.

California Energy Commission. 2009. "California Statewide Residential Appliance Saturation Study: Final Report."

Caputo, Paola, Gaia Costa, and Simone Ferrari. 2013. "A Supporting Method for Defining Energy Strategies in the Building Sector at Urban Scale." *Energy Policy* 55 (April). Elsevier: 261–70. doi:10.1016/j.enpol.2012.12.006.

Chan, A.L.S. 2015. "Investigation on the Appropriate Floor Level of Residential Building for Installing Balcony, from a View Point of Energy and Environmental Performance. A Case Study in Subtropical Hong Kong." *Energy* 85. Elsevier Ltd: 620–34. doi:10.1016/j.energy.2015.04.001.

Choi, In Young, Sung Heui Cho, and Jeong Tai Kim. 2012. "Energy Consumption Characteristics of High-Rise Apartment Buildings according to Building Shape and Mixed-Use Development." *Energy and Buildings* 46 (March). Elsevier B.V.: 123–31. doi:10.1016/j.enbuild.2011.10.038.

Costa, Dora L, and Matthew E Kahn. 2011. "Electricity Consumption and Durable Housing: Understanding Cohort Effects." *American Economic Review* 101 (3): 88–92. doi:10.1257/aer.101.3.88.

Dall'O', Giuliano, Annalisa Galante, and Giulia Pasetti. 2012. "A Methodology for Evaluating the Potential Energy Savings of Retrofitting Residential Building Stocks." *Sustainable Cities and Society* 4 (October). Elsevier B.V.: 12–21. doi:10.1016/j.scs.2012.01.004.

Davis, Lucas W. 2010. "Evaluating the Slow Adoption of Energy Efficient Investments: Are Renters Less Likely to Have Energy Efficient Appliances?" Vol. 16114. Cambridge, MA. http://www.nber.org/chapters/c12130.pdf.

Duque, Juan C., Luc Anselin, and Sergio J. Rey. 2012. "THE MAX-P-REGIONS

PROBLEM*." *Journal of Regional Science* 52 (3): 397–419. doi:10.1111/j.1467-9787.2011.00743.x.

Florides, G.A, S.A Tassou, S.A Kalogirou, and L.C Wrobel. 2002. "Measures Used to Lower Building Energy Consumption and Their Cost Effectiveness." *Applied Energy* 73 (3-4): 299–328. doi:10.1016/S0306-2619(02)00119-8.

Fritzsche, David J. 1981. "An Analysis of Energy Consumption Patterns by Stage of Family Life Cycle." *Journal of Marketing Research* 18 (2): 227. doi:10.2307/3150956.

Gillingham, K, Richard G Newell, and K Palmer. 2009. "Energy Efficiency Economics and Policy." *Annual Review of Resource Economics* 1: 597–619. doi:10.1146/annurev.resource.102308.124234.

Heiple, Shem, and David J Sailor. 2008. "Using Building Energy Simulation and Geospatial Modeling Techniques to Determine High Resolution Building Sector Energy Consumption Profiles." *Energy and Buildings* 40 (8): 1426–36. doi:10.1016/j.enbuild.2008.01.005.

Howard, B, L Parshall, J Thompson, S Hammer, J Dickinson, and V Modi. 2012. "Spatial Distribution of Urban Building Energy Consumption by End Use." *Energy & Buildings* 45. Elsevier B.V.: 141–51. doi:10.1016/j.enbuild.2011.10.061.

Jakob, Martin. 2006. "Marginal Costs and Co-Benefits of Energy Efficiency Investments." *Energy Policy* 34 (2): 172–87. doi:10.1016/j.enpol.2004.08.039.

Jones, Phil, Joanne Patterson, and Simon Lannon. 2007. "Modelling the Built Environment at an Urban scale—Energy and Health Impacts in Relation to Housing." *Landscape and Urban Planning* 83 (1): 39–49. doi:10.1016/j.landurbplan.2007.05.015.

Kavousian, Amir, Ram Rajagopal, and Martin Fischer. 2013. "Determinants of Residential Electricity Consumption: Using Smart Meter Data to Examine the Effect of Climate,

Building Characteristics, Appliance Stock, and Occupants' Behavior." *Energy* 55 (June). Elsevier Ltd: 184–94. doi:10.1016/j.energy.2013.03.086.

Larivière, Isabelle, and Gaëtan Lafrance. 1999. "Modelling the Electricity Consumption of Cities: Effect of Urban Density." *Energy Economics* 21 (1): 53–66. doi:10.1016/S0140-9883(98)00007-3.

Longstreth, Molly, and Michael Topliff. 1990. "Determinants of Energy Savings and Increases after Installing Energy-Conserving Devices." *Energy* 15 (6): 523–37. doi:10.1016/0360-5442(90)90057-9.

Los Angeles County Assessor Office. 2009. "Los Angeles County Database."

New York City Department of City Planning. 2009. "MapPLUTO (release 09c)."

Pan, Yiqun, Rongxin Yin, and Zhizhong Huang. 2008. "Energy Modeling of Two Office Buildings with Data Center for Green Building Design." *Energy and Buildings* 40 (7): 1145–52. doi:10.1016/j.enbuild.2007.10.008.

Pincetl, Stephanie, Robert Graham, Sinnott Murphy, and Deepak Sivaraman. 2015. "Analysis of High-Resolution Utility Data for Understanding Energy Use in Urban Systems: The Case of Los Angeles, California." *Journal of Industrial Ecology*, June, n/a – n/a. doi:10.1111/jiec.12299.

Ratti, Carlo, Nick Baker, and Koen Steemers. 2005. "Energy Consumption and Urban Texture." *Energy and Buildings* 37 (7): 762–76. doi:10.1016/j.enbuild.2004.10.010.

Reiss, Peter C, and Matthew W White. 2005. "Household Electricity Demand, Revisited." *Review of Economic Studies* 72 (3): 853–83. doi:10.1111/0034-6527.00354.

Rey, S. J., L. Anselin, D. C. Folch, D. Arribas-Bel, M. L. Sastre Gutierrez, and L. Interlante. 2011. "Measuring Spatial Dynamics in Metropolitan Areas." *Economic Development Quarterly* 25 (1): 54–64. doi:10.1177/0891242410383414.

Rey, S. J., and Myrna L. Sastré-Gutiérrez. 2010. "Interregional Inequality Dynamics in Mexico." *Spatial Economic Analysis* 5 (3): 277–98. doi:10.1080/17421772.2010.493955.

Sanquist, Thomas F, Heather Orr, Bin Shui, and Alvah C Bittner. 2012. "Lifestyle Factors in U.S. Residential Electricity Consumption." *Energy Policy* 42 (March). Elsevier: 354–64. doi:10.1016/j.enpol.2011.11.092.

Shimoda, Yoshiyuki, Takuro Fujii, Takao Morikawa, and Minoru Mizuno. 2004. "Residential End-Use Energy Simulation at City Scale." *Building and Environment* 39 (8): 959–67. doi:10.1016/j.buildenv.2004.01.020.

Stephan, André, and Laurent Stephan. 2014. "Reducing the Total Life Cycle Energy Demand of Recent Residential Buildings in Lebanon." *Energy* 74 (September): 618–37. doi:10.1016/j.energy.2014.07.028.

Tso, Geoffrey K.F., and Jingjing Guan. 2014. "A Multilevel Regression Approach to Understand Effects of Environment Indicators and Household Features on Residential Energy Consumption." *Energy* 66. Elsevier Ltd: 722–31. doi:10.1016/j.energy.2014.01.056.

Tso, Geoffrey K.F., and Kelvin K.W. Yau. 2007. "Predicting Electricity Energy Consumption: A Comparison of Regression Analysis, Decision Tree and Neural Networks." *Energy* 32 (9): 1761–68. doi:10.1016/j.energy.2006.11.010.

U.S. Census Bureau. 2012. "American Community Survey." www.census.gov/acs/www/.

U.S. Department of Energy. 2008. "Energy Efficiency Trends in Residential and Commercial Buildings." http://apps1.eere.energy.gov/buildings/publications/pdfs/corporate/bt_stateindustry.pdf.

———. 2009. "Building America Climate Zones."

http://energy.gov/eere/buildings/climate-zones .

U.S. Energy Information Administration. 2005. "Residential Energy Consumption Survey."

———. 2013a. "Electricity Flow Mapping."

http://www.eia.gov/totalenergy/data/monthly/pdf/flow/electricity.pdf.

———. 2013b. "Energy Flow Mapping by Sector."

http://www.eia.gov/totalenergy/data/monthly/pdf/flow/total_energy.pdf.

CHAPTER 4

EXPANDING ENERGY EFFICIENCY TO REDUCE RESIDENTIAL ELECTRICITY DEMAND UNDER CLIMATE CHANGE

This chapter is an article in preparation for *Nature Communications*. As such, the majority of the methods can be found in Appendix C.

Climate change could significantly affect consumer demand for energy in buildings. Changing temperatures may alter heating and cooling loads of buildings. Warming climates could lead to the increased saturation of cooling technologies (Sailor and Pavlova 2003; Davis and Gertler 2015) thereby increasing electricity consumption. I develop an assessment of changing residential electricity and natural gas (NG) demand in Los Angeles County, California (LAC) under multiple climate change projections and investigate the potential for energy efficient technologies to offset increased demand. I calibrate prototypical residential building energy use with actual energy use by neighborhood accounting for differences in building materials, appliances, and energy consumption. Under temperature increases, I find that without policy intervention, residential electricity demand could increase by as much as 55-68% between 2020 and 2060. However, aggressive policy intervention aimed at upgrading heating systems, cooling systems, and appliances could result in electricity use increases as low as 13%, potentially avoiding the installation of new generation capacity. I therefore recommend aggressive energy efficiency measures to mitigate projected increases in LAC's energy consumption.

In the southwestern United States (U.S.), climate change could lead to particularly large increases in electricity demand via increased need for cooling (Sailor and Pavlova 2003;

Davis and Gertler 2015). Increased cooling demands could strain the electricity supply, at the same time that generation and transmission capacity could be affected by decreases in water availability and increases in water and air temperatures (Bartos et al. 2016; Sathaye et al. 2011). LAC has 3.1% of the national population and consumes 2% of total electricity in the U.S. with a relatively low saturation of air conditioning in homes (40%) (California Energy Commission 2009). The state of California predicts that the population of LAC will increase by 17% to 11.5 million inhabitants by 2060, creating new demands for housing and energy (Department of Finance 2013). Under Assembly Bill 32, California targets greenhouse gas (GHG) emissions reductions of 80% below 1990 levels by 2050, and previous research suggests that increased electrification of space heating, water heating, and transportation coupled with de-carbonization of the electricity supply will be fundamental to meeting this goal (Morrison et al. 2015). Current trends also suggest that consumers are already fuel switching from fossil fuels to electricity for residential space conditioning (U.S. Energy Information Administration 2014b) . While fuel switching could help meet GHG mitigation targets, it will increase demand for electricity, and there is mounting evidence that these traditional power supplies could be constrained by drought and climate change impacts (Bartos and Chester 2015b; van Vliet et al. 2016). Without proper planning, meeting these demands could come at high economic and environmental costs. Faced with this potentially constrained supply, forecasting demand changes under future climate change is critical to identifying cost-effective paths to meet or mitigate the demand.

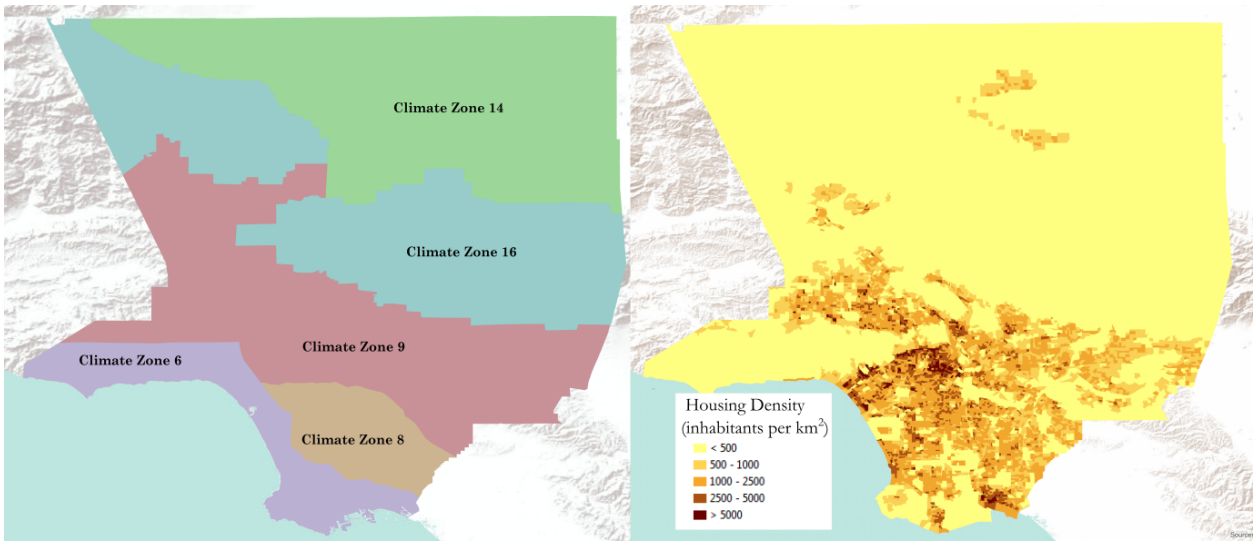


Figure 12: Climate Zones and Population Density of LAC. LAC has five climate zones as designated by the California Energy Commission (left). Climate Zone 9 contains the City of Los Angeles and is the most densely population area of LAC (right).

I develop a spatially and temporally resolute model of residential energy use in LAC, which I calibrate against actual consumption data (Pincetl et al. 2015). Using survey data and physical information about the building stock, I create 84 building simulations as prototypes to represent all residential buildings in LAC. I subdivide the prototypes based upon 1) year of construction, 2) classification (i.e. single family detached, townhouse, etc.), and 3) climate zone. LAC has five major climate zones ranging from temperate coastal areas to inland mountainous areas (Figure 12). I map every residential building in LAC to a prototype and scale energy use to the census block group (CBG) level. There are 6,422 CBGs in LAC, and my calibration set includes 2501 CBGs (Appendix C). I develop weather files based on local weather station and solar radiation data for each climate zone for the time period of the calibration data (June 2011 - July 2012). I adjust the prototypes' thermal properties and appliance consumption until the modeled electricity falls within 2% of actual use (Appendix C). With a calibrated model, I then develop electricity and NG forecasts for each prototype under various climate change scenarios, and scale the results to the county level, including

the projected population increase of 17% by scaling the housing stock. I utilize downscaled output from 10 general circulation models (GCMs) and representative concentration pathways (RCPs) 2.6, 4.5, 6.0, and 8.5 for each of the LAC climate zones to create weather predictions between 2020 and 2060 (Appendix C). I simulate all prototypes under 10 GCMs and 39 types of heating and cooling equipment, and then I average the results to obtain a mean prediction of total energy with the differentiation in the GCMs representing the variability of the forecast (Appendix C). I also maintain spatial resolution in my simulation ensemble to investigate spatial differences in changing energy demand under climate change (Figure 13).

Within the forecast, I evaluate appliance technology adoption and efficiency gains to test the potential to offset increases in demand. I develop four scenarios to test with each of the climate predictions: 1) Business as Usual, 2) Business as Usual + High Electrification, 3) Moderate Efficiency Intervention, and 4) Aggressive Efficiency Intervention. For each of the scenarios, I include dynamic building turnover rates based upon stock modeling in LAC (Reyna and Chester 2015), stock expansion due to population growth, appliances (water heaters, televisions, ovens etc.) (California Energy Commission 2009), and heating/cooling equipment (California Energy Commission 2009). These variables are dynamically changed within each prototype category for each year between 2020 and 2060 so that there is a distinct forecast for electricity and NG in each hour over this time period. For heating/cooling equipment, I use a weighted average consumption of different technologies within each prototype as opposed to only using the most prevalent technology (e.g. NG furnaces for heating), which captures the variability of technologies used throughout LAC. Scenario 1 includes existing and proposed policies and normal building and appliance turnover. Scenario 2 includes the same assumptions except that all retired water and space

heating equipment, regardless of original fuel type, is replaced with an electric version. This scenario captures aggressive electrification which previous studies claim is necessary to meet AB 32 GHG goals. Scenario 3 includes heavy electrification (as in Scenario 2), but adds in moderate efficiency gains in appliances beyond existing standards and increased building turnover. Scenario 4 also starts with heavy electrification, but includes efficiency and building gains beyond current technologies (Appendix C). These mitigation strategies are based upon augmented versions of existing policies at the state and federal level and apply to both electric and NG appliances. Efficiency improvements in homes can also lead to changes in energy consumption behavior, potentially offsetting some of the savings from efficiency. I include a 10% rebound penalty across all scenarios based upon residential efficiency elasticities (Kenneth Gillingham, Rapson, and Wagner 2016) (Appendix C). The true value of the rebound is somewhat uncertain, but is likely small compared to the other variables in the model such as housing stock growth and climate change.

Without intervention, electricity demand in LAC could increase by as much as 68% under BAU with heavy electrification (Scenario 2 and RCP 8.5) or by nearly 40% in BAU without increased electrification (Scenario 1 and RCP 8.5) (Figure 14). Scenario 1 represents an energy future with minimal efficiency increases beyond current policies, and Scenario 2 represents a future which incentivizes heavy electrification of water and space heating without improving efficiency beyond Scenario 1. Under the most optimistic climate RCP 2.6, electricity demand increases for Scenarios 1 and 2 are 31% and 55%, respectively. I develop these two cases to represent the upper and lower bounds of potential energy savings. In these scenarios, increasing demand is driven by 1) increased adoption of cooling equipment, 2) increased use of cooling equipment as average temperatures increase, 3) population growth, and 4) moderate increases in plug loads. These baseline scenarios also include a

decrease in NG use, but total energy consumption increases of 14 -19% for Scenario 1 and 16%-25% for Scenario 2, indicating that without increases in efficiency, climate change and population growth will continue to demand further energy resources. These increases are comparable to previous energy forecasts for LAC (Morrison et al. 2015).

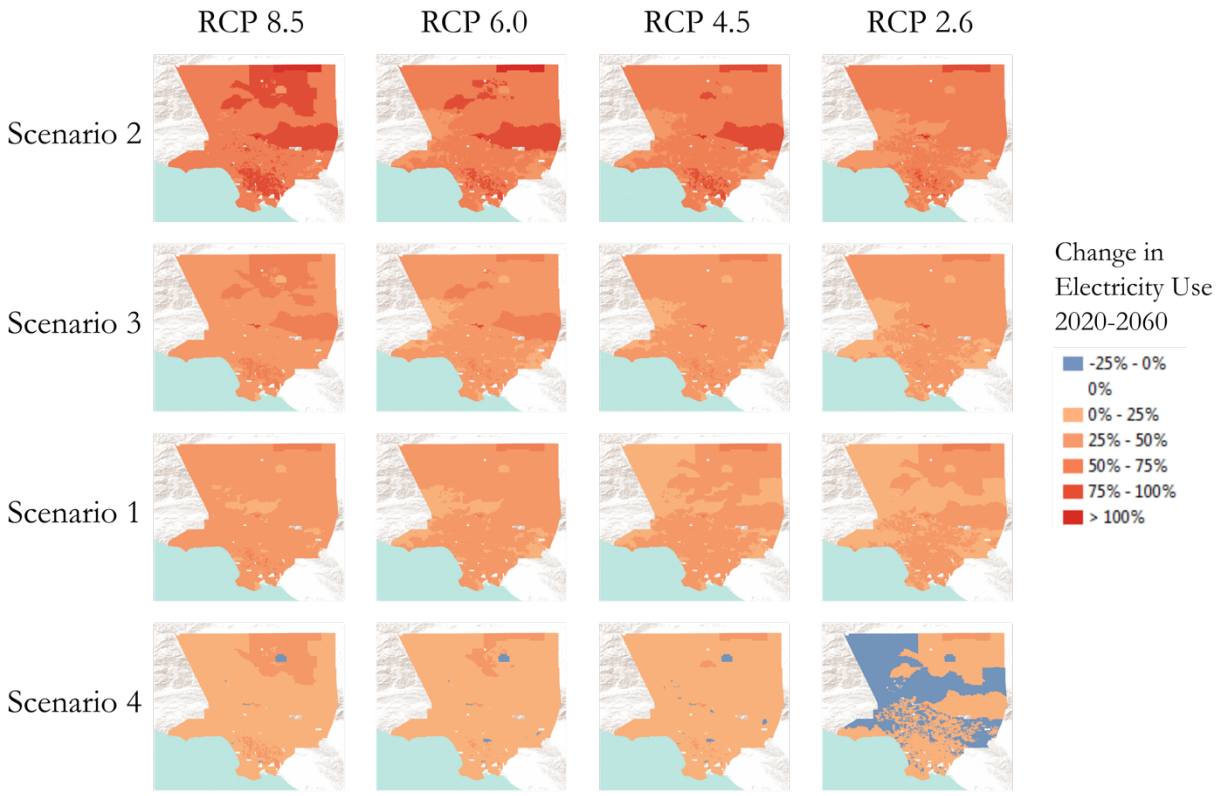


Figure 13: Change in Electricity Use Across Los Angeles County by Census Block Group between 2020 and 2060. Each map displays the average percent change in residential electricity demand for that CBG between 2020 and 2060 under a specific RCP and mitigation scenario. Increases are represented in shades of red and decreases are represented in shades of blue. Changes in use are not evenly distributed throughout LAC, and spatially targeted efficiency policies could help optimize application of subsidies.

My results show that while BAU Scenarios 1 and 2 forecast increases in total energy use under all RCPs, accelerating the adoption of efficient appliances (Scenarios 3 and 4) can offset some or most of the increased demand (Figure 14). In the two mitigation scenarios under RCP 8.5, energy efficiency can narrow increases in electricity consumption to between 21% and 44%, and total energy use changes between -8% and 8%. In Scenario 4 under RCP

2.6 (the most optimistic climate and aggressive policy scenario) electricity use is projected to increase by only 13%, and total energy use to decline by 16% (driven by NG reductions). This is over a period with a projected population increase of 17%. This suggests that energy efficiency could be a viable resource for mitigating increases in energy use.

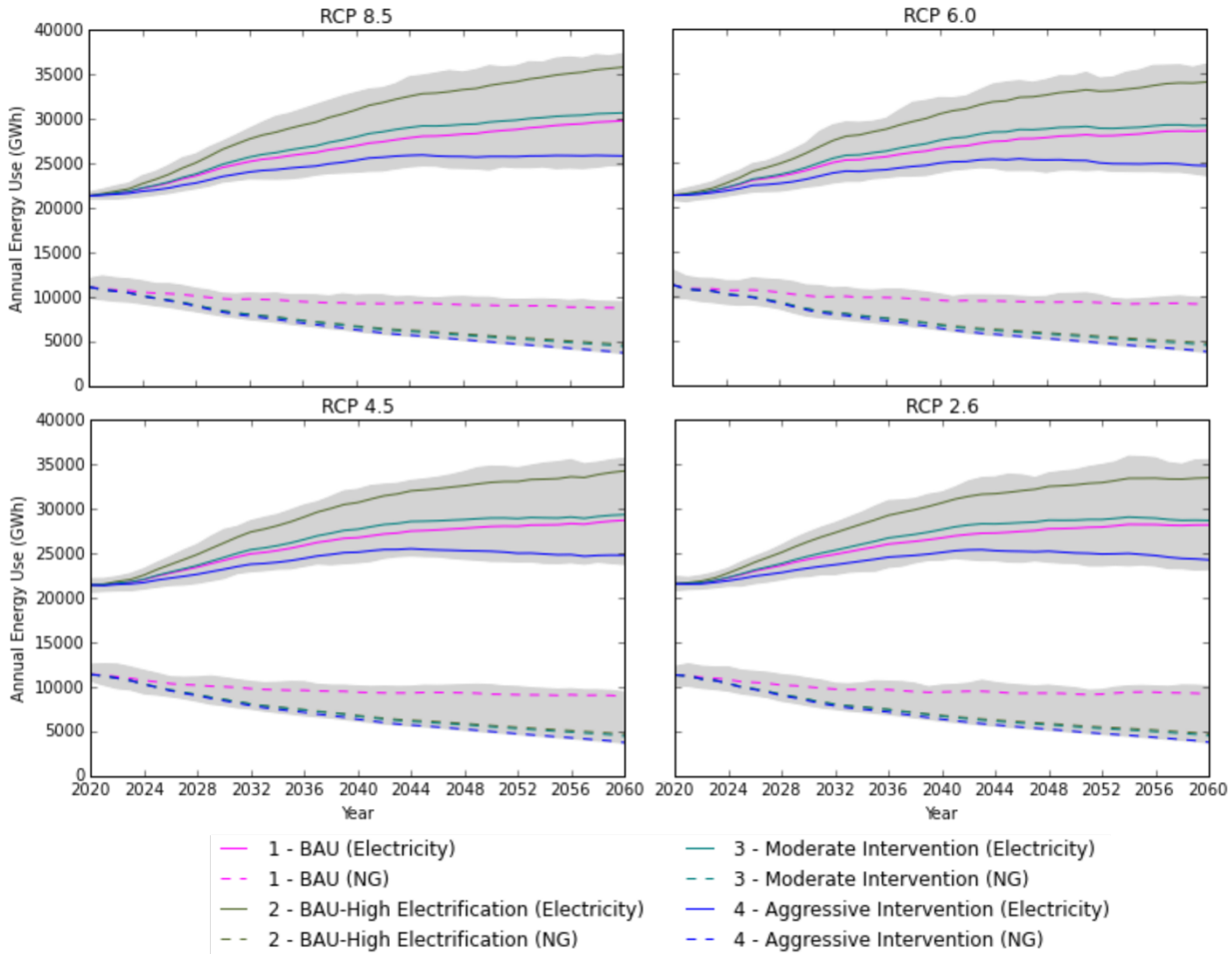


Figure 14: Total Energy Use 2020-2060. Here I present change in total energy use for all four RCPs and scenarios between 2020 and 2060. The upper line of plots subdivides changes in energy use between electricity and natural gas, with electricity presented as a solid line and natural gas as a dashed line. In the lower figure, the two are added together to show the total change in energy consumption. The grey area shows the variability in my forecast due to the different climate models.

To ensure reliability, electrical grids must be designed to meet highest demand periods which occur in hot summer months, and my simulations show that the peak demand could more than double under RCP 8.5 (Figure 15). This is a larger capacity expansion than

what total annual consumption would suggest (a 68% increase). Unlike NG, which is available on-site and on-demand, electricity provision is met from capacity across states which must be planned in advance and actively managed so that supply can continually meet demand. A scenario with large-scale fuel-switching between electricity and NG could mean an expansion of electricity infrastructure including the addition of expensive generation stations. A more cost-effective approach might be investing in efficiency; in RCP 8.5, aggressive efficiency reduces the 40-year maximum annual demand increase from 128% to 57%. Efficiency can save money for homeowners (Brown et al. 2008) and avoid costly upgrades for utility companies (Molina 2014; Billingsley et al. 2014). For 2060 in Scenario 2 under RCP 8.5, air conditioning is responsible for 82% of electricity consumption at the peak hour, so targeting energy efficiency in cooling equipment (and building thermal shells) could be the most effective approach for reducing peak electricity demand.

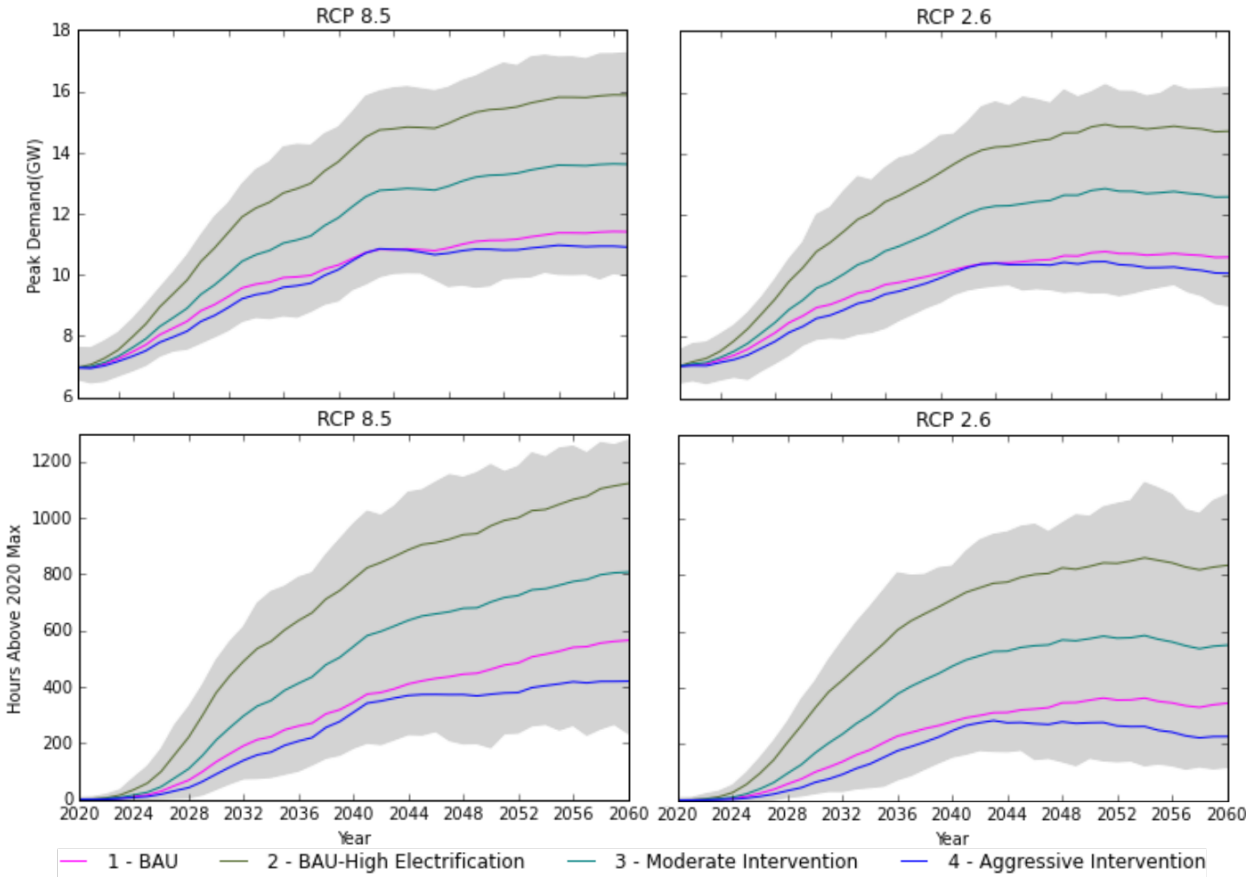


Figure 15: Electricity Demand 2020-2060. The upper row of figures displays the maximum annual electricity demand 2020 – 2060, and the bottom row shows the number of hours per year with an electricity demand above the maximum of 2020. The colored lines are the average values across all models and the grey is the variability due to differences in the GCMs.

My results show that the majority of projected electricity increases can be offset and net energy use can decline through the aggressive application of energy efficient technologies. Whereas electricity consumption varies significantly under different RCPs and scenarios, NG consumption is stagnant or declining in all cases. RCP 8.5, my results indicate that aggressive energy efficiency (Scenario 4) can save nearly 10 TWh of electricity consumption and 0.9 TWh (3.9 PJ) of NG compared to Scenario 2 in 2060 alone. In RCP 8.5 – Scenario 4, each household would save approximately $300 in 2060 compared to Scenario 2, including the added cost of appliance upgrades without subsidies or rebates

(Appendix C). Space conditioning is a major driver of the increases in electricity consumption in Scenario 2 due to both increased air conditioning saturation and the electrification of heating technologies. My results indicate that directly targeting these increases through efficiency could be an effective means of mitigating electricity increases. Most electricity savings (~38%) come from the targeting of space heating and cooling: switching the majority of the stock to high efficiency heat pumps, incentivizing building turnover, and improving building thermal shells. Additionally, a reduction of 17% can be achieved from efficient heat pump water heaters, 17% from lower consumption of TVs and computers, and 11% from upgraded refrigerators (Appendix C).

Aggressive building upgrades and appliance efficiency improvements have the potential to offset projected increases in energy demand. If large-scale fuel switching between electricity and NG occurs, it will additionally be imperative to reduce consumption as electricity supply could be constrained. According to my simulations, in the heating and cooling sector existing technologies could be enough to substantially offset increases in this area, however, timely intervention is necessary to ensure near universal adoption as annual temperatures continue to climb (Intergovernmental Panel on Climate Change 2014). LAC will have to continually phase-out older technologies and raise the standard for minimum acceptable efficiency, and this will need to be done in a series of stages to avoid large energy and appliance purchase cost increases for consumers. In other appliance categories, aggressive efficiency upgrades will require technology innovation that significantly improves upon commercially existing models. For example, water heaters, which currently consume 28% of energy in LAC, will need to decrease energy consumption in homes by 70% over the next 45 years (Appendix C). Implementation of policies impacting these efficiency upgrades will need to happen within the next decade if these aggressive goals are to be met. If such

investments are made at the same time as de-carbonizing the energy supply, there can be co-benefits which could significantly lower the GHG emissions of residential power consumption.

4.1 References

Bartos, Matthew D., and Mikhail V. Chester. 2015. "Impacts of Climate Change on Electric Power Supply in the Western United States." *Nature Climate Change* 5 (8): 748–52. doi:10.1038/nclimate2648.

Bartos, Matthew D., Mikhail V. Chester, Nathan Johnson, Brandon Gorman, Daniel Eisenberg, Igor Linkov, and Matthew Bates. 2016. "Impacts of Climate Change on Electric Transmission Capacity and Peak Electricity Load in the United States." *Environmental Research Letters* In Review.

Billingsley, Megan a, Ian M Hoffman, Elizabeth Stuart, Steven R Schiller, Charles a Goldman, and Kristina Lacommare. 2014. "The Program Administrator Cost of Saved Energy for Utility Customer-Funded Energy Efficiency Programs." *Lawrence Berkeley National Laboratory*. https://emp.lbl.gov/sites/all/files/lbnl-6595e.pdf.

Brown, Rich, Sam Borgeson, Jon Koomey, and Peter Biermayer. 2008. "U.S. Building-Sector Energy Efficiency Potential. LBNL-1096E." Berkeley, CA. http://escholarship.org/uc/item/8vs9k2q8.

California Energy Commission. 2009. "California Statewide Residential Appliance Saturation Study: Final Report."

Davis, Lucas W., and Paul J. Gertler. 2015. "Contribution of Air Conditioning Adoption to Future Energy Use under Global Warming." *Proceedings of the National Academy of Sciences* 112 (19): 5962–67. doi:10.1073/pnas.1423558112.

Department of Finance. 2013. "New Population Projections: California To Surpass 50

Million in 2049," 2.

Gillingham, Kenneth, David Rapson, and Gernot Wagner. 2016. "The Rebound Effect and Energy Efficiency Policy." *Review of Environmental Economics and Policy* 10 (1): 68–88. doi:10.1093/reep/rev017.

Intergovernmental Panel on Climate Change. 2014. "Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II, and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change." Geneva, Switzerland. http://www.ipcc.ch/report/ar5/syr/.

Molina, Maggie. 2014. "The Best Value for America's Energy Dollar : A National Review of the Cost of Utility Energy Efficiency Programs." http://www.aceee.org/research-report/u1402.

Morrison, Geoffrey M., Sonia Yeh, Anthony R. Eggert, Christopher Yang, James H. Nelson, Jeffery B. Greenblatt, Raphael Isaac, et al. 2015. "Comparison of Low-Carbon Pathways for California." *Climatic Change* 131 (4): 545–57. doi:10.1007/s10584-015-1403-5.

Pincetl, Stephanie, Robert Graham, Sinnott Murphy, and Deepak Sivaraman. 2015. "Analysis of High-Resolution Utility Data for Understanding Energy Use in Urban Systems: The Case of Los Angeles, California." *Journal of Industrial Ecology*, June, n/a – n/a. doi:10.1111/jiec.12299.

Reyna, Janet L, and Mikhail V Chester. 2015. "The Growth of Urban Building Stock: Unintended Lock-in and Embedded Environmental Effects." *Journal of Industrial Ecology* 19 (4): 524–37. doi:10.1111/jiec.12211.

Sailor, David J., and A.A. Pavlova. 2003. "Air Conditioning Market Saturation and Long-Term Response of Residential Cooling Energy Demand to Climate Change." *Energy* 28

(9): 941–51. doi:10.1016/S0360-5442(03)00033-1.

Sathaye, Jayant, Larry Dale, Peter Larsen, Gary Fitts, Kevin Koy, Sarah Lewis, and Andre Lucena. 2011. "Estimating Risk to California Energy Infrastructure From Projected Climate Change." Berkeley, CA (United States). doi:10.2172/1026811.

U.S. Energy Information Administration. 2014. "Everywhere but Northeast, Fewer Homes Choose Natural Gas as Heating Fuel." *Today in Energy*. https://www.eia.gov/todayinenergy/detail.cfm?id=18131.

van Vliet, Michelle T. H., David Wiberg, Sylvain Leduc, and Keywan Riahi. 2016. "Power-Generation System Vulnerability and Adaptation to Changes in Climate and Water Resources." *Nature Climate Change*, no. January (January). doi:10.1038/nclimate2903.

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Author contributions

J.L.R. and M.V.C designed the study jointly. J.L.R. performed the analyses and collaborated with M.V.C. in interpreting the results and writing the manuscript.

CHAPTER 5

CONCLUSION

In this dissertation, I developed a detailed case study of urban growth and energy use in LAC in order test a combined methodology for energy forecasting. This research not only provides directly recommendations for reduction potential in LAC, but it also contributes to the larger understanding of urban energy use. This study links historic growth trends to future energy forecasting, and it also explores the importance of geographical boundaries and spatial resolution for urban-scale energy assessment. All of this can contribute to improved urban energy assessment in other cities beyond LAC. In this section, I overview trends in urban growth and energy throughout the United States and the application of my methodological framework to other areas.

5.1 Energy Trends

Buildings are a major consumer of energy globally, and growth in population, HVAC adoption, and increased time indoors will continue to drive increased consumption in the future (Pérez-Lombard, Ortiz, and Pout 2008). In addition to these (relatively) well-documented drivers of future energy use, there are several other sources of potential increases. Plug loads in homes in the United States have been projected to increase by as much as 5% per year in the near future (Gorin 2015) as consumer electronics proliferate in homes. As discussed, climate change could increase air conditioning adoption and use. In some areas of this country, climate change could also decrease heating in winter in response to warmer temperatures, but this shift to lower heating and increased cooling will also be a shift in fuels, as cooling technologies are nearly exclusively electric, whereas heating fuels are currently primarily petroleum based. Another major shift towards electricity could come in

the form of transportation electrification. The U.S. has 38% of the total electric vehicles worldwide, and this population is projected to grow to 20 million vehicles by 2020 (a >10,000% increase in the stock) (Trigg et al. 2013). As these vehicles enter the stock and begin charging with electricity at residences and commercial facilities, this might increase not only the total units required from the electric grid, but also shift temporal use patterns of energy in buildings. In future research, quantifying these potential changes in consumption and reducing uncertainty of predictions will be crucial to planning for and managing future energy use. It will be especially important to co-manage electric demand and supply (via development of renewable generation sources) as technologies fuel switch towards electricity.

In formulating responses to rising energy use, building technology lock-in has constricted the options for mitigating energy demand increases in buildings in many mature cities throughout the U.S. In my LAC case study, major changes to the building stock itself are not possible, as the stock is relatively locked-in and fixed. Other mature cities, such as New York City, will face similar challenges in reducing energy demand. In these cases, the shell of most of the building stock is set so the options for upgrading the stock include appliance efficiency upgrades (including efficiency) or upgrades to the thermal shell such as windows or improved insulation. Regulations improving thermal properties of buildings in new construction will likely be ineffectual to reducing total energy use because of the long residence time of buildings within a stock. Efficiency, however, is still a large resource for locked-in cities. Even in LAC, which is located in a state with the most aggressive energy efficiency programs in the United States, has potential for substantial reduction in consumption through increased efficiency measures, much of which could still be cost-effective (Brown et al. 2008). Understanding spatial patterns of energy use could also allow

these cities to specifically target areas where efficiency potential is the greatest, leading to a more efficient distribution of resources for efficiency programs. Although not quantified here, targeting energy conservation through behavioral changes either through voluntary or economic related means is another potential path to reduced building energy use.

Another subset of cities in the United States are experiencing periods of population and urban expansion, so these cities would be best positioned by integrating more aggressive new building codes geared towards lower energy consumption now as infrastructure expands. This could help to avoid lock-in at a higher energy consuming regime as infrastructure matures. The U.S. population is forecasted to grow 41% by 2050 (U.S. Census Bureau 2009), and much of that growth with be in urban areas (U.S. Conference of Mayors 2012). The mean population center of the United States continues to shift south and west (U.S. Census Bureau 2010), and it is the cities in these areas that will grow rapidly. For U.S. metropolitan statistical areas that will have over 1.3 million inhabitants by 2042, 20 of them will experience growth rates over 50%, and all of them are in the southern or western part of the country (Table 6). As these areas are all warmer climates (that might become even warmer under climate change), they would be best positioned by targeting the thermal shells of new construction buildings, as this will have a long-lasting impact on the energy consumption due to cooling. Additionally, as personal transportation could become increasingly electrified, cities should consider the transportation-related energy consequences of low-density development as these burdens could be shifted to electric grid. Public transportation also requires a minimum population density to be viable, so there could also be energy co-benefits in moving riders onto transit.

Table 6: Projected 30-Year Population Change for U.S. Cities (U.S. Conference of Mayors 2012)

	2012 Population	*2042 Population*	*Percent Change*
Fort Myers, FL	640,000	1,310,000	103%
McAllen, TX	820,000	1,610,000	96%
Austin, TX	1,840,000	3,520,000	91%
Phoenix, AZ	4,330,000	8,160,000	88%
Raleigh, NC	1,190,000	2,230,000	87%
Riverside, CA	4,380,000	8,010,000	83%
Orlando, FL	2,210,000	3,980,000	80%
Atlanta, GA	5,450,000	9,140,000	68%
Las Vegas, NV	1,990,000	3,320,000	67%
Salt Lake City, UT	1,170,000	1,950,000	67%
Dallas, TX	6,700,000	11,030,000	66%
Charlotte, NC	1,830,000	3,010,000	65%
Houston, TX	6,220,000	10,180,000	64%
San Antonio, TX	2,240,000	3,650,000	62%
Denver, CO	2,650,000	4,220,000	59%
Jacksonville, FL	1,380,000	2,140,000	56%
Sacramento, CA	2,200,000	3,420,000	55%
Nashville, TN	1,640,000	2,510,000	53%
Tampa, FL	2,870,000	4,360,000	52%
Miami, FL	5,770,000	8,610,000	50%

5.2 Framework for Energy Forecasting

Based upon the conclusions of this dissertation, I now present a generalized methodological framework for applying my urban energy assessment to other cities. The methods that I present are applicable to both developed and developing urban areas in the United States. I propose three phases of research: Phase 1 – Prototype Development, Phase 2 – Model Calibration, and Phase 3 – Forecasting. These phases allow for a through understanding of how the city has grown (what the current development phase is) and creating a bottom-up energy forecast. This will help identify the best strategies for energy conservation and efficiency based upon the growth of the city and drivers of building energy use. These core phases are summarized in Figure 16.

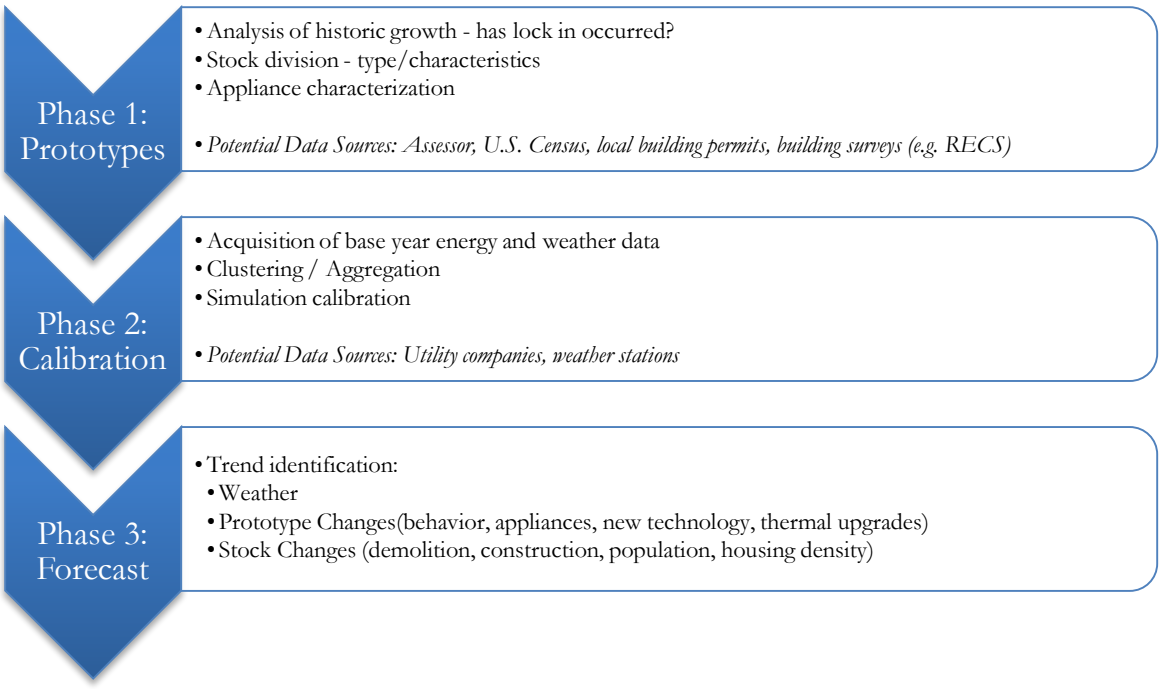


Figure 16: Energy Forecasting Framework

5.2.1 Phase 1 – Prototype Development

The first phase in the reproducible framework involves identifying the general growth pattern of the city and creating building energy prototypes. This should identify 1) if lock-in has already occurred, and 2) the current building turnover trends. This can be estimated with a growth model as presented in Chapter 2, but it is possible, particularly in younger cities, that quality data describing construction and demolition already exist for direct use in the model. Local building permits could provide detailed data on building construction. If data exist, turnover rates should be characterized by vintage and building type.

Once the building stock dynamics have been characterized, prototypical energy simulations should be developed. The stock should be divided into prototypes based upon building type (e.g. single family, multi-family, etc.) and other characteristics which might impact energy consumption (e.g. vintage, size). County Assessor databases are a potential data source for creating a full census of a region's building stock. Additionally, appliance

distributions should be developed for all major energy consuming appliances within each prototype. National appliance surveys (e.g. RECS) filtered to the specific locale could be used for this, but ideally, local surveys and data would be developed specifically for this purpose. The goal of this portion is to create prototypes which are as homogenous as possible within each category while balancing the additional resources and computation time necessary to have more prototype categories.

With a fully characterized ensemble of building prototypes, simulations should be developed to estimate energy use within each building type. Potential softwares include EnergyPlus, eQuest, or TRNSYS. The models should be built with the data-based characteristics of the prototypes.

5.2.2 Phase 2 – Model Calibration

Once the full prototyping simulation ensemble has been developed, data should be collected for calibrating the model to the base year. Ideally, energy consumption data for all sources (electricity, natural gas, propane, etc.) at a resolute temporal and spatial scale could be obtained. Generally, these will need to be obtained from utility companies, but occasionally local government agencies might have some energy data available. Detailed spatial data is helpful if sub-urban detail is desired in the final model, but highly resolute data might need aggregating. The clustering algorithm tested in Chapter 3 is a potential method to intelligently aggregate energy data.

In addition to energy data, weather data for the same time period as the energy consumption data are needed. This includes at least temperature data, but potentially other information such as precipitation or solar radiation as well. Potential sources of data for this include data recorded at weather stations. With this data, weather files for the energy simulation software need to be developed for the time period of the assessment.

With the energy and weather data obtained, the simulation ensemble should be run for the base year and calibrated. Beyond the calibration method used in Chapter 5, if the energy data are spatially resolute, the data associated with different geographies could be segregated into training and testing sets. The training set could be used to adjust the prototypes to match the calibration data, and the testing data could be used to test the adjustments to ensure that the model does not over-fit the calibration data.

5.2.3 Phase 3 - Forecasting

For phase three, it is important to identify potential trends unique to the urban area of interest. Trends should inform how one of the following changes over time: 1) weather, 2) energy use within each prototype category, and 3) the count of each prototype within the city. For weather, climate change predictions can provide estimates of how the temperature and other weather conditions might change with increased carbon levels in the atmosphere. Energy use within each prototype category includes both changes in inhabitant behavior, modifications to the prototypes themselves, or adoption of different energy consuming equipment. Behavioral changes could be in response to changes in energy pricing, number of inhabitants in the home, or changing preferences overtime (e.g. cooler internal temperatures in the summer). Not all of these trends can necessarily be predicted, as behavior will change in response to many factors, but different behavioral scenarios could be developed. Changes to the buildings themselves or equipment involve forecasting building turnover rates, the projected lifetimes of appliances, and changing appliance efficiency. Additionally, homeowners might obtain completely new technologies that change energy consumption patterns, for example electric vehicles. For the count of each prototype, potential factors influencing this are population growth, building construction, building

turnover rates, and changes in housing density. Not all of these trends necessarily have to be included in a forecast, but they are all factors to consider in the forecast development

5.3 Conclusion

In this dissertation, I have explored the connections between building infrastructure growth, lock-in, and energy using a mixture of detailed engineering models. Building decisions have a long lasting influence on urban energy consumption, as eventually cities reach a state of "lock-in" where after large-scale expansion of the urban building stock is not possible. Growing cities are best positioned by incentivizing efficiency building construction practices to arrive at a lower energy regime by the lock-in phase. Applying my modeling methods to these growing cities can help in evaluating different building stock expansion scenarios by quantifying the long-term energy use of different combinations of new prototypes. This could also be expanded to include a spatial component impacting the travel distance (and electricity consumption) from electric vehicles. These two components can inform where would be most beneficial to expand stock within the city and what type of buildings the city would be best positioned to incentivize building. Mature cities that have already become locked in, such as LAC, should instead focus on efficiency of appliances and incremental upgrades to the building stock. In these cities, the model can help identify which appliances to target, and when paired with a cost assessment, which ones can be deployed at cost savings to the consumer and which will require additional incentives. As my model can be applied in diverse cities, it has the potential for identifying reduction strategies in multiple contexts.

5.4 References

Brown, Rich, Sam Borgeson, Jon Koomey, and Peter Biermayer. 2008. "U.S. Building-Sector Energy Efficiency Potential. LBNL-1096E." Berkeley, CA.

http://escholarship.org/uc/item/8vs9k2q8.

Gorin, Tom. 2015. "Plug Loads in the Residential and Commercial Forecasts." http://docketpublic.energy.ca.gov/PublicDocuments/15-IEPR-05/TN205066_20150618T095153_Plug_Loads_in_the_Residential_and_Commercial_Forecasts.pptx.

Pérez-Lombard, Luis, José Ortiz, and Christine Pout. 2008. "A Review on Buildings Energy Consumption Information." *Energy and Buildings* 40 (3): 394–98. doi:10.1016/j.enbuild.2007.03.007.

Trigg, T, P Telleen, R Boyd, and F Cuenot. 2013. "Global EV Outlook: Understanding the Electric Vehicle Landscape to 2020." http://www.iea.org/publications/freepublications/publication/name-37024-en.html\nhttp://scholar.google.com/scholar?hl=en&btnG=Search&q=intitle:Global+EV+Outlook:+Understanding+the+Electric+Vehicle+Landscape+to+2020#0.

U.S. Census Bureau. 2009. "United States Population Projections: 2000 to 2050." https://www.census.gov/population/projections/files/analytical-document09.pdf.

———. 2010. "Mean Center of Population for the United States : 1790 to 2010." https://www.census.gov/2010census/news/pdf/centerpop_mean2010_1.pdf.

U.S. Conference of Mayors. 2012. "U.S. Metro Economies." http://usmayors.org/metroeconomies/2014/06/report.pdf.

FULL REFERENCES

110th U.S. Congress. 2007. *Energy Independence and Security Act of 2007*.

Akbari, H., J. Eto, S. Konopacki, A. Afzal, K. Heinemeier, and L. Rainer. 1993. "Integrated Estimation of Commercial Sector End-Use Load Shapes and Energy Use Intensities in the PG&E Service Area, LBL-34263." Berkeley, CA. doi:10.2172/10140911.

Akbari, Hashem, J Eto, S Konopacki, Asim Afzal, K Heinemeier, and Leo Rainer. 1993. "Integrated Estimation of Commercial Sector End-Use Load Shapes and Energy Use Intensities in the PG&E Service Area, LBL-34263."

American Society of Civil Engineers. 2012. "Report Card for Los Angeles County Infrastructure." http://www.ascemlab.org/pdf/2012-ASCE-Report Card-Revised-10-2-2012-REVISED_FINAL_FOR THE WEBSITE.pdf.

———. 2013. *Minimum Design Loads for Buildings and Other Structures*.

Anderson, John E., Gebhard Wulfhorst, and Werner Lang. 2015. "Energy Analysis of the Built environment—A Review and Outlook." *Renewable and Sustainable Energy Reviews* 44 (April). Elsevier: 149–58. doi:10.1016/j.rser.2014.12.027.

Anderson, Kent P. 1973. "Residential Demand for Electricity: Econometric Estimates for California and the United States." *The Journal of Business* 46 (4): 526. doi:10.1086/295576.

Athena Sustainable Materials Institute. 2012. "Athena Impact Estimator for Buildings, Version 4.1.1412."

Barter, Paul. 2004. "Transport, Urban Structure and 'Lock-In' in the Kuala Lumpur Metropolitan Area." *International Development Planning Review* 26 (1): 1–24. doi:10.3828/idpr.26.1.1.

Bartos, Matthew D., and Mikhail V. Chester. 2015a. "Supplementary Information: Impacts of Climate Change on Electric Power Supply in the Western United States." *Nature Climate Change* 5 (8): 748–52. doi:10.1038/nclimate2648.

———. 2015b. "Impacts of Climate Change on Electric Power Supply in the Western United States." *Nature Climate Change* 5 (8): 748–52. doi:10.1038/nclimate2648.

Bartos, Matthew D., Mikhail V. Chester, Nathan Johnson, Brandon Gorman, Daniel Eisenberg, Igor Linkov, and Matthew Bates. 2016. "Impacts of Climate Change on Electric Transmission Capacity and Peak Electricity Load in the United States." *Environmental Research Letters* In Review.

Belcher, S. E., J. N. Hacker, and D. S. Powell. 2005. "Constructing Design Weather Data for Future Climates." *Buildind Services Engineering Research & Technology* 1 (26): 49–61. doi:10.1191/0143624405bt112oa.

Berkhout, Frans. 2002. "Technological Regimes, Path Dependency and the Environment." *Global Environmental Change* 12 (1): 1–4. doi:10.1016/S0959-3780(01)00025-5.

Billingsley, Megan a, Ian M Hoffman, Elizabeth Stuart, Steven R Schiller, Charles a Goldman, and Kristina Lacommare. 2014. "The Program Administrator Cost of Saved Energy for Utility Customer-Funded Energy Efficiency Programs." *Lawrence Berkeley National Laboratory*. https://emp.lbl.gov/sites/all/files/lbnl-6595e.pdf.

Brounen, Dirk, Nils Kok, and John M. Quigley. 2012. "Residential Energy Use and Conservation: Economics and Demographics." *European Economic Review* 56 (5). Elsevier: 931–45. doi:10.1016/j.euroecorev.2012.02.007.

———. 2013. "Energy Literacy, Awareness, and Conservation Behavior of Residential Households." *Energy Economics* 38 (July). Elsevier B.V.: 42–50. doi:10.1016/j.eneco.2013.02.008.

Brown, Rich, Sam Borgeson, Jon Koomey, and Peter Biermayer. 2008. "U.S. Building-Sector Energy Efficiency Potential. LBNL-1096E." Berkeley, CA. http://escholarship.org/uc/item/8vs9k2q8.

California Energy Commission. 2009. "California Statewide Residential Appliance Saturation Study: Final Report."

———. 2015. "Computer, Computer Monitors, and Electronic Displays: Docket Number 14-AAER-2." http://docketpublic.energy.ca.gov/PublicDocuments/14-AAER-02/TN203854_20150312T094326_Staff_Report__FINAL.pdf.

California State Board of Equalization. 2010. "Assessors' Handbook, Section 531: Residential Building Costs."

Cantarelli, Chantal C, Bent Flyvbjerg, Bert van Wee, and Eric J E Molin. 2010. "Lock-in and Its Influence on the Project Performance of Large-Scale Transportation Infrastructure Projects: Investigating the Way in Which Lock-in Can Emerge and Affect Cost Overruns." *Environment and Planning B: Planning and Design* 37 (5): 792–807. doi:10.1068/b36017.

Caputo, Paola, Gaia Costa, and Simone Ferrari. 2013. "A Supporting Method for Defining Energy Strategies in the Building Sector at Urban Scale." *Energy Policy* 55 (April). Elsevier: 261–70. doi:10.1016/j.enpol.2012.12.006.

Carlo, Joyce Correna, Enedir Ghisi, and Roberto Lamberts. 2003. "The Use of Computer Simulation to Establish Energy Efficiency Parameters for a Building Code of a City in Brazil." *8 International IBPSA Conference*, 131–38.

Chan, A.L.S. 2015. "Investigation on the Appropriate Floor Level of Residential Building for Installing Balcony, from a View Point of Energy and Environmental Performance. A Case Study in Subtropical Hong Kong." *Energy* 85. Elsevier Ltd: 620–34. doi:10.1016/j.energy.2015.04.001.

Chavez, S., and J. Quinn. 1987. "Sustandard Housing Garages: Immigrants In, Cars Out." *Los Angeles Times*, May 24.

Chester, Mikhail V., Matthew J. Nahlik, Andrew M. Fraser, Mindy a. Kimball, and Venu M. Garikapati. 2013. "Integrating Life-Cycle Environmental and Economic Assessment with Transportation and Land Use Planning." *Environmental Science and Technology* 47 (21): 12020–28. doi:10.1021/es402985g.

Chester, Mikhail V, and Arpad Horvath. 2009. "Environmental Assessment of Passenger Transportation Should Include Infrastructure and Supply Chains." *Environmental Research Letters* 4 (2): 024008. doi:10.1088/1748-9326/4/2/024008.

Choi, In Young, Sung Heui Cho, and Jeong Tai Kim. 2012. "Energy Consumption Characteristics of High-Rise Apartment Buildings according to Building Shape and Mixed-Use Development." *Energy and Buildings* 46 (March). Elsevier B.V.: 123–31. doi:10.1016/j.enbuild.2011.10.038.

City of Los Angeles. 2007. *Sustainability Practices in the City of Los Angeles*. . http://ens.lacity.org/mayor/villaraigosa/mayorvillaraigosa331283124_0718 2007.pdf.

cityLAB. 2010. "Backyard Homes Los Angeles."

Clean Power Research. 2015. "SolarAnywhere Radiation Data."

Coleman, Andrew. 2010. "Transport Infrastructure, Lock-Out and Urban Form: Highway Development in Auckland and the United States." *Policy Quarterly* 6 (4): 23–27.

Costa, Dora L, and Matthew E Kahn. 2011. "Electricity Consumption and Durable Housing: Understanding Cohort Effects." *American Economic Review* 101 (3): 88–92. doi:10.1257/aer.101.3.88.

Dall'O', Giuliano, Annalisa Galante, and Giulia Pasetti. 2012. "A Methodology for Evaluating the Potential Energy Savings of Retrofitting Residential Building Stocks." *Sustainable Cities and Society* 4 (October). Elsevier B.V.: 12–21. doi:10.1016/j.scs.2012.01.004.

Davis, Lucas W. 2010. "Evaluating the Slow Adoption of Energy Efficient Investments: Are Renters Less Likely to Have Energy Efficient Appliances?" Vol. 16114. Cambridge, MA. http://www.nber.org/chapters/c12130.pdf.

Davis, Lucas W., and Paul J. Gertler. 2015. "Contribution of Air Conditioning Adoption to Future Energy Use under Global Warming." *Proceedings of the National Academy of Sciences* 112 (19): 5962–67. doi:10.1073/pnas.1423558112.

Department of Finance. 2013. "New Population Projections: California To Surpass 50 Million in 2049," 2.

DiMascio, Marianne. 2015. "Water Heaters Get an Efficiency Makeover Courtesy of the Department of Energy." *American Council for an Energy-Efficient Economy*. http://aceee.org/blog/2015/02/water-heaters-get-efficiency-makeover.

Duque, Juan C., Luc Anselin, and Sergio J. Rey. 2012. "THE MAX-P-REGIONS PROBLEM*." *Journal of Regional Science* 52 (3): 397–419. doi:10.1111/j.1467-9787.2011.00743.x.

Esteves, Gheisa R. T, Bruno Q. Bastos, Fernando L. Cyrino, Rodrigo F. Calili, and Reinaldo C. Souza. 2015. "Long Term Electricity Forecast: A Systematic Review." *Procedia Computer Science* 55 (Itqm). Elsevier Masson SAS: 549–58. doi:10.1016/j.procs.2015.07.041.

Federal Highway Administration. 2014. "Historic Statistics Series." https://www.fhwa.dot.gov/policy/ohpi/hss/hsspubsarc.cfm.

Florides, G.A, S.A Tassou, S.A Kalogirou, and L.C Wrobel. 2002. "Measures Used to Lower Building Energy Consumption and Their Cost Effectiveness." *Applied Energy* 73 (3-4): 299–328. doi:10.1016/S0306-2619(02)00119-8.

Frijia, Stephane, Subhrajit Guhathakurta, and Eric Williams. 2012. "Functional Unit, Technological Dynamics, and Scaling Properties for the Life Cycle Energy of Residences." *Environmental Science & Technology* 46 (3): 1782–88. doi:10.1021/es202202q.

Fritzsche, David J. 1981. "An Analysis of Energy Consumption Patterns by Stage of Family Life Cycle." *Journal of Marketing Research* 18 (2): 227. doi:10.2307/3150956.

Garreau, J. 1991. *Edge City: Life on the New Frontier*. New York: Doubleday.

Gillingham, K, Richard G Newell, and K Palmer. 2009. "Energy Efficiency Economics and Policy." *Annual Review of Resource Economics* 1: 597–619. doi:10.1146/annurev.resource.102308.124234.

Gillingham, Kenneth, Matthew J. Kotchen, David S. Rapson, and Gernot Wagner. 2013. "Energy Policy: The Rebound Effect Is Overplayed." *Nature* 493 (7433): 475–76. doi:10.1038/493475a.

Gillingham, Kenneth, David Rapson, and Gernot Wagner. 2016. "The Rebound Effect and Energy Efficiency Policy." *Review of Environmental Economics and Policy* 10 (1): 68–88. doi:10.1093/reep/rev017.

Gorin, Tom. 2015. "Plug Loads in the Residential and Commercial Forecasts." http://docketpublic.energy.ca.gov/PublicDocuments/15-IEPR-05/TN205066_20150618T095153_Plug_Loads_in_the_Residential_and_Commercial_Forecasts.pptx.

Guggemos, Angela Acree, and Arpad Horvath. 2005. "Comparison of Environmental Effects of Steel- and Concrete-Framed Buildings." *Journal of Infrastructure Systems* 11 (2): 93–101. doi:10.1061/(ASCE)1076-0342(2005)11:2(93).

Gustavsson, Leif, Anna Joelsson, and Roger Sathre. 2010. "Life Cycle Primary Energy Use and Carbon Emission of an Eight-Storey Wood-Framed Apartment Building." *Energy and Buildings* 42 (2): 230–42. doi:10.1016/j.enbuild.2009.08.018.

Heiple, Shem, and David J Sailor. 2008. "Using Building Energy Simulation and Geospatial Modeling Techniques to Determine High Resolution Building Sector Energy Consumption Profiles." *Energy and Buildings* 40 (8): 1426–36. doi:10.1016/j.enbuild.2008.01.005.

Howard, B, L Parshall, J Thompson, S Hammer, J Dickinson, and V Modi. 2012. "Spatial Distribution of Urban Building Energy Consumption by End Use." *Energy and Buildings* 45 (February). Elsevier B.V.: 141–51. doi:10.1016/j.enbuild.2011.10.061.

Huang, Joe, Hashem Akbari, Leo Rainer, and Ron Ritschard. 1991. "481 Prototypical Commerical Buildings for 20 Urban Market Areas, LBL-29798." Berkeley, CA.

Huang, Joe, Ellen Franconi, Environmental Energy, Technologies Division, and Lawrence Berkeley. 1999. "Commercian Heating and Cooling Loads Component Analysis, LBL-37208." Berkeley, CA.

ICF International. 2013. "Los Angeles County Regional 2010 Community Greenhouse Gas Inventory." San Francisco, CA.

Intergovernmental Panel on Climate Change. 2001. *Climate Change 2001: The Scientific Basis*. New York: Cambridge University Press.

———. 2014. "Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II, and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change." Geneva, Switzerland. http://www.ipcc.ch/report/ar5/syr/.

Iowa Environmental Mesonet. 2015. "Automated Surface Observing System Historical Data." http://mesonet.agron.iastate.edu/ASOS/.

Jakob, Martin. 2006. "Marginal Costs and Co-Benefits of Energy Efficiency Investments." *Energy Policy* 34 (2): 172–87. doi:10.1016/j.enpol.2004.08.039.

Jones, Phil, Joanne Patterson, and Simon Lannon. 2007. "Modelling the Built Environment at an Urban scale—Energy and Health Impacts in Relation to Housing." *Landscape and Urban Planning* 83 (1): 39–49. doi:10.1016/j.landurbplan.2007.05.015.

Joyeux, Roselyne, and Ronald D. Ripple. 2007. "Household Energy Consumption versus Income and Relative Standard of Living: A Panel Approach." *Energy Policy* 35 (1): 50–60. doi:10.1016/j.enpol.2005.10.012.

Kavgic, M, A Mavrogianni, D Mumovic, A Summerfield, Z Stevanovic, and M. Djurovic-Petrovic. 2010. "A Review of Bottom-up Building Stock Models for Energy Consumption in the Residential Sector." *Building and Environment* 45 (7). Elsevier Ltd: 1683–97. doi:10.1016/j.buildenv.2010.01.021.

Kavousian, Amir, Ram Rajagopal, and Martin Fischer. 2013. "Determinants of Residential Electricity Consumption: Using Smart Meter Data to Examine the Effect of Climate, Building Characteristics, Appliance Stock, and Occupants' Behavior." *Energy* 55 (June). Elsevier Ltd: 184–94. doi:10.1016/j.energy.2013.03.086.

Kimball, M., Mikhail V. Chester, C. Gino, and J. Reyna. 2013. "Assessing the Potential for Reducing Life-Cycle Environmental Impacts through Transit-Oriented Development Infill along Existing Light Rail in Phoenix." *Journal of Planning Education and Research* 33 (4): 395–410. doi:10.1177/0739456X13507485.

Landis, JD. 2000. "Raising the Roof: California Housing Development Projections and Constraints, 1997-2020." *City*. Sacramento, CA. http://escholarship.org/uc/item/1391n947.pdf.

Larivière, Isabelle, and Gaëtan Lafrance. 1999. "Modelling the Electricity Consumption of Cities: Effect of Urban Density." *Energy Economics* 21 (1): 53–66. doi:10.1016/S0140-9883(98)00007-3.

Lawrence Berkeley National Laboratory. 2016. "Estimated U.S. Energy Use in 2014." Accessed January 5. https://flowcharts.llnl.gov/content/assets/images/energy/us/Energy_US_2014.png.

Lippke, Bruce By Bruce, Jim Wilson, John Perez-garcia, Jim Bowyer, and Jamie Meil. 2004. "CORRIM : Life-Cycle Environmental Performance of Renewable Building Materials." *Forest Products Journal* 54 (6): 8–19.

Longstreth, Molly, and Michael Topliff. 1990. "Determinants of Energy Savings and Increases after Installing Energy-Conserving Devices." *Energy* 15 (6): 523–37. doi:10.1016/0360-5442(90)90057-9.

Los Angeles County Assessor Office. 2009. "Los Angeles County Database."

Marshall, Julian D. 2008. "Energy-Efficient Urban Form." *Environmental Science & Technology* 42 (9): 3133–37. doi:10.1021/es087047l.

Martin, N., Ernst Worrell, and Lynn Price. 1999. "Energy Efficiency and Carbon Dioxide Emisions: Reduction Opportunities in the U.S. Cement Industry, LBNL-44182."

Masanet, Eric, Alexander Stadel, and Petek Gursel. 2012. "Life-Cycle Evaluation of Concrete Building Construction as a Strategy for Sustainable Cities, SN3119." Skokie, Illinois.

Mathew, T.V., and K.V. Krishna Rao. 2006. "Chapter 8. Trip Distribution." In *Introduction to Transportation Engineering*. ITT Bombay. http://www.cdeep.iitb.ac.in/nptel/Civil Engineering/Transportation Engg 1/08-Ltexhtml/nptel_ceTEI_L08.pdf.

Mohareb, Eugene, and Christopher Kennedy. 2012. "Gross Direct and Embodied Carbon Sinks for Urban Inventories." *Journal of Industrial Ecology* 16 (3): 302–16. doi:10.1111/j.1530-9290.2011.00445.x.

Molina, Maggie. 2014. "The Best Value for America's Energy Dollar : A National Review of the Cost of Utility Energy Efficiency Programs." http://www.aceee.org/research-report/u1402.

Morrison, Geoffrey M., Sonia Yeh, Anthony R. Eggert, Christopher Yang, James H. Nelson, Jeffery B. Greenblatt, Raphael Isaac, et al. 2015. "Comparison of Low-Carbon Pathways for California." *Climatic Change* 131 (4): 545–57. doi:10.1007/s10584-015-1403-5.

National Academy of Sciences. 2010. *Real Prospects for Energy Efficiency in the United States*. Washington, D.C.: National Academies Press. doi:10.17226/12621.

Navigant Consulting. 2014. "Energy Savings Forecast of Solid-State Lighting in General Illumination Applications." *U.S. Department of Energy Report*.

New York City Department of City Planning. 2009. "MapPLUTO (Release 09c)."

Norman, Jonathan, Heather L. MacLean, and Christopher A Kennedy. 2006. "Comparing High and Low Residential Density: Life-Cycle Analysis of Energy Use and Greenhouse Gas Emissions." *Journal of Urban Planning and Development* 132 (1): 10–21. doi:10.1061/(ASCE)0733-9488(2006)132:1(10).

Ochoa Franco, Luis A. 2004. "Life Cycle Assessment of Residential Buildings." Carnegie Mellon University.

Ochsendorf, John, Leslie Keith Norford, Dorothy Brown, Hannah Durschlag, Sophia Lisbeth Hsu, Andrea Love, Nicholas Santero, Omar Swei, Amanda Webb, and Margaret Wildnauer. 2011. "Methods, Impacts, and Opportunities in the Concrete Building Life Cycle." *Research Report R11-01, Concrete and Sustainability Hub, Department of Civil and Environmental Engineering, Massachusetts Institute of Technology*, Research Report, , no. August. Concrete Sustainability Hub, Department of Civil and Environmental Engineering, Massachusetts Institute of Technology: 119. http://www.greenconcrete.info/downloads/MITBuildingsLCAreport.pdf.

Opitz, M W, L K Norford, Yu A Matrosov, and I N Butovsky. 1997. "Energy Consumption and Conservation in the Russian Apartment Building Stock." *Energy and Buildings* 25: 75–92.

Pacific Energy Center. 2006. "Pacific Energy Center's Guide to California Climate Zones and Bioclimatic Design." http://www.pge.com/includes/docs/pdfs/about/edusafety/training/pec/toolbox/arch/climate/california_climate_zones_01-16.pdf.

Pan, Yiqun, Rongxin Yin, and Zhizhong Huang. 2008. "Energy Modeling of Two Office Buildings with Data Center for Green Building Design." *Energy and Buildings* 40 (7): 1145–52. doi:10.1016/j.enbuild.2007.10.008.

Pérez-Lombard, Luis, José Ortiz, and Christine Pout. 2008. "A Review on Buildings Energy Consumption Information." *Energy and Buildings* 40 (3): 394–98. doi:10.1016/j.enbuild.2007.03.007.

Petersen, Ann Kristin, and Birger Solberg. 2005. "Environmental and Economic Impacts of Substitution between Wood Products and Alternative Materials: A Review of Micro-Level Analyses from Norway and Sweden." *Forest Policy and Economics* 7 (3): 249–59. doi:10.1016/S1389-9341(03)00063-7.

Pincetl, Stephanie, Robert Graham, Sinnott Murphy, and Deepak Sivaraman. 2015. "Analysis of High-Resolution Utility Data for Understanding Energy Use in Urban Systems: The Case of Los Angeles, California." *Journal of Industrial Ecology*, June, n/a – n/a. doi:10.1111/jiec.12299.

Power, Anne. 2008. "Does Demolition or Refurbishment of Old and Inefficient Homes Help to Increase Our Environmental, Social and Economic Viability?" *Energy Policy* 36 (12): 4487–4501. doi:10.1016/j.enpol.2008.09.022.

Ratti, Carlo, Nick Baker, and Koen Steemers. 2005. "Energy Consumption and Urban Texture." *Energy and Buildings* 37 (7): 762–76. doi:10.1016/j.enbuild.2004.10.010.

Reap, John, Felipe Roman, Scott Duncan, and Bert Bras. 2008. "A Survey of Unresolved Problems in Life Cycle Assessment." *The International Journal of Life Cycle Assessment* 13 (5): 374–88. doi:10.1007/s11367-008-0009-9.

Reiss, Peter C, and Matthew W White. 2005. "Household Electricity Demand, Revisited." *Review of Economic Studies* 72 (3): 853–83. doi:10.1111/0034-6527.00354.

Rey, S. J., L. Anselin, D. C. Folch, D. Arribas-Bel, M. L. Sastre Gutierrez, and L. Interlante. 2011. "Measuring Spatial Dynamics in Metropolitan Areas." *Economic Development Quarterly* 25 (1): 54–64. doi:10.1177/0891242410383414.

Rey, S. J., and Myrna L. Sastré-Gutiérrez. 2010. "Interregional Inequality Dynamics in Mexico." *Spatial Economic Analysis* 5 (3): 277–98. doi:10.1080/17421772.2010.493955.

Reyna, Janet L, and Mikhail V Chester. 2015. "The Growth of Urban Building Stock: Unintended Lock-in and Embedded Environmental Effects." *Journal of Industrial Ecology* 19 (4): 524–37. doi:10.1111/jiec.12211.

RSMeans. 2009. *2008 Square Foot Costs: Residential, Commercial, Industrial, Institutional.* 15th ed. Kingston, MA: RSMeans Company.

Sailor, David J. 2014. "Risks of Summertime Extreme Thermal Conditions in Buildings as a Result of Climate Change and Exacerbation of Urban Heat Islands." *Building and Environment* 78. Elsevier Ltd: 81–88. doi:10.1016/j.buildenv.2014.04.012.

Sailor, David J., and A.A. Pavlova. 2003. "Air Conditioning Market Saturation and Long-Term Response of Residential Cooling Energy Demand to Climate Change." *Energy* 28 (9): 941–51. doi:10.1016/S0360-5442(03)00033-1.

Salazar, James, and Jamie Meil. 2009. "Prospects for Carbon-Neutral Housing: The Influence of Greater Wood Use on the Carbon Footprint of a Single-Family Residence." *Journal of Cleaner Production* 17 (17): 1563–71. doi:10.1016/j.jclepro.2009.06.006.

Sanquist, Thomas F, Heather Orr, Bin Shui, and Alvah C Bittner. 2012. "Lifestyle Factors in U.S. Residential Electricity Consumption." *Energy Policy* 42 (March). Elsevier: 354–64. doi:10.1016/j.enpol.2011.11.092.

Sartori, I., and A.G. Hestnes. 2007. "Energy Use in the Life Cycle of Conventional and Low-Energy Buildings: A Review Article." *Energy and Buildings* 39 (3): 249–57. doi:10.1016/j.enbuild.2006.07.001.

Sathaye, Jayant, Larry Dale, Peter Larsen, Gary Fitts, Kevin Koy, Sarah Lewis, and Andre Lucena. 2011. "Estimating Risk to California Energy Infrastructure From Projected Climate Change." Berkeley, CA (United States). doi:10.2172/1026811.

Sezgen, Osman, Ellen M Franconi, Jonathan G Koomey, Steve E Greenberg, Asim Afzal, and Leslie Shown. 1995. "Technology Data Characterizing Space Conditioning in Commercial Buildings: Application to End-Use Forecasting with Commend, LBL-37065."

Shimoda, Yoshiyuki, Takuro Fujii, Takao Morikawa, and Minoru Mizuno. 2004. "Residential End-Use Energy Simulation at City Scale." *Building and Environment* 39 (8): 959–67. doi:10.1016/j.buildenv.2004.01.020.

Shin, Stephanie. 2002. "Planning for a Multi-Generational Future : Policies, Regulations, and Designs for Multi-Generational Housing in the United States." Massachussets Institute of Technology. http://hdl.handle.net/1721.1/73825.

Snow, Lester A. 2008. "Managing An Uncertain Future: Climate Change Adaptation Strategies for California's Water." *State of California Department of Water Resources*.

Sorensen, Paul. 2009. "Moving Los Angeles." *Access* 35: 16–24.

State of California. 2003. *Assembly Bill 1866*. http://www.leginfo.ca.gov/pub/05-06/bill/asm/ab_0001-0050/ab_32_bill_20060927_chaptered.pdf.

———. 2008. *Sustainable Communities and Climate Protection Act*. California State Senate. http://www.leginfo.ca.gov/pub/07-08/bill/sen/sb_0351-0400/sb_375_bill_20080930_chaptered.pdf.

Stephan, André, and Laurent Stephan. 2014. "Reducing the Total Life Cycle Energy Demand of Recent Residential Buildings in Lebanon." *Energy* 74 (September): 618–37. doi:10.1016/j.energy.2014.07.028.

Swan, Lukas G, and V Ismet Ugursal. 2009. "Modeling of End-Use Energy Consumption in the Residential Sector: A Review of Modeling Techniques." *Renewable and Sustainable Energy Reviews* 13 (8): 1819–35. doi:10.1016/j.rser.2008.09.033.

Tanikawa, Hiroki, and Seiji Hashimoto. 2009. "Urban Stock over Time: Spatial Material Stock Analysis Using 4d-GIS." *Building Research & Information* 37 (5-6): 483–502. doi:10.1080/09613210903169394.

Texas Transportation Institute. 2011. "Urban Area Summary: Los Angeles." http://d2dtl5nnlpfr0r.cloudfront.net/tti.tamu.edu/documents/ums/congestion-data/losan.pdf.

Trigg, T, P Telleen, R Boyd, and F Cuenot. 2013. "Global EV Outlook: Understanding the Electric Vehicle Landscape to 2020." http://www.iea.org/publications/freepublications/publication/name-37024-en.html\nhttp://scholar.google.com/scholar?hl=en&btnG=Search&q=intitle:Global+EV+Outlook:+Understanding+the+Electric+Vehicle+Landscape+to+2020#0.

Tso, Geoffrey K.F., and Jingjing Guan. 2014. "A Multilevel Regression Approach to Understand Effects of Environment Indicators and Household Features on Residential Energy Consumption." *Energy* 66. Elsevier Ltd: 722–31. doi:10.1016/j.energy.2014.01.056.

Tso, Geoffrey K.F., and Kelvin K.W. Yau. 2007. "Predicting Electricity Energy Consumption: A Comparison of Regression Analysis, Decision Tree and Neural Networks." *Energy* 32 (9): 1761–68. doi:10.1016/j.energy.2006.11.010.

U.S. Bureau of Labor Statistics. 2016. "Average Energy Prices, Los Angeles-Riverside-Orange County February 2016." http://www.bls.gov/regions/west/news-release/averageenergyprices_losangeles.htm.

U.S. Census Bureau. 2014. "Social Explorer Tables." Accessed January 1. www.socialexplorer.com.

———. 2009. "United States Population Projections: 2000 to 2050." https://www.census.gov/population/projections/files/analytical-document09.pdf.

———. 2010. "Mean Center of Population for the United States : 1790 to 2010." https://www.census.gov/2010census/news/pdf/centerpop_mean2010_1.pdf.

———. 2012. "American Community Survey." www.census.gov/acs/www/.

U.S. Conference of Mayors. 2012. "U.S. Metro Economies." http://usmayors.org/metroeconomies/2014/06/report.pdf.

U.S. Department of Energy. 2007a. "Final Rule, Techincal Supporting Document Residential Refrigeration."

———. 2007b. "U . S . Energy Requirements for Aluminum Production," 150. http://www1.eere.energy.gov/industry/aluminum/pdfs/al_theoretical.pdf.

———. 2008. "Energy Efficiency Trends in Residential and Commercial Buildings." http://apps1.eere.energy.gov/buildings/publications/pdfs/corporate/bt_stateindustry.pdf.

———. 2009a. "Building America Climate Zones." http://energy.gov/eere/buildings/climate-zones.

———. 2009b. "Water Heater Market Profile 2009." https://www.energystar.gov/ia/partners/prod_development/new_specs/downloads/water_heaters/Water_Heater_Market_Profile_Sept2009.pdf.

———. 2013. "New Energy Efficient Standards for Microwave Ovens to Save Consumers on Energy Bills." http://energy.gov/articles/new-energy-efficiency-standards-microwave-ovens-save-consumers-energy-bills.

———. 2015. "Building Energy Databook." http://buildingsdatabook.eren.doe.gov/.

U.S. Department of the Interior, and U.S. Bureau of Reclamation. 2013. "Downscaled CMIP3 and CMIP5 Climate and Hydrology Projections: Release of Downscaled CMIP5 Climate Projections, Comparison with Preceding Information, and Summary of User Needs." Denver. http://gdo-dcp.ucllnl.org/downscaled_ cmip_projections.

U.S. Energy Information Administration. 2005. "Residential Energy Consumption Survey."

———. 2013a. "Electricity Flow Mapping." http://www.eia.gov/totalenergy/data/monthly/pdf/flow/electricity.pdf.

———. 2013b. "Energy Flow Mapping by Sector." http://www.eia.gov/totalenergy/data/monthly/pdf/flow/total_energy.pdf.

———. 2013c. "International Energy Outlook 2013." http://www.eia.gov/forecasts/archive/ieo13/ieo_tables.cfm.

———. 2014a. "Annual Energy Outlook 2015." http://www.eia.gov/forecasts/aeo/index.cfm.

———. 2014b. "Everywhere but Northeast, Fewer Homes Choose Natural Gas as Heating Fuel." *Today in Energy*. https://www.eia.gov/todayinenergy/detail.cfm?id=18131.

U.S. Environmental Protection Agency. 2012. "Light-Duty Automotive Technology, Carbon Dioxide Emissions, and Fuel Economy Trends: 1975 Through 2011."

United Nations Environment Programme. 2015. "Sustainable Buildings and Climate Initiative." http://www.unep.org/sbci/AboutSBCI/Background.asp.

University of Southern California, Southern California Studies Center, and Brookings Center on Urban and Metropolitan Policy. 2001a. "Sprawl Hits the Wall, Confronting the Realities of Metropolitan Los Angeles." In *The Atlas of Southern California*, 1–57. http://scholar.google.com/scholar?hl=en&btnG=Search&q=intitle:Sprawl+hits+the+wall,+confronting+the+realities+of+metropolitan+Los+Angeles#0.

———. 2001b. "Sprawl Hits the Wall: Confronting the Realities of Metropolitan Los Angeles." *The Atlas of Southern Califronia* 4.

Unruh, Gregory C. 2000. "Understanding Carbon Lock-In." *Energy Policy* 28 (12): 817–30. doi:10.1016/S0301-4215(00)00070-7.

Upton, Brad, Reid Miner, Mike Spinney, and Linda S. Heath. 2008. "The Greenhouse Gas and Energy Impacts of Using Wood instead of Alternatives in Residential Construction in the United States." *Biomass and Bioenergy* 32 (1): 1–10. doi:10.1016/j.biombioe.2007.07.001.

van Vliet, Michelle T. H., David Wiberg, Sylvain Leduc, and Keywan Riahi. 2016. "Power-Generation System Vulnerability and Adaptation to Changes in Climate and Water Resources." *Nature Climate Change*, no. January (January). doi:10.1038/nclimate2903.

Verinnovation. 2012. "NEEA Water Heater Market Update 2011 Report #12-234." Seattle, WA. http://neea.org/docs/reports/2011WaterHeaterMarketUpdateA273DBB87CA3.pdf?sfvrsn=6.

Whittemore, Andrew H. 2012a. "Requiem for a Growth Machine: Homeowner Preeminence in 1980s Los Angeles." *Journal of Planning History* 11 (2): 124–40. doi:10.1177/1538513211417344.

———. 2012b. "Zoning Los Angeles: A Brief History of Four Regimes." *Planning Perspectives* 27 (3): 393–415. doi:10.1080/02665433.2012.681140.

Worrell, Ernst, Lynn Price, and Nathan Martin. 2001. "Energy Efficiency and Carbon Dioxide Emissions Reduction Opportunities in the US Iron and Steel Sector." *Energy* 26 (5): 513–36. doi:10.1016/S0360-5442(01)00017-2.

Yamaguchi, Y, Y Shimoda, and M Mizuno. 2007. "Proposal of a Modeling Approach Considering Urban Form for Evaluation of City Level Energy Management." *Energy and Buildings* 39 (5): 580–92. doi:10.1016/j.enbuild.2006.09.011.

APPENDIX A

SUPPLEMENTARY DATA FOR CHAPTER 2

A.1 Turnover

Estimates of vintage distribution were obtained from each decadal census and the American Community Survey, both from the U.S. Census Bureau (Table 7). The standard error of the percent by decade was calculated based on the published protocol for each census which was then multiplied by z=1.96 and the total number of units in that decade to obtain the upper and lower bounds for a 95% confidence interval. For example, the protocol for standard error of percentages in the 2000 Census is $SE(\hat{p}) = \sqrt{\left(\frac{5}{B}\right)\hat{p}(100-\hat{p})}$ where B is the base of the estimated percentage (U.S. Census 2000).

Table 7: 95% Confidence Interval of Census Dwelling Unit Estimates

	Census 1940		Census 1950		Census 1960		Census 1970		Census 1980		Census 1990		Census 2000		ACS 2008	
Vintage	Lower	Upper	Lower	Upper	Lower	Upper	Lower	Upper	Lower	Upper	Lower	Upper	Lower	Upper	Lower	Upper
Pre-1900	18,367	37,391														
1900 to 1909	68,111	101,257	214,401	270,459												
1910 to 1919	137,979	183,635			753,341	855,328	596,266	687,443	464,640	545,553	386,818	460,958	384,962	458,933	506,626	540,458
1920 to 1929	393,402	468,018	372,181	444,909												
1930 to 1939	203,750	258,464	243,931	303,489												
1940 to 1949			431,265	509,275	381,144	454,733	454,675	534,745	461,901	542,585	401,951	477,459	366,205	438,438	380,607	412,519
1950 to 1959					699,915	798,355	738,470	839,529	745,402	846,936	691,261	789,184	680,807	778,018	709,042	744,496
1960 to 1969							539,390	683,432	577,207	666,985	535,582	622,201	538,787	625,657	495,746	531,512
1970 to 1979									368,229	493,576	420,126	497,244	469,595	550,929	469,271	498,333
1980 to 1989											452,688	591,215	366,205	438,438	372,367	402,979
1990 to 1999													181,387	269,997	191,518	213,348
2000 to 2008															137,662	165,482
Total Stock	**961,531**		**1,442,691**		**2,143,059**		**2,537,578**		**2,855,578**		**3,163,343**		**3,270,909**		**3,385,983**	

For construction, the diagonal of the matrix (Table 8), the census estimates were first used, then modified slightly according to a set of rules.

i) Matrix Constraints: The number of dwelling units constructed (C_j) had to be greater than the number remaining by 2008 (R_j) and also the total change in stock for that decade (ΔS_j). This establishes that there must be more buildings initially constructed than observed in 2008, and the stock can only increase for a decade through new construction. If the census construction estimates did not meet these two conditions, they were increased to meet the constraint condition.

ii) Total stock demolition: To provide an upper limit on new construction, the program does not allow turnover of more than 20% of a stock within a decade. This constraint is: $\frac{\sum_{1900}^{i} D_{i,j}}{S_j} \leq 0.1$, for all j, where $S_j = \sum_{1900}^{j} \Delta S_j$. From the matrix, recall that demolition is related to construction by $\Delta S_j = C_j - \sum_{1900}^{i} D_{i,j}$, so in terms of construction the constraint is $\frac{C_j - \Delta S_j}{\sum_{1900}^{j} S_j} \leq 0.1$. Additionally, the turnover was compared to that of the decade preceding and following the decade of interest. Where demolition estimates resulted in a 4 turnover percent different (e.g. 8% demolition one decade, but only 4% in the following decade), results were reassessed. The overarching modeling goal was to have consistent patterns between decades.

iii) Survival Rates. The survival rate to 2008 for each vintage, $\frac{C_i}{R_i}$, was checked to ensure a generally increasing longevity as the construction year increased. For example an increase of more than 0.2 of ratios between decades would be considered suspicious.

Table 8: Turnover Matrix Structure

		Changes in Dwelling Units by Year							
		Pre-1900	1901-1910	1911-1920	..	y_d	..	2000-2007	**2008 Totals**
Initial Construction Year	Pre-1900	$\boldsymbol{C_{1900}}$	$-D_{1900,1910}$	$-D_{1900,1920}$	..	$-D_{1900,d}$	..	$-D_{1900,2008}$	R_{1900}
	1901-1910	0	$\boldsymbol{C_{1910}}$	$-D_{1910,1920}$	...	$-D_{1910,d}$	..	$-D_{1910,2008}$	R_{1910}
	1911-1920	0	0	$\boldsymbol{C_{1920}}$	..	$-D_{1920,d}$	..	$-D_{1920,2008}$	R_{1920}
	…	…	…	…	..	...	..	…	…
	b_v	0	0	0	..	$\boldsymbol{C_v}$	..	$-D_{v,2008}$	R_v
	…	…	…	…	..	…	..	…	…
	2000-2008	0	0	0	..	0	..	$\boldsymbol{C_{2008}}$	R_{2008}
Change in Units		ΔS_{1900}	$\Delta S_{1901-1910}$	$\Delta S_{1911-1921}$	..	ΔS_d	..	$\Delta S_{2001-2008}$	$\sum_v \boldsymbol{R_v} = \sum_d \boldsymbol{\Delta S_d}$

The results of the construction estimation, with the calculations for survival and demolition are shown in Table 3:

Table 9: Construction Estimates and Metrics

Vintage		*1900*	*1910*	*1920*	*1930*	*1940*	*1950*	*1960*	*1970*	*1980*	*1990*	*2000*	*2008*	R	*Survival*
	pre-1900	58,782												5,970	10%
	1900-1909		118,711											34,693	29%
	1910-1919			157,308										62,566	40%
	1920-1929				461,943									295,366	64%
	1930-1939					232,871								124,947	54%
	1940-1949						520,000							396,563	76%
	1950-1959							814,724						726,769	89%
	1960-1969								600,000					513,629	86%
	1970-1979									550,000				483,802	88%
	1980-1989										455,000			387,673	85%
	1990-1999											215,000		202,433	94%
	2000-2008												151,572	151,572	100%
	ΔS	58,782	115,231	149,227	439,074	199,217	481,160	700,368	394,519	318,000	307,765	107,566	115,074		
	S	58,782	174,013	323,240	762,314	961,531	1,442,691	2,143,059	2,537,578	2,855,578	3,163,343	3,270,909	3,385,983		
	Turnover		2.0%	2.5%	3.0%	3.5%	2.7%	5.3%	8.1%	8.1%	4.7%	3.3%	1.1%		

The model is iterated, comparing the expected demolition sum to the matrix demolition sum, and multiplying the ratio of the expected to the actual first across all columns, then across all rows. The final solution is shown in Table 10.

Table 10: Turnover Solution

	1900	*1910*	*1920*	*1930*	*1940*	*1950*	*1960*	*1970*	*1980*	*1990*	*2000*	*2008*	***R***	$D_{Expected}$	D_{Actual}	*Ratio*
pre-1900	58,782	-3,480	-4,502	-4,050	-5,127	-4,956	-5,306	-14,706	-6,831	-2,981	-802	-50	5,970	-49,310	-49,332	1.000
1900-1909		118,711	-3,579	-16,099	-9,060	-5,254	-11,250	-15,590	-14,483	-6,321	-1,700	-529	34,693	-83,866	-84,018	1.002
1910-1919			157,308	-2,721	-11,482	-12,169	-14,258	-20,498	-18,355	-8,011	-6,502	-671	62,566	-94,666	-94,742	1.001
1920-1929				461,943	-7,984	-12,348	-33,049	-45,799	-42,546	-18,568	-4,994	-1,554	295,366	-166,843	-166,577	0.998
1930-1939					232,871	-4,112	-23,481	-32,540	-30,228	-13,192	-3,548	-1,104	124,947	-108,206	-107,924	0.997
1940-1949						520,000	-27,011	-39,935	-34,773	-15,176	-5,426	-1,209	396,563	-123,529	-123,437	0.999
1950-1959						0	814,724	-36,412	-31,706	-13,837	-4,947	-1,102	726,769	-88,004	-87,955	0.999
1960-1969						0	0	600,000	-53,078	-23,165	-8,282	-1,845	513,629	-86,370	-86,371	1.000
1970-1979						0	0	0	550,000	-45,984	-16,440	-3,662	483,802	-66,086	-66,198	1.002
1980-1989						0	0	0	0	455,000	-54,795	-12,206	387,673	-67,000	-67,327	1.005
1990-1999						0	0	0	0	0	215,000	-12,567	202,433	-12,567	-12,567	1
2000-2008						0	0	0	0	0	0	151,572	151,572			
ΔS	58,782	115,231	149,227	439,074	199,217	481,160	700,368	394,519	318,000	307,765	107,566	115,074				
S	58,782	174,013	323,240	762,314	961,531	1,442,691	2,143,059	2,537,578	2,855,578	3,163,343	3,270,909	3,385,983				
$D_{Expected}$		-3,480	-8,081	-22,869	-33,654	-38,840	-114,356	-205,481	-232,000	-147,235	-107,434	-36,498		1,379	**Error**	
D_{Actual}		-3,480	-8,081	-22,869	-33,654	-38,840	-114,356	-205,481	-232,000	-147,235	-107,434	-36,498				
Ratio		1	1	1	1	1	1	1	1	1	1	1				

A.1.1 Validation of Turnover Rates

The percent vintage breakdown by decade is presented in Table A.11. That is, every column represents the vintage percent contribution to the stock in that decade and must sum to 100%.

Table A.11: Percent Vintage by Decade (Turnover Model)

	1900	*1910*	*1920*	*1930*	*1940*	***1950***	*1960*	*1970*	***1980***	*1990*	***2000***	*2008*
pre-1900	100%	32%	16%	6%	4%	3%	1%	1%	0%	0%	0%	0%
1900-1909	0%	68%	36%	13%	9%	6%	3%	2%	2%	1%	1%	1%
1910-1919	0%	0%	49%	20%	15%	9%	5%	4%	3%	2%	2%	2%
1920-1929	0%	0%	0%	61%	47%	31%	19%	14%	11%	10%	9%	9%
1930-1939	0%	0%	0%	0%	24%	**16%**	10%	7%	5%	4%	4%	4%
1940-1949	0%	0%	0%	0%	0%	36%	23%	18%	15%	13%	12%	12%
1950-1959	0%	0%	0%	0%	0%	0%	38%	31%	26%	23%	**22%**	21%
1960-1969	0%	0%	0%	0%	0%	0%	0%	24%	19%	17%	16%	15%
1970-1979	0%	0%	0%	0%	0%	0%	0%	0%	**19%**	16%	15%	14%
1980-1989	0%	0%	0%	0%	0%	0%	0%	0%	0%	14%	12%	11%
1990-1999	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	7%	6%
2000-2008	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	4%
Median Age	pre-1900	1900-1909	1900-1909	1920-1929	1920-1929	1930-1939	1940-1949	1950-1959	1950-1959	1950-1959	1950-1959	1960-1969

These model outputs are compared to the same statistics published by the U.S. Census Bureau for each decadal census (Table 12). When comparing the model outputs to the U.S. Census Bureau, the results are mostly consistent, with the highest observed variation between the two being 4 stock percent points. Outputs with the highest deviation have been highlighted in red in both tables for easy identification.

Table 12: Census Vintage by Decade

	1940	***1950***	*1960*	*1970*	***1980***	*1990*	***2000***	*2008*
Pre-1900	3%	17%	41%	25%	18%	13%	13%	15%
1900 to 1909	9%							
1910 to 1919	17%							
1920 to 1929	46%	29%						
1930 to 1939	25%	**20%**						
1940 to 1949	0%	34%	21%	19%	18%	14%	12%	12%
1950 to 1959	0%	0%	38%	31%	28%	23%	22%	21%
1960 to 1969	0%	0%	0%	24%	22%	18%	**18%**	15%
1970 to 1979	0%	0%	0%	0%	**15%**	15%	16%	14%
1980 to 1989	0%	0%	0%	0%	0%	16%	12%	11%
1990 to 1999	0%	0%	0%	0%	0%	0%	7%	6%
2000 to 2008	0%	0%	0%	0%	0%	0%	0%	4%

During model development, a 4.3% difference between the total dwelling units from the Census and that from the Assessor was identified. This difference could possibly be due to the Census capturing a large number of illegal dwelling units present in Los Angeles County, estimated to be 2.5% of the housing stock in the 1980's, which are likely absent from the Assessor database (University of Southern California, Southern California Studies Center, and Brookings Center on Urban and Metropolitan Policy 2001b; cityLAB 2010; Chavez and Quinn 1987). Because of this discrepancy, the American Community Survey, published annually by the U.S. Census bureau, was substituted for the Assessor database as an estimate of the current building stock.

A.1.2 Commercial / Industrial Turnover Sensitivity and Uncertainty Analysis

No data were identified to estimate the turnover rates of commercial and industrial buildings, so the estimated turnover rates for residential buildings were used for commercial and industrial buildings. To explore the potential variability this introduces into the model, a

sensitivity analysis was performed. Four scenarios were developed: two modifying the shape of the turnover curves, but retaining the same survival rates and two scenarios modifying survival.

A.1.2.1 Scenario 1: Same Survival, Rapid Initial Decay

In this scenario, the final survival rates for each vintage were retained, but an exponential decay curve was applied to the years in between. Exponential decay is of the form: $F = F_0 e^{-\lambda t}$. The final decay curves were:

Table 13: Rapid Decay Curves

	1900	*1910*	*1920*	*1930*	*1940*	*1950*	*1960*	*1970*	*1980*	*1990*	*2000*	*2008*
pre-1900	1	0.81	0.66	0.54	0.44	0.35	0.29	0.23	0.19	0.15	0.13	0.10
1900-1909		1	0.88	0.78	0.69	0.61	0.54	0.48	0.42	0.38	0.33	0.29
1910-1919			1	0.90	0.81	0.74	0.66	0.60	0.54	0.49	0.44	0.40
1920-1929				1	0.95	0.89	0.85	0.80	0.76	0.71	0.68	0.64
1930-1939					1	0.91	0.84	0.77	0.70	0.64	0.59	0.54
1940-1949						1	0.96	0.91	0.87	0.83	0.80	0.76
1950-1959							1	0.98	0.96	0.93	0.91	0.89
1960-1969								1	0.96	0.93	0.89	0.86
1970-1979									1	0.96	0.92	0.88
1980-1989										1	0.92	0.85
1990-1999											1	0.94
2000-2008												1

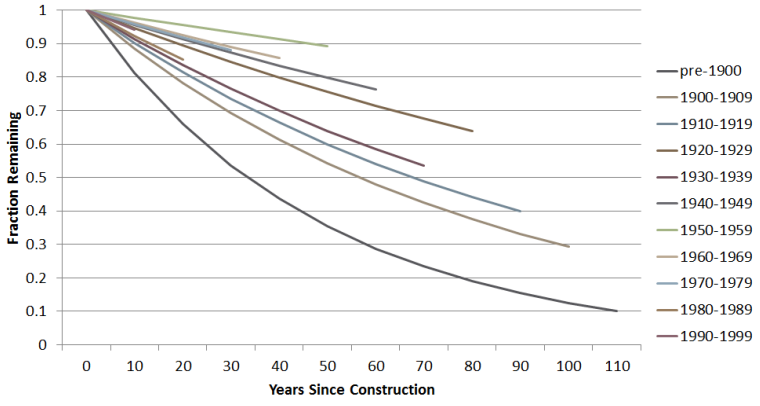


Figure 17: Rapid Decay Curves

This led to the cumulative embedded GHG as follows:

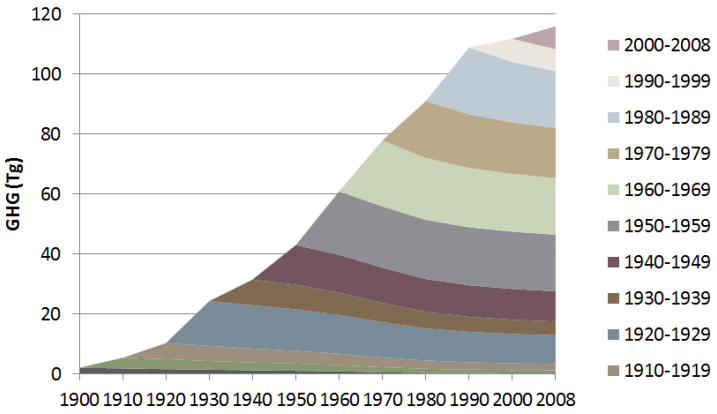


Figure A.18: Rapid Decay Cumulative GHG

A.1.2.2 Scenario 2: Same Survival, Slow Initial Decay

In this scenario, the final survival rates for each vintage were retained, but a logistic decay curve was applied to the years in between. The logistic decay is of the form: $F = \frac{a}{1+bc^{-x}}$. For all curves $c = 0.5$ and a and b are determined by the final survival. The final decay curves are:

Table 14:Slow Decay Curves

	1900	*1910*	*1920*	*1930*	*1940*	*1950*	*1960*	*1970*	*1980*	*1990*	*2000*	*2008*
pre-1900	1	1.00	0.99	0.97	0.94	0.88	0.79	0.65	0.48	0.31	0.19	0.10
1900-1909		1	1.00	0.99	0.98	0.97	0.93	0.87	0.77	0.63	0.45	0.29
1910-1919			1	1.00	0.99	0.98	0.96	0.92	0.84	0.73	0.57	0.40
1920-1929				1	1.00	0.99	0.98	0.97	0.94	0.88	0.78	0.64
1930-1939					1	0.99	0.98	0.95	0.91	0.83	0.70	0.54
1940-1949						1	1.00	0.99	0.97	0.93	0.87	0.76
1950-1959							1	1.00	0.99	0.97	0.94	0.89
1960-1969								1	0.99	0.97	0.93	0.86
1970-1979									1	0.98	0.94	0.88
1980-1989										1	0.95	0.85
1990-1999											1	0.94
2000-2008												1

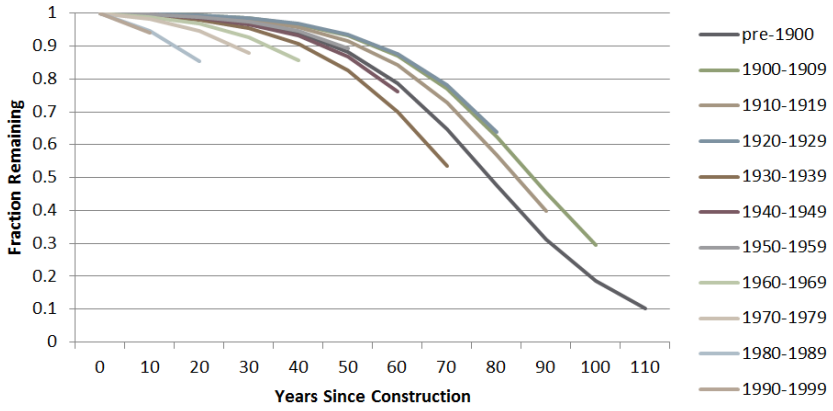


Figure 19: Slow Decay

This led to the cumulative embedded GHG as follows:

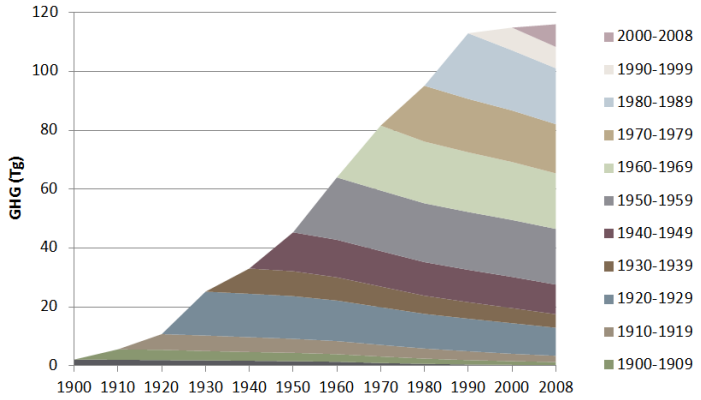


Figure A.20: Slow Decay Cumulative GHG

A.1.2.3 Scenario 3: Half Decay

In this scenario, the change in buildings between decades was modified to be half that estimated in the residential assessment. The final decay curves are:

Table 15: Half Decay Curves

	1900	*1910*	*1920*	*1930*	*1940*	*1950*	*1960*	*1970*	*1980*	*1990*	*2000*	*2008*
pre-1900	1	0.95	0.88	0.81	0.74	0.66	0.58	0.35	0.24	0.20	0.19	0.18
1900-1909		1	0.98	0.87	0.81	0.78	0.71	0.60	0.51	0.47	0.46	0.45
1910-1919			1	0.99	0.94	0.88	0.82	0.72	0.64	0.60	0.57	0.57
1920-1929				1	0.99	0.97	0.93	0.87	0.81	0.79	0.78	0.78
1930-1939					1	0.99	0.92	0.83	0.75	0.71	0.70	0.70
1940-1949						1	0.97	0.93	0.89	0.87	0.87	0.87
1950-1959							1	0.98	0.96	0.95	0.94	0.94
1960-1969								1	0.95	0.93	0.92	0.92
1970-1979									1	0.96	0.94	0.94
1980-1989										1	0.94	0.92
1990-1999											1	0.97
2000-2008												1

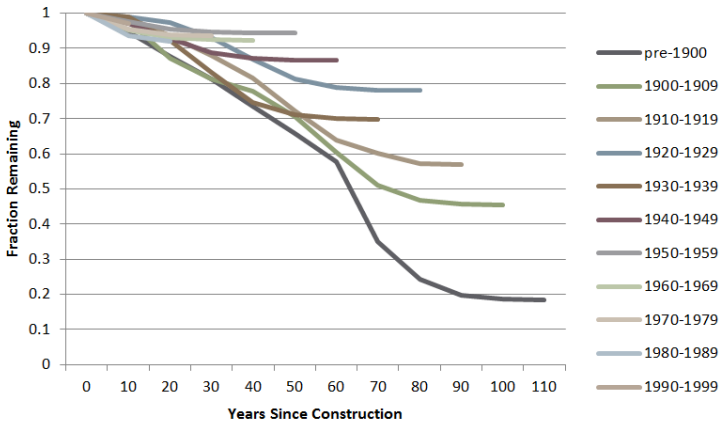


Figure 21: Half Decay Curves

This led to the initial construction floor area and cumulative embedded GHG as follows:

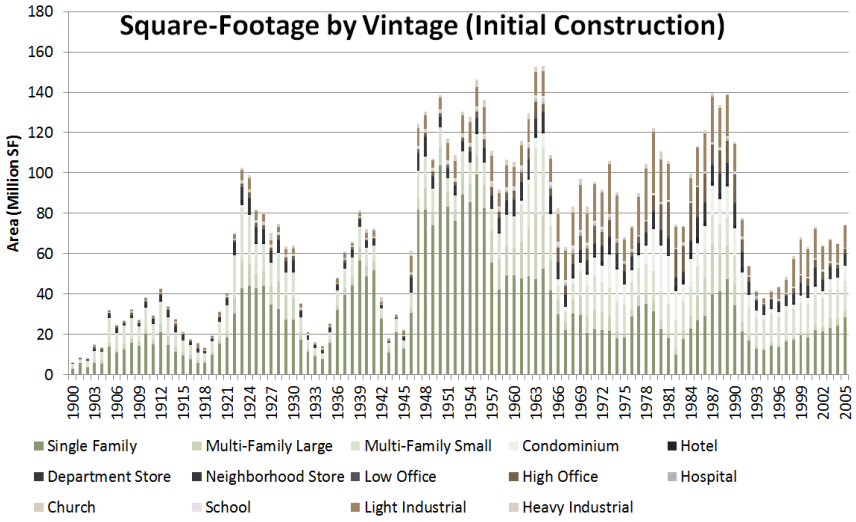


Figure 22: Half Decay Floor Area

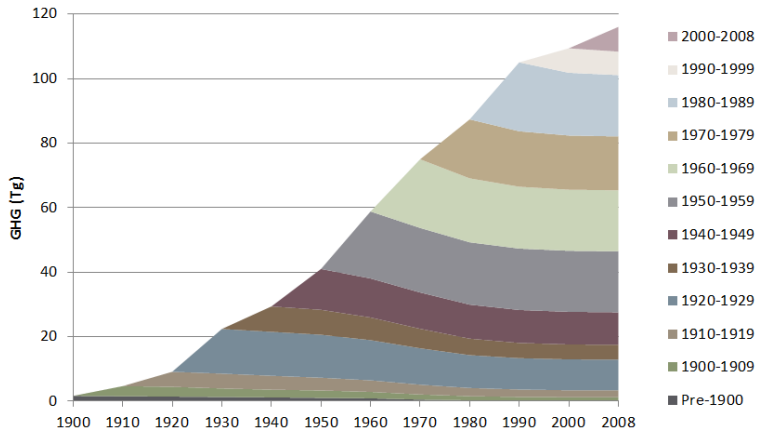


Figure 23: Half Decay Cumulative GHG

A.1.2.4 Scenario 4: Double Decay

In this scenario, the change in buildings between decades was modified to be double that estimated in the residential assessment. The final decay curves are:

Table 16: Double Decay Curves

	1900	1910	1920	1930	1940	1950	1960	1970	1980	1990	2000	2008
pre-1900	1	0.94	0.86	0.78	0.69	0.60	0.51	0.24	0.12	0.07	0.05	0.05
1900-1909		1	0.96	0.81	0.72	0.66	0.55	0.40	0.26	0.19	0.18	0.17
1910-1919			1	0.98	0.89	0.79	0.68	0.51	0.37	0.31	0.25	0.25
1920-1929				1	0.97	0.94	0.83	0.68	0.55	0.49	0.47	0.47
1930-1939					1	0.98	0.84	0.65	0.47	0.39	0.37	0.37
1940-1949						1	0.92	0.79	0.68	0.64	0.62	0.62
1950-1959							1	0.92	0.85	0.82	0.81	0.81
1960-1969								1	0.85	0.78	0.75	0.75
1970-1979									1	0.85	0.80	0.79
1980-1989										1	0.79	0.74
1990-1999											1	0.89
2000-2008												1

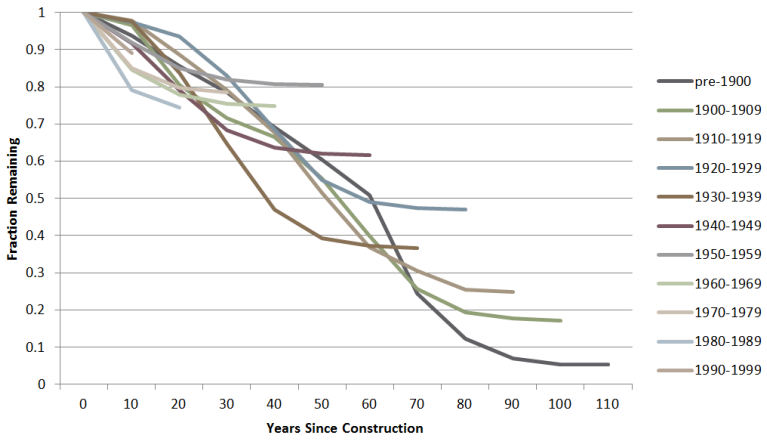


Figure A.24: Half Decay Curves

This led to the initial construction floor area and cumulative embedded GHG as follows:

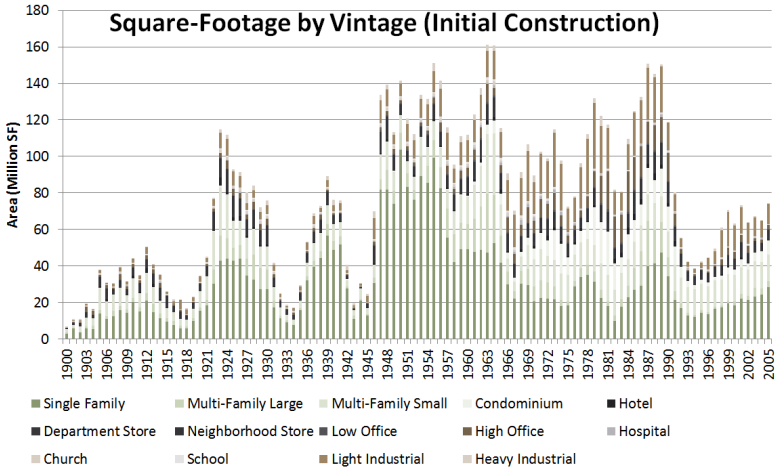


Figure A.25: Double Decay Floor Area

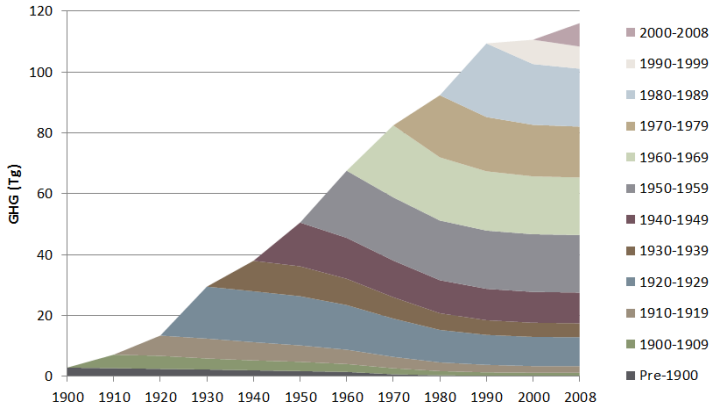


Figure A.26: Double Decay Cumulative GHG

Scenarios 1 and 2 for commercial/industrial turnover have the same initial construction impacts as the turnover developed for the residential buildings. The only variance is in the timing of building demolition (i.e. the decay curves). In these cases the beginning and end states are the same, but the path is different. This has little impact on the environmental outcomes, but has distinct implications for analyzing trends in building turnover. Scenarios 3 and 4 modify the turnover rates to be double or half that of residential turnover. This increases or decreases, respectively, the initial buildings constructed. For the doubling scenario, the total floor area constructed over 110 years in Los Angeles is 5%

higher than predicted with the residential turnover rates and the associated GHG emissions are 8.5% higher. In the halving scenario, the GHG impacts are 4.2% lower. This is not significantly different than the estimates from the residential turnover rates and does not impact the conclusions of this chapter.

A.2 Prototypes

Sixteen building models are initially developed using Athena Impact Estimator. This software estimates construction and material manufacturing practices in the U.S. and Canada. It is widely used in building life cycle assessment. Athena estimates energy use and air emissions for building construction in several U.S. and Canadian cities, including Los Angeles. Correspondence with the developers of Athena revealed that steps had been taken to improve location-specific accuracy of the estimates, such as material supply chains and electricity mixes.

In the following sub-sections, each of the sixteen initial models is presented in detail. There are fourteen categories of buildings, but additionally the bill of materials for single family homes has been modified for three time periods due to the prevalence of these buildings in Los Angeles County. Following the bill of materials and source information for each model, the Athena outputs are presented.

A.2.1 R1: Single Family Detached, Pre-1950

Base data source: Assessors' Handbook, Single-Family Residential, "D" Construction, D-5 Quality, Conventional (California State Board of Equalization 2010)

Dimensions: 30'x40', 3 bed, 2 bath

Project	*SFD Conventional D-5*	
Material	Quantity	Unit
#15 Organic Felt	147.42	100sf
Aluminum	0.31	Tons
Ballast (aggregate stone)	42229.36	lbs
Batt. Fiberglass	37.03	sf(1")
EPDM membrane (black, 60 mil)	146.72	lbs
Galvanized Sheet	0.52	Tons
Low E Tin Glazing	115.14	sf
Nails	0.18	Tons
Organic Felt shingles 20yr	50.40	100sf
Roofing Asphalt	5759.92	lbs
Screws Nuts & Bolts	0.066	Tons
Small Dimension Softwood Lumber, Green	2.09	Mbfm
Small Dimension Softwood Lumber, kiln-dried	5.24	Mbfm
Softwood Plywood	4.43	msf (3/8 Basis)
Standard Glazing	345.42	sf
Stucco over metal mesh	2376.00	sf
Water Based Latex Paint	85.64	US Gallon

	Manufacturing			***Construction***		
	Material	Transportation	**Total**	Material	Transportation	**Total**
Hydro MJ	5,671	2	**5,673**	546	18	**564**
Coal MJ	23,883	31	**23,914**	641	263	**904**
Diesel MJ	7,733	4,477	**12,209**	1,085	39,570	**40,655**
Feedstock MJ	78,426	0	**78,426**	0	0	**0**
Gasoline MJ	132	0	**132**	0	0	**0**
Heavy Fuel Oil MJ	11,161	274	**11,435**	9	1,794	**1,802**
LPG MJ	197	5	**202**	2	39	**41**
Natural Gas MJ	39,912	190	**40,101**	3,690	1,607	**5,297**
Nuclear MJ	93,049	8	**93,057**	544	70	**614**
Wood MJ	16,690	0	**16,690**	0	0	**0**
Total Primary Energy Consumption MJ	276,852	4,987	**281,839**	6,517	43,361	**49,878**

	Manufacturing			*Construction*		
Summary Measures	Material	Transportation	**Total**	Material	Transportation	**Total**
Fossil Fuel Consumption (MJ)	161,443	4,976	**166,419**	5,426	43,273	**48,699**
Global Warming Potential (kg CO2 eq)	8,922	369	**9,291**	453	3,129	**3,582**
Acidification Potential (moles of H+ eq)	2,710	116	**2,826**	208	1,022	**1,230**
HH Criteria (kg PM10 eq)	75	0	**75**	0	1	**2**
Eutrophication Potential (kg N eq)	3	0	**3**	0	1	**1**
Ozone Depletion Potential (kg CFC-11 eq)	0	0	**0**	0	0	**0**
Smog Potential (kg O3 eq)	393	62	**455**	34	549	**583**

A.2.2 R1: Single Family Detached, 1950-1990

Base data source: Assessors' Handbook, Single-Family Residential, "D" Construction, D-6 Quality, Modern, Pre-1990 (California State Board of Equalization 2010)

Dimensions: perimeter: 166', area: 1400 ft^2, 3 bed, 2 bath

Project	*SFD Modern Pre-1990 D-6*	
Material	Quantity	Unit
#15 Organic Felt	101.17	100sf
6 mil Polyethylene	1485.12	sf
Aluminum	0.31	Tons
Ballast (aggregate stone)	53726.60	lbs
Batt. Fiberglass	37.03	sf(1")
Concrete 20 MPa (flyash av)	17.86	yd^3
EPDM membrane (black, 60 mil)	146.72	lbs
Galvanized Sheet	0.44	Tons
Nails	0.19	Tons
Organic Felt shingles 20yr	65.10	100sf
Pine Wood Bevel Siding	1964.75	sf
Roofing Asphalt	7344.11	lbs
Screws Nuts & Bolts	0.08	Tons
Small Dimension Softwood Lumber, Green	2.15	Mbfm
Small Dimension Softwood Lumber, kiln-dried	5.89	Mbfm
Softwood Plywood	4.73	msf (3/8 Basis)
Solvent Based Alkyd Paint	24.08	US Gallon
Standard Glazing	518.13	sf
Stucco over metal mesh	1088.27	sf
Water Based Latex Paint	60.73	US Gallon
Welded Wire Mesh / Ladder Wire	0.13	Tons

	Manufacturing			***Construction***		
	Material	Transportation	**Total**	Material	Transportation	**Total**
Hydro MJ	6,672	2	**6,674**	569	20	**588**
Coal MJ	27,340	36	**27,376**	667	286	**953**
Diesel MJ	8,618	5,229	**13,847**	1,269	43,212	**44,481**
Feedstock MJ	90,988	0	**90,988**	0	0	**0**
Gasoline MJ	153	0	**153**	0	0	**0**
Heavy Fuel Oil MJ	13,124	309	**13,433**	9	1,964	**1,973**
LPG MJ	235	5	**240**	2	43	**45**
Natural Gas MJ	46,272	221	**46,493**	3,840	1,750	**5,589**
Nuclear MJ	93,644	10	**93,654**	566	76	**642**
Wood MJ	19,547	0	**19,547**	0	0	**0**
Total Primary Energy Consumption MJ	306,592	5,813	**312,405**	6,921	47,351	**54,272**

	Manufacturing			*Construction*		
Summary Measures	Material	Transportation	**Total**	Material	Transportation	**Total**
Fossil Fuel Consumption (MJ)	186,729	5,801	**192,530**	5,786	47,256	**53,042**
Global Warming Potential (kg CO2 eq)	10,060	431	**10,491**	476	3,407	**3,883**
Acidification Potential (moles of H+ eq)	3,058	135	**3,193**	219	1,116	**1,335**
HH Criteria (kg PM10 eq)	85.73	0.18	**85.91**	0.49	1.45	**1.94**
Eutrophication Potential (kg N eq)	3.57	0.15	**3.72**	0.07	1.21	**1.28**
Ozone Depletion Potential (kg CFC-11 eq)	4.84E-05	1.72E-08	**4.84E-05**	7.64E-10	1.36E-07	**1.37E-07**
Smog Potential (kg O3 eq)	430	72	**502**	35	599	**634**

A.2.3 R1: Single Family Detached, Post-1990

Base data source: Assessors' Handbook, Single-Family Residential, "D" Construction, D-7 Quality, Modern, Post-1990 (California State Board of Equalization 2010)

Dimensions: perimeter: 42'x50', 4 bed, 3 bath

Project	*SFD Modern Post-1990 D-7*	
Material	Quantity	Unit
#15 Organic Felt	71.82	100sf
6 mil Polyethylene	2227.68	sf
Aluminum	0.31	Tons
Ballast (aggregate stone)	73901.39	lbs
Batt. Fiberglass	37.03	sf(1")
Concrete 20 MPa (flyash av)	26.79	yd^3
EPDM membrane (black, 60 mil)	146.72	lbs
Galvanized Sheet	0.51	Tons
Low E Silver Argon Filled Glazing	402.99	sf
Nails	0.25	Tons
Organic Felt shingles 20yr	88.20	100sf
Pine Wood Bevel Siding	2129.31	sf
Pine Wood Shiplap Siding	5674.83	sf
Roofing Asphalt	10079.86	lbs
Screws Nuts & Bolts	0.10	Tons
Small Dimension Softwood Lumber, Green	3.21	Mbfm
Small Dimension Softwood Lumber, kiln-dried	9.56	Mbfm
Softwood Plywood	7.80	msf (3/8 Basis)
Solvent Based Alkyd Paint	53.02	US Gallon
Water Based Latex Paint	83.43	US Gallon
Welded Wire Mesh / Ladder Wire	0.19	Tons

	Manufacturing			***Construction***		
	Material	Transportation	**Total**	Material	Transportation	**Total**
Hydro MJ	8,696	4	**8,700**	626	25	**651**
Coal MJ	44,583	59	**44,641**	733	367	**1,100**
Diesel MJ	11,650	8,454	**20,104**	6,620	56,019	**62,639**
Feedstock MJ	130,791	0	**130,791**	0	0	**0**
Gasoline MJ	297	0	**297**	0	0	**0**
Heavy Fuel Oil MJ	24,238	459	**24,697**	10	2,313	**2,323**
LPG MJ	519	9	**528**	2	55	**57**
Natural Gas MJ	65,101	357	**65,458**	4,224	2,241	**6,465**
Nuclear MJ	95,574	15	**95,590**	623	97	**720**
Wood MJ	31,511	0	**31,511**	0	0	**0**
Total Primary Energy Consumption MJ	412,958	9,358	**422,316**	12,838	61,117	**73,955**

	Manufacturing			*Construction*		
Summary Measures	Material	Transportation	**Total**	Material	Transportation	**Total**
Fossil Fuel Consumption (MJ)	277,177	9,338	**286,516**	11,589	60,995	**72,584**
Global Warming Potential (kg CO2 eq)	15,063	696	**15,759**	878	4,363	**5,241**
Acidification Potential (moles of H+ eq)	7,320	218	**7,538**	408	1,436	**1,844**
HH Criteria (kg PM10 eq)	136.36	0.28	**136.65**	0.64	1.87	**2.51**
Eutrophication Potential (kg N eq)	7.98	0.24	**8.22**	0.25	1.56	**1.81**
Ozone Depletion Potential (kg CFC-11 eq)	9.41E-05	2.78E-08	**9.42E-05**	8.41E-10	1.74E-07	**1.75E-07**
Smog Potential (kg O3 eq)	2342	116	**2459**	135	771	**906**

A.2.4 R2: Multi-Family Large

Base data source: RS Means 2008 Square Foot costs, M.030 model: Apartment, 8-24 sotry (RSMeans 2009)

Dimensions: 10 units per floor, 1000 sf per unit, 10 floors, 200'x50' (each unit 25'x40')

Project *MultiFamily, Large, 1950-1990*

Material	Quantity	Unit
#15 Organic Felt	684.02	100sf
1/2" Gypsum Fibre Gypsum Board	83,655.73	sf
1/2" Moisture Resistant Gypsum Board	11,000.00	sf
5/8" Fire-Rated Type X Gypsum Board	52,528.66	sf
6 mil Polyethylene	10,608.00	sf
Aluminum	25.48	Tons
Ballast (aggregate stone)	112,203.63	lbs
Cold Rolled Sheet	0.99	Tons
Concrete 20 MPa (flyash av)	1,122.78	yd^3
Concrete 60 MPa (flyash av)	127.59	yd^3
Concrete Blocks	89,913.49	Blocks
Concrete Brick	50,141.00	sf
EPDM membrane (black, 60 mil)	2,779.93	lbs
Expanded Polystyrene	31,500.36	sf(1")
Galvanized Decking	101.38	Tons
Galvanized Sheet	27.57	Tons
Galvanized Studs	50.50	Tons
Glazing Panel	5.59	Tons
Joint Compound	13.92	Tons
Mortar	2,360.75	yd^3
Nails	4.81	Tons
Open Web Joists	92.32	Tons
Oriented Strand Board	66.69	msf (3/8 Basis)
Paper Tape	0.16	Tons
Rebar, Rod, Light Sections	333.65	Tons
Roofing Asphalt	75,160.05	lbs
Screws Nuts & Bolts	1.82	Tons
Small Dimension Softwood Lumber, kiln-dried	18.13	Mbfm
Softwood Plywood	106.21	msf (3/8 Basis)
Solvent Based Alkyd Paint	2,524.43	US Gallon
Standard Glazing	8,726.40	sf
Type III Glass Felt	1,368.04	100sf
Water Based Latex Paint	237.43	US Gallon
Welded Wire Mesh / Ladder Wire	0.93	Tons

	Manufacturing			***Construction***		
	Material	Transportation	**Total**	Material	Transportation	**Total**
Hydro MJ	855,168	245	**855,413**	5,848	1,592	**7,440**
Coal MJ	5,315,266	3,573	**5,318,839**	6,856	23,230	**30,086**
Diesel MJ	776,071	513,421	**1,289,492**	234,862	3,550,215	**3,785,077**
Feedstock MJ	6,139,247	0	**6,139,247**	0	0	**0**
Gasoline MJ	3,413	0	**3,413**	0	0	**0**
Heavy Fuel Oil MJ	3,024,409	70,376	**3,094,785**	93	88,171	**88,264**
LPG MJ	33,752	534	**34,287**	23	3,475	**3,498**
Natural Gas MJ	9,233,392	21,820	**9,255,212**	39,491	141,878	**181,370**
Nuclear MJ	14,978,273	948	**14,979,221**	5,823	6,136	**11,959**
Wood MJ	409,405	0	**409,405**	0	0	**0**
Total Primary Energy Consumption MJ	40,768,398	610,916	**41,379,314**	292,995	3,814,697	**4,107,692**

	Manufacturing			***Construction***		
Summary Measures	Material	Transportation	**Total**	Material	Transportation	**Total**
Fossil Fuel Consumption (MJ)	24,525,551	609,723	**25,135,275**	281,324	3,806,969	**4,088,293**
Global Warming Potential (kg CO2 eq)	2,037,194	42,437	**2,079,630**	20,067	276,444	**296,511**
Acidification Potential (moles of H+ eq)	612,156	13,943	**626,099**	9,273	89,152	**98,425**
HH Criteria (kg PM10 eq)	7246.20	18.15	**7264.34**	9.35	115.94	**125.29**
Eutrophication Potential (kg N eq)	925.88	15.17	**941.05**	7.95	96.96	**104.91**
Ozone Depletion Potential (kg CFC-11 eq)	9.35E-03	1.70E-06	**9.35E-03**	7.86E-09	1.10E-05	**1.10E-05**
Smog Potential (kg O3 eq)	96540	7489	**104029**	4576	47743	**52318**

A.2.5 R3: Multi-Family Small

Base data source: Assessors' Handbook, Multiple-Family Residences, "D" Construction, D-6 Quality (California State Board of Equalization 2010)

Dimensions: 5 units per floor, 720 or 1040 sf per unit, 3 floors, 80'x52', each unit 26'x30'(1bed 1 bath) or 20'x52'(2bed 2 bath and 2bed 2 bath)

Project *MultiFamily, Small, 1950-1990*

Material	Quantity	Unit
#15 Organic Felt	871.24	100sf
6 mil Polyethylene	4,412.93	sf
Aluminum	3.62	Tons
Concrete 20 MPa (flyash av)	53.08	yd³
EPDM membrane (black, 60 mil)	378.73	lbs
Galvanized Sheet	2.37	Tons
Large Dimension Softwood Lumber, kiln-dried	44.43	Mbfm
Nails	0.99	Tons
Organic Felt shingles 25yr	131.04	100sf
Screws Nuts & Bolts	0.37	Tons
Small Dimension Softwood Lumber, Green	12.02	Mbfm
Small Dimension Softwood Lumber, kiln-dried	8.05	Mbfm
Softwood Plywood	16.55	msf (3/8 Basis)
Solvent Based Varnish	227.44	US Gallon
Standard Glazing	1,308.96	sf
Stucco over metal mesh	44,192.55	sf
Water Based Latex Paint	571.71	US Gallon
Welded Wire Mesh / Ladder Wire	0.39	Tons

	Manufacturing			***Construction***		
	Material	Transportation	**Total**	Material	Transportation	**Total**
Hydro MJ	67,304	13	**67,317**	1,895	110	**2,005**
Coal MJ	140,434	185	**140,619**	2,222	1,608	**3,830**
Diesel MJ	63,145	26,715	**89,860**	12,848	239,902	**252,750**
Feedstock MJ	236,757	0	**236,758**	0	0	**0**
Gasoline MJ	1,272	0	**1,272**	0	0	**0**
Heavy Fuel Oil MJ	56,438	1,417	**57,855**	30	13,156	**13,186**
LPG MJ	864	28	**891**	7	241	**248**
Natural Gas MJ	264,737	1,130	**265,867**	12,797	9,823	**22,621**
Nuclear MJ	1,657,669	49	**1,657,717**	1,887	426	**2,313**
Wood MJ	124,014	0	**124,014**	0	0	**0**
Total Primary Energy Consumption MJ	2,612,635	29,535	**2,642,170**	31,686	265,266	**296,952**

	Manufacturing			***Construction***		
Summary Measures	Material	Transportation	**Total**	Material	Transportation	**Total**
Fossil Fuel Consumption (MJ)	763,648	29,474	**793,121**	27,904	264,730	**292,634**
Global Warming Potential (kg CO2 eq)	52,321	2,200	**54,521**	2,157	19,120	**21,277**
Acidification Potential (moles of H+ eq)	18,481	689	**19,170**	994	6,279	**7,273**
HH Criteria (kg PM10 eq)	328.17	0.90	**329.07**	1.80	8.17	**9.97**
Eutrophication Potential (kg N eq)	16.65	0.75	**17.40**	0.51	6.83	**7.35**
Ozone Depletion Potential (kg CFC-11 eq)	2.15E-04	8.78E-08	**2.15E-04**	2.55E-09	7.65E-07	**7.68E-07**
Smog Potential (kg O3 eq)	2,288	368	**2,655**	274	3,372	**3,646**

A.2.6 R4: Condominium

Base data source: Assessors' Handbook, Multiple-Family Residences, "D" Construction, D-7 Quality, Modern, Pre-1990 (California State Board of Equalization 2010)

Dimensions: 5 units, each 3 floors, 1296 ft^2 per unit, block 90'x24', each unit floor 18'x24'(2bed 2bath)

Project	*Condo Modern Pre-1990 D-7*	
Material	Quantity	Unit
#15 Organic Felt	75.45	100sf
1/2" Regular Gypsum Board	15,001.80	sf
6 mil Polyethylene	2,291.33	sf
Aluminum	10.67	Tons
Ballast (aggregate stone)	85,393.19	lbs
Cedar Wood Tongue and Groove Siding	8,402.53	sf
Concrete 20 MPa (flyash av)	27.56	yd^3
EPDM membrane (black, 60 mil)	866.41	lbs
Galvanized Sheet	0.53	Tons
Joint Compound	1.53	Tons
Low E Tin Argon Filled Glazing	2,719.73	sf
Nails	0.81	Tons
Organic Felt shingles 20yr	91.99	100sf
Paper Tape	0.02	Tons
Roofing Asphalt	11,693.97	lbs
Screws Nuts & Bolts	0.32	Tons
Small Dimension Softwood Lumber, Green	11.09	Mbfm
Small Dimension Softwood Lumber, kiln-dried	7.49	Mbfm
Softwood Plywood	16.59	msf (3/8 Basis)
Solvent Based Alkyd Paint	258.14	US Gallon
Stucco over porous surface	10,792.36	sf
Water Based Latex Paint	229.59	US Gallon
Welded Wire Mesh / Ladder Wire	0.20	Tons

	Manufacturing			Construction		
	Material	Transportation	**Total**	Material	Transportation	**Total**
Hydro MJ	96,800	6	**96,805**	1,848	58	**1,906**
Coal MJ	156,932	81	**157,013**	2,167	847	**3,013**
Diesel MJ	33,620	11,855	**45,474**	2,198	127,461	**129,659**
Feedstock MJ	154,398	0	**154,398**	0	0	**0**
Gasoline MJ	434	0	**434**	0	0	**0**
Heavy Fuel Oil MJ	42,405	603	**43,008**	29	6,905	**6,934**
LPG MJ	663	12	**675**	7	127	**134**
Natural Gas MJ	183,009	496	**183,505**	12,480	5,170	**17,650**
Nuclear MJ	4,270,859	21	**4,270,881**	1,840	224	**2,064**
Wood MJ	61,966	0	**61,966**	0	0	**0**
Total Primary Energy Consumption MJ	5,001,085	13,074	**5,014,159**	20,569	140,792	**161,361**

	Manufacturing			Construction		
Summary Measures	Material	Transportation	**Total**	Material	Transportation	**Total**
Fossil Fuel Consumption (MJ)	571,460	13,047	**584,507**	16,881	140,510	**157,390**
Global Warming Potential (kg CO2 eq)	37,914	967	**38,881**	1,398	10,063	**11,461**
Acidification Potential (moles of H+ eq)	20,832	305	**21,136**	633	3,328	**3,961**
HH Criteria (kg PM10 eq)	339.96	0.40	**340.35**	1.55	4.33	**5.88**
Eutrophication Potential (kg N eq)	10.84	0.33	**11.18**	0.17	3.62	**3.79**
Ozone Depletion Potential (kg CFC-11 eq)	1.56E-04	3.86E-08	**1.56E-04**	2.48E-09	4.03E-07	**4.05E-07**
Smog Potential (kg O3 eq)	1,867	163	**2,030**	77	1,789	**1,866**

A.2.7 C1: Hotel

Base data source: RS Means 2008 Square Foot costs, M.350 model: Hotel, 4-7 story

(RSMeans 2009)

Dimensions: 135,000 ft^2, 6 floors, 150'x150'

Project *Hotel*

Material	Quantity	Unit
#15 Organic Felt	1,539.05	100sf
#30 Organic Felt	3,847.63	100sf
1/2" Fire-Rated Type X Gypsum Board	134,199.99	sf
6 mil Polyethylene	25,140.96	sf
Aluminum	65.60	Tons
Ballast (aggregate stone)	305,607.25	lbs
Blown Cellulose	27,924.75	sf(1")
Cold Rolled Sheet	0.59	Tons
Concrete 20 MPa (flyash av)	423.08	yd^3
Concrete Blocks	33,917.37	Blocks
Concrete Tile	144,449.99	sf
EPDM membrane (black, 60 mil)	8,972.17	lbs
Expanded Polystyrene	389,437.60	sf(1")
Galvanized Decking	22.81	Tons
Galvanized Sheet	138.34	Tons
Galvanized Studs	195.29	Tons
Glazing Panel	0.16	Tons
Joint Compound	13.72	Tons
MDI resin	14,387.13	lbs
Mortar	949.01	yd^3
Nails	10.47	Tons
Ontario (Standard) Brick	30,122.40	sf
Open Web Joists	34.72	Tons
Oriented Strand Board	292.22	msf (3/8 Basis)
Paper Tape	0.16	Tons
Rebar, Rod, Light Sections	734.71	Tons
Roofing Asphalt	93,010.56	lbs
Screws Nuts & Bolts	5.92	Tons
Small Dimension Softwood Lumber, kiln-dried	123.96	Mbfm
Softwood Plywood	170.37	msf (3/8 Basis)
Solvent Based Alkyd Paint	117.10	US Gallon
Standard Glazing	36,360.00	sf
Type III Glass Felt	3,078.10	100sf
Welded Wire Mesh / Ladder Wire	2.08	Tons

	Manufacturing			***Construction***		
	Material	Transportation	**Total**	Material	Transportation	**Total**
Hydro MJ	1,209,830	227	**1,210,058**	8,059	2,276	**10,335**
Coal MJ	5,734,927	3,319	**5,738,246**	9,999	33,209	**43,208**
Diesel MJ	1,188,100	476,763	**1,664,863**	215,886	5,267,516	**5,483,402**
Feedstock MJ	13,994,384	0	**13,994,384**	0	0	**0**
Gasoline MJ	12,001	0	**12,001**	0	0	**0**
Heavy Fuel Oil MJ	1,899,614	62,978	**1,962,592**	2,111	145,172	**147,283**
LPG MJ	70,650	496	**71,146**	120	4,968	**5,088**
Natural Gas MJ	13,777,122	20,269	**13,797,392**	57,790	202,830	**260,620**
Nuclear MJ	19,171,542	881	**19,172,423**	8,134	8,782	**16,916**
Wood MJ	1,501,666	0	**1,501,666**	0	0	**0**
Total Primary Energy Consumption MJ	58,559,836	564,934	**59,124,770**	302,099	5,664,753	**5,966,852**

	Manufacturing			***Construction***		
Summary Measures	Material	Transportation	**Total**	Material	Transportation	**Total**
Fossil Fuel Consumption (MJ)	36,676,797	563,826	**37,240,623**	285,905	5,653,695	**5,939,601**
Global Warming Potential (kg CO2 eq)	2,266,058	39,425	**2,305,483**	20,496	395,136	**415,632**
Acidification Potential (moles of H+ eq)	867,209	12,914	**880,123**	6,692	131,809	**138,501**
HH Criteria (kg PM10 eq)	6,468.27	16.80	**6,485.08**	13.55	171.61	**185.17**
Eutrophication Potential (kg N eq)	1741.95	14.05	**1756.00**	4.64	143.43	**148.08**
Ozone Depletion Potential (kg CFC-11 eq)	3.85E-03	1.58E-06	**3.86E-03**	2.95E-07	1.58E-05	**1.61E-05**
Smog Potential (kg O3 eq)	160,502	6,933	**167,435**	2,436	70,946	**73,383**

A.2.8 C2: Department Store

Base data source: RS Means 2008 Square Foot costs, M.610 model: Store, Department, 1 Story (RSMeans 2009)

Dimensions: 95,000 ft^2, 1 floor, 475'x200'

Project

Material	Quantity	Unit
#15 Organic Felt	7,851.30	100sf
1/2" Fire-Rated Type X Gypsum Board	21,231.47	sf
6 mil Polyethylene	103,640.16	sf
Aluminum	11.06	Tons
Ballast (aggregate stone)	1,565,738.78	lbs
Blown Cellulose	117,904.50	sf(1")
Cold Rolled Sheet	0.35	Tons
Concrete 20 MPa (flyash av)	1,525.22	yd^3
Concrete 30 MPa (flyash av)	606.04	yd^3
Concrete Blocks	20,000.31	Blocks
EPDM membrane (black, 60 mil)	1,493.49	lbs
Galvanized Sheet	25.94	Tons
Galvanized Studs	6.36	Tons
Glazing Panel	0.28	Tons
Joint Compound	2.17	Tons
Mortar	559.46	yd^3
Nails	6.00	Tons
Ontario (Standard) Brick	17,762.50	sf
Paper Tape	0.02	Tons
Precast Concrete	1,061.45	yd^3
Rebar, Rod, Light Sections	127.30	Tons
Roofing Asphalt	433,597.20	lbs
Screws Nuts & Bolts	0.27	Tons
Solvent Based Alkyd Paint	652.68	US Gallon
Standard Glazing	9,544.50	sf
Type III Glass Felt	15,702.59	100sf
Welded Wire Mesh / Ladder Wire	21.30	Tons

	Manufacturing			***Construction***		
	Material	Transportation	**Total**	Material	Transportation	**Total**
Hydro MJ	398,780	183	**398,963**	850	844	**1,694**
Coal MJ	3,368,222	2,671	**3,370,893**	997	12,309	**13,306**
Diesel MJ	596,650	385,658	**982,308**	513,902	1,893,618	**2,407,520**
Feedstock MJ	8,323,701	0	**8,323,700**	0	0	**0**
Gasoline MJ	16,070	0	**16,070**	0	0	**0**
Heavy Fuel Oil MJ	2,026,687	35,722	**2,062,409**	13	51,446	**51,459**
LPG MJ	39,783	400	**40,183**	3	1,841	**1,845**
Natural Gas MJ	6,069,351	16,312	**6,085,663**	5,743	75,176	**80,919**
Nuclear MJ	3,632,620	707	**3,633,327**	847	3,253	**4,099**
Wood MJ	0	0	**0**	0	0	**0**
Total Primary Energy Consumption MJ	24,471,864	441,653	**24,913,516**	522,355	2,038,486	**2,560,841**

	Manufacturing			*Construction*		
Summary Measures	Material	Transportation	**Total**	Material	Transportation	**Total**
Fossil Fuel Consumption (MJ)	20,440,464	440,762	**20,881,226**	520,658	2,034,390	**2,555,048**
Global Warming Potential (kg CO2 eq)	1,349,301	31,750	**1,381,051**	18,636	146,463	**165,099**
Acidification Potential (moles of H+ eq)	381,897	10,193	**392,090**	8,774	47,631	**56,405**
HH Criteria (kg PM10 eq)	4,857.38	13.25	**4,870.63**	5.65	61.96	**67.61**
Eutrophication Potential (kg N eq)	350.31	11.08	**361.40**	8.32	51.81	**60.13**
Ozone Depletion Potential (kg CFC-11 eq)	8.31E-03	1.27E-06	**8.31E-03**	1.14E-09	5.85E-06	**5.85E-06**
Smog Potential (kg O3 eq)	57,651	5,455	**63,106**	4,755	25,540	**30,296**

A.2.9 C3: Neighborhood Store

Base data source: RS Means 2008 Square Foot costs, M.630 model: Store, Retail (RSMeans 2009)

Dimensions: 4,100 ft^2, 1 floor, 82'x50'

Project

Material	Quantity	Unit
#15 Organic Felt	280.45	100sf
24 Ga. Steel Roof (Commercial)	6,013.33	sf
6 mil Polyethylene	4,909.38	sf
Aluminum	1.92	Tons
Ballast (aggregate stone)	55,688.43	lbs
Blown Cellulose	5,088.51	sf(1")
Concrete 20 MPa (flyash av)	109.36	yd^3
Concrete Blocks	3,932.28	Blocks
EPDM membrane (black, 60 mil)	262.58	lbs
Galvanized Decking	4.16	Tons
Galvanized Sheet	1.15	Tons
Galvanized Studs	0.29	Tons
Modified Bitumen membrane	2,267.05	lbs
Mortar	98.49	yd^3
Nails	0.34	Tons
Open Web Joists	3.79	Tons
Oriented Strand Board	1.19	msf (3/8 Basis)
Rebar, Rod, Light Sections	21.05	Tons
Roofing Asphalt	16,948.59	lbs
Screws Nuts & Bolts	0.02	Tons
Solvent Based Alkyd Paint	107.56	US Gallon
Standard Glazing	1,868.50	sf
Stucco over porous surface	9,930.49	sf
Type III Glass Felt	560.90	100sf
Water Based Latex Paint	125.56	US Gallon
Welded Wire Mesh / Ladder Wire	0.38	Tons

	Manufacturing			***Construction***		
	Material	Transportation	**Total**	Material	Transportation	**Total**
Hydro MJ	45,592	12	**45,604**	38	77	**114**
Coal MJ	438,335	170	**438,504**	44	1,116	**1,160**
Diesel MJ	42,890	24,655	**67,545**	20,377	170,576	**190,953**
Feedstock MJ	611,811	0	**611,811**	0	0	**0**
Gasoline MJ	226	0	**226**	0	0	**0**
Heavy Fuel Oil MJ	155,957	2,713	**158,670**	1	4,192	**4,192**
LPG MJ	1,107	25	**1,132**	0	167	**167**
Natural Gas MJ	489,948	1,036	**490,984**	254	6,819	**7,072**
Nuclear MJ	587,485	45	**587,530**	37	295	**332**
Wood MJ	3,637	0	**3,637**	0	0	**0**
Total Primary Energy Consumption MJ	2,376,986	28,656	**2,405,642**	20,750	183,241	**203,992**

	Manufacturing			*Construction*		
Summary Measures	Material	Transportation	**Total**	Material	Transportation	**Total**
Fossil Fuel Consumption (MJ)	1,740,273	28,599	**1,768,872**	20,675	182,870	**203,545**
Global Warming Potential (kg CO2 eq)	119,054	2,016	**121,070**	1,388	13,286	**14,674**
Acidification Potential (moles of H+ eq)	36,984	658	**37,641**	668	4,282	**4,951**
HH Criteria (kg PM10 eq)	409.70	0.86	**410.55**	0.41	5.57	**5.98**
Eutrophication Potential (kg N eq)	53.73	0.72	**54.45**	0.63	4.66	**5.29**
Ozone Depletion Potential (kg CFC-11 eq)	8.36E-04	8.07E-08	**8.36E-04**	5.05E-11	5.30E-07	**5.30E-07**
Smog Potential (kg O3 eq)	4,898	353	**5,251**	364	2,293	**2,657**

A.2.10 C4: Low Office

Base data source: RS Means 2008 Square Foot costs, M.460 model: Office, 2-4 Story

(RSMeans 2009)

Dimensions: 7000 ft^2, 1 floor, 140'x50'

Project

Material	Quantity	Unit
#15 Organic Felt	342.01	100sf
1/2" Gypsum Fibre Gypsum Board	3,901.33	sf
24 Ga. Steel Roof (Commercial)	6,600.00	sf
6 mil Polyethylene	8,189.38	sf
Aluminum	10.16	Tons
Ballast (aggregate stone)	67,912.72	lbs
Blown Cellulose	6,205.50	sf(1")
Cold Rolled Sheet	0.07	Tons
Commercial(26 ga.) Steel Cladding	1,320.00	sf
Concrete 20 MPa (flyash av)	166.84	yd^3
Concrete Blocks	3,865.28	Blocks
EPDM membrane (black, 60 mil)	1,389.96	lbs
Expanded Polystyrene	178.57	sf(1")
Galvanized Sheet	3.00	Tons
Galvanized Studs	8.38	Tons
Glass Fibre	462.97	lbs
Glazing Panel	0.26	Tons
Joint Compound	0.40	Tons
Laminated Veneer Lumber	7.85	ft^3
Modified Bitumen membrane	2,488.23	lbs
Mortar	108.71	yd^3
Nails	0.95	Tons
Ontario (Standard) Brick	3,432.80	sf
Oriented Strand Board	4.95	msf (3/8 Basis)
Paper Tape	0.00	Tons
Rebar, Rod, Light Sections	18.42	Tons
Roofing Asphalt	20,669.01	lbs
Screws Nuts & Bolts	0.21	Tons
Small Dimension Softwood Lumber, kiln-dried	0.18	Mbfm
Solvent Based Alkyd Paint	207.45	US Gallon
Standard Glazing	4,363.20	sf
Type III Glass Felt	684.02	100sf
Water Based Latex Paint	17.42	US Gallon
Welded Wire Mesh / Ladder Wire	0.65	Tons

	Manufacturing			***Construction***		
	Material	Transportation	**Total**	Material	Transportation	**Total**
Hydro MJ	99,067	15	**99,082**	162	109	**271**
Coal MJ	580,129	225	**580,354**	209	1,586	**1,796**
Diesel MJ	60,994	32,620	**93,613**	29,156	246,696	**275,852**
Feedstock MJ	729,366	0	**729,366**	0	0	**0**
Gasoline MJ	365	0	**365**	0	0	**0**
Heavy Fuel Oil MJ	197,553	4,046	**201,600**	71	6,522	**6,592**
LPG MJ	2,645	34	**2,679**	4	237	**241**
Natural Gas MJ	718,584	1,372	**719,956**	1,213	9,689	**10,902**
Nuclear MJ	2,839,358	60	**2,839,418**	166	419	**585**
Wood MJ	16,084	0	**16,084**	0	0	**0**
Total Primary Energy Consumption MJ	5,244,145	38,372	**5,282,517**	30,981	265,259	**296,240**

	Manufacturing			***Construction***		
Summary Measures	Material	Transportation	**Total**	Material	Transportation	**Total**
Fossil Fuel Consumption (MJ)	2,289,637	38,297	**2,327,933**	30,653	264,731	**295,384**
Global Warming Potential (kg CO2 eq)	161,995	2,670	**164,664**	2,068	18,878	**20,945**
Acidification Potential (moles of H+ eq)	58,466	877	**59,343**	876	6,187	**7,063**
HH Criteria (kg PM10 eq)	651.56	1.14	**652.70**	0.75	8.05	**8.81**
Eutrophication Potential (kg N eq)	62.21	0.95	**63.16**	0.79	6.73	**7.52**
Ozone Depletion Potential (kg CFC-11 eq)	1.07E-03	1.07E-07	**1.07E-03**	9.99E-09	7.54E-07	**7.64E-07**
Smog Potential (kg O3 eq)	7,934	471	**8,405**	451	3,321	**3,772**

A.2.11 C5: High Office

Base data source: RS Means 2008 Square Foot costs, M.470 model: Office, 5-10 Story

(RSMeans 2009)

Dimensions: 156,000 ft^2, 6 floors, 162.5'x160'

Project

Material	Quantity	Unit
#15 Organic Felt	1,778.46	100sf
1/2" Fire-Rated Type X Gypsum Board	60,632.00	sf
24 Ga. Steel Roof (Commercial)	38,133.33	sf
6 mil Polyethylene	28,949.23	sf
Aluminum	53.84	Tons
Ballast (aggregate stone)	353,146.15	lbs
Blown Cellulose	32,268.60	sf(1")
Concrete 20 MPa (flyash av)	4,403.48	yd^3
EPDM membrane (black, 60 mil)	7,324.83	lbs
Galvanized Decking	26.36	Tons
Galvanized Sheet	40.57	Tons
Galvanized Studs	18.41	Tons
Glazing Panel	0.56	Tons
Joint Compound	6.20	Tons
Modified Bitumen membrane	14,376.41	lbs
Nails	5.36	Tons
Open Web Joists	43.68	Tons
Oriented Strand Board	76.98	msf (3/8 Basis)
Paper Tape	0.07	Tons
Rebar, Rod, Light Sections	182.94	Tons
Roofing Asphalt	107,478.87	lbs
Screws Nuts & Bolts	0.93	Tons
Solvent Based Alkyd Paint	530.23	US Gallon
Standard Glazing	46,904.40	sf
Type III Glass Felt	3,556.92	100sf
Welded Wire Mesh / Ladder Wire	2.41	Tons

	Manufacturing			***Construction***		
	Material	Transportation	**Total**	Material	Transportation	**Total**
Hydro MJ	662,722	217	**662,939**	2,393	890	**3,283**
Coal MJ	4,853,801	3,164	**4,856,965**	2,805	12,988	**15,794**
Diesel MJ	439,893	457,679	**897,572**	917,906	1,989,070	**2,906,975**
Feedstock MJ	5,159,536	0	**5,159,536**	0	0	**0**
Gasoline MJ	3,239	0	**3,239**	0	0	**0**
Heavy Fuel Oil MJ	1,956,735	42,407	**1,999,141**	38	49,961	**49,999**
LPG MJ	27,157	473	**27,630**	9	1,943	**1,952**
Natural Gas MJ	5,525,450	19,327	**5,544,776**	16,159	79,328	**95,487**
Nuclear MJ	15,571,581	838	**15,572,419**	2,383	3,431	**5,814**
Wood MJ	236,031	0	**236,031**	0	0	**0**
Total Primary Energy Consumption MJ	34,436,143	524,105	**34,960,248**	941,693	2,137,611	**3,079,304**

	Manufacturing			*Construction*		
Summary Measures	Material	Transportation	**Total**	Material	Transportation	**Total**
Fossil Fuel Consumption (MJ)	17,965,809	523,050	**18,488,860**	936,917	2,133,290	**3,070,207**
Global Warming Potential (kg CO2 eq)	1,396,614	37,617	**1,434,232**	63,476	154,565	**218,041**
Acidification Potential (moles of H+ eq)	475,583	12,093	**487,676**	33,717	49,947	**83,665**
HH Criteria (kg PM10 eq)	5,983.04	15.73	**5,998.76**	21.71	64.96	**86.67**
Eutrophication Potential (kg N eq)	596.38	13.15	**609.54**	33.13	54.32	**87.46**
Ozone Depletion Potential (kg CFC-11 eq)	9.88E-03	1.50E-06	**9.88E-03**	3.22E-09	6.17E-06	**6.17E-06**
Smog Potential (kg O3 eq)	81,778	6,473	**88,251**	18,840	26,756	**45,596**

A.2.12 C6: Hospital

Base data source: RS Means 2008 Square Foot costs, M.330 model: Hospital, 2-3 Story

(RSMeans 2009)

Dimensions: 55,080 ft^2, 3 floors, 135'x136'

Project

Material	Quantity	Unit
#15 Organic Felt	1,246.63	100sf
1/2" Fire-Rated Type X Gypsum Board	68,217.60	sf
6 mil Polyethylene	20,626.19	sf
Aluminum	20.15	Tons
Ballast (aggregate stone)	247,541.87	lbs
Blown Cellulose	22,619.05	sf(1")
Cold Rolled Sheet	0.34	Tons
Concrete 20 MPa (flyash av)	2,234.69	yd^3
Concrete Blocks	92,594.13	Blocks
Concrete Brick	17,117.10	sf
EPDM membrane (black, 60 mil)	2,698.10	lbs
Galvanized Sheet	56.69	Tons
Galvanized Studs	21.67	Tons
Glazing Panel	0.84	Tons
Joint Compound	6.97	Tons
Mortar	2,350.65	yd^3
Nails	3.51	Tons
Paper Tape	0.08	Tons
Rebar, Rod, Light Sections	649.03	Tons
Roofing Asphalt	75,338.55	lbs
Screws Nuts & Bolts	1.06	Tons
Solvent Based Alkyd Paint	47.66	US Gallon
Standard Glazing	14,796.50	sf
Type III Glass Felt	2,493.26	100sf
Welded Wire Mesh / Ladder Wire	1.70	Tons

	Manufacturing			***Construction***		
	Material	Transportation	**Total**	Material	Transportation	**Total**
Hydro MJ	679,010	254	**679,264**	2,816	1,423	**4,239**
Coal MJ	5,012,011	3,703	**5,015,714**	3,302	20,760	**24,062**
Diesel MJ	625,452	535,193	**1,160,646**	490,063	3,184,795	**3,674,859**
Feedstock MJ	7,173,985	0	**7,173,985**	0	0	**0**
Gasoline MJ	905	0	**905**	0	0	**0**
Heavy Fuel Oil MJ	3,304,476	48,455	**3,352,931**	45	75,307	**75,351**
LPG MJ	27,754	554	**28,308**	11	3,106	**3,117**
Natural Gas MJ	8,811,642	22,614	**8,834,256**	19,018	126,795	**145,813**
Nuclear MJ	6,722,707	980	**6,723,687**	2,804	5,483	**8,287**
Wood MJ	0	0	**0**	0	0	**0**
Total Primary Energy Consumption MJ	32,357,942	611,753	**32,969,695**	518,059	3,417,668	**3,935,727**

	Manufacturing			*Construction*		
Summary Measures	Material	Transportation	**Total**	Material	Transportation	**Total**
Fossil Fuel Consumption (MJ)	24,956,225	610,519	**25,566,744**	512,438	3,410,762	**3,923,201**
Global Warming Potential (kg CO2 eq)	1,938,218	44,016	**1,982,234**	35,195	247,063	**282,259**
Acidification Potential (moles of H+ eq)	544,764	14,128	**558,892**	16,147	79,799	**95,947**
HH Criteria (kg PM10 eq)	6,443.37	18.37	**6,461.75**	11.49	103.78	**115.27**
Eutrophication Potential (kg N eq)	1053.97	15.36	**1069.33**	15.50	86.79	**102.29**
Ozone Depletion Potential (kg CFC-11 eq)	1.02E-02	1.76E-06	**1.02E-02**	3.79E-09	9.86E-06	**9.87E-06**
Smog Potential (kg O3 eq)	78,312	7,561	**85,872**	8,907	42,744	**51,651**

A.2.13 C7: Church

Base data source: RS Means 2008 Square Foot costs, M.090 model: Church (RSMeans 2009)

Dimensions: 8,000 ft^2, 1 floor, 80'x100'

Project

Material	Quantity	Unit
#15 Organic Felt	547.22	100sf
6 mil Polyethylene	9,250.18	sf
Aluminum	10.02	Tons
Ballast (aggregate stone)	108,660.35	lbs
Blown Cellulose	9,928.80	sf(1")
Cold Rolled Sheet	0.14	Tons
Concrete 20 MPa (flyash av)	180.18	yd^3
Concrete Blocks	8,061.60	Blocks
EPDM membrane (black, 60 mil)	1,370.52	lbs
Expanded Polystyrene	175.18	sf(1")
Galvanized Sheet	3.72	Tons
Galvanized Studs	1.28	Tons
Mortar	226.12	yd^3
Nails	1.29	Tons
Ontario (Standard) Brick	7,159.60	sf
Rebar, Rod, Light Sections	71.35	Tons
Roofing Asphalt	33,070.42	lbs
Screws Nuts & Bolts	0.03	Tons
Small Dimension Softwood Lumber, kiln-dried	3.43	Mbfm
Softwood Plywood	20.72	msf (3/8 Basis)
Solvent Based Alkyd Paint	1.95	US Gallon
Standard Glazing	8,726.40	sf
Stucco over porous surface	13,216.76	sf
Type III Glass Felt	1,094.44	100sf
Water Based Latex Paint	167.11	US Gallon
Welded Wire Mesh / Ladder Wire	0.74	Tons

	Manufacturing			***Construction***		
	Material	Transportation	**Total**	Material	Transportation	**Total**
Hydro MJ	123,003	26	**123,029**	184	200	**384**
Coal MJ	563,692	381	**564,073**	216	2,921	**3,136**
Diesel MJ	90,479	55,234	**145,713**	36,536	457,937	**494,473**
Feedstock MJ	1,188,391	0	**1,188,391**	0	0	**0**
Gasoline MJ	530	0	**530**	0	0	**0**
Heavy Fuel Oil MJ	314,959	4,052	**319,011**	3	11,557	**11,560**
LPG MJ	4,566	57	**4,623**	1	437	**438**
Natural Gas MJ	1,244,096	2,326	**1,246,422**	1,243	17,837	**19,080**
Nuclear MJ	2,811,430	101	**2,811,531**	183	772	**955**
Wood MJ	39,674	0	**39,674**	0	0	**0**
Total Primary Energy Consumption MJ	6,380,820	62,177	**6,442,997**	38,365	491,661	**530,027**

	Manufacturing			*Construction*		
Summary Measures	Material	Transportation	**Total**	Material	Transportation	**Total**
Fossil Fuel Consumption (MJ)	3,406,713	62,050	**3,468,763**	37,998	490,689	**528,687**
Global Warming Potential (kg CO2 eq)	217,132	4,530	**221,661**	2,568	34,753	**37,321**
Acidification Potential (moles of H+ eq)	73,918	1,442	**75,360**	1,201	11,450	**12,651**
HH Criteria (kg PM10 eq)	893.44	1.87	**895.31**	0.80	14.90	**15.70**
Eutrophication Potential (kg N eq)	116.23	1.57	**117.80**	1.09	12.46	**13.55**
Ozone Depletion Potential (kg CFC-11 eq)	9.45E-04	1.81E-07	**9.45E-04**	2.47E-10	1.39E-06	**1.39E-06**
Smog Potential (kg O3 eq)	8,962	771	**9,733**	633	6,152	**6,785**

A.2.14 C8: School

Base data source: RS Means 2008 Square Foot costs, M.560 model: School, Elementary

(RSMeans 2009)

Dimensions: 11,600 ft^2, 1 floor, 116'x100'

Project

Material	Quantity	Unit
#15 Organic Felt	793.47	100sf
24 Ga. Steel Roof (Commercial)	17,013.33	sf
6 mil Polyethylene	12,394.39	sf
Aluminum	12.70	Tons
Ballast (aggregate stone)	157,557.51	lbs
Blown Cellulose	14,396.76	sf(1")
Cold Rolled Sheet	0.09	Tons
Concrete 20 MPa (flyash av)	267.69	yd^3
Concrete Blocks	15,259.35	Blocks
EPDM membrane (black, 60 mil)	1,737.45	lbs
Expanded Polystyrene	386.53	sf(1")
Galvanized Decking	11.76	Tons
Galvanized Sheet	3.51	Tons
Glazing Panel	0.48	Tons
Modified Bitumen membrane	6,414.09	lbs
Mortar	397.89	yd^3
Nails	1.41	Tons
Ontario (Standard) Brick	4,750.20	sf
Open Web Joists	10.71	Tons
Rebar, Rod, Light Sections	84.50	Tons
Roofing Asphalt	47,952.11	lbs
Screws Nuts & Bolts	0.01	Tons
Solvent Based Alkyd Paint	503.46	US Gallon
Standard Glazing	8,181.00	sf
Type III Glass Felt	1,586.93	100sf
Welded Wire Mesh / Ladder Wire	1.07	Tons

	Manufacturing			***Construction***		
	Material	Transportation	**Total**	Material	Transportation	**Total**
Hydro MJ	187,227	38	**187,265**	0	250	**250**
Coal MJ	1,419,520	554	**1,420,073**	0	3,650	**3,650**
Diesel MJ	147,731	80,521	**228,252**	61,916	567,057	**628,973**
Feedstock MJ	1,915,305	0	**1,915,305**	0	0	**0**
Gasoline MJ	554	0	**554**	0	0	**0**
Heavy Fuel Oil MJ	542,318	8,473	**550,791**	0	13,641	**13,641**
LPG MJ	4,870	83	**4,953**	0	546	**546**
Natural Gas MJ	1,821,081	3,381	**1,824,461**	0	22,293	**22,293**
Nuclear MJ	3,661,253	147	**3,661,400**	0	964	**964**
Wood MJ	0	0	**0**	0	0	**0**
Total Primary Energy Consumption MJ	9,699,859	93,196	**9,793,055**	61,916	608,401	**670,317**

	Manufacturing			*Construction*		
Summary Measures	Material	Transportation	**Total**	Material	Transportation	**Total**
Fossil Fuel Consumption (MJ)	5,851,379	93,012	**5,944,391**	61,916	607,186	**669,102**
Global Warming Potential (kg CO2 eq)	404,922	6,578	**411,500**	4,151	43,437	**47,588**
Acidification Potential (moles of H+ eq)	130,379	2,141	**132,521**	1,978	14,182	**16,160**
HH Criteria (kg PM10 eq)	1,447.45	2.79	**1,450.24**	1.15	18.45	**19.60**
Eutrophication Potential (kg N eq)	186.37	2.33	**188.70**	1.92	15.43	**17.35**
Ozone Depletion Potential (kg CFC-11 eq)	2.63E-03	2.63E-07	**2.64E-03**	0.00E+00	1.73E-06	**1.73E-06**
Smog Potential (kg O3 eq)	15,704	1,149	**16,852**	1,116	7,609	**8,724**

A.2.15 I1: Light Industrial

Base data source: RS Means 2008 Square Foot costs, M.560 model: School, Elementary

(RSMeans 2009)

Dimensions: 30,000 ft^2, 1 floor, 200'x150'

Project

Material	Quantity	Unit
#15 Organic Felt	2,052.07	100sf
24 Ga. Steel Roof (Commercial)	44,000.00	sf
6 mil Polyethylene	31,824.00	sf
Ballast (aggregate stone)	407,476.33	lbs
Blown Cellulose	44,679.60	sf(1")
Concrete 20 MPa (flyash av)	884.69	yd³
Concrete 30 MPa (flyash av)	382.76	yd³
Concrete Blocks	23,765.49	Blocks
Expanded Polystyrene	350.37	sf(1")
Galvanized Decking	60.83	Tons
Galvanized Sheet	4.75	Tons
Modified Bitumen membrane	16,588.17	lbs
Mortar	592.97	yd³
Nails	1.62	Tons
Open Web Joists	55.39	Tons
Rebar, Rod, Light Sections	196.12	Tons
Roofing Asphalt	124,014.08	lbs
Screws Nuts & Bolts	0.03	Tons
Solvent Based Alkyd Paint	693.79	US Gallon
Type III Glass Felt	4,104.13	100sf
Welded Wire Mesh / Ladder Wire	2.78	Tons

	Manufacturing			***Construction***		
	Material	Transportation	**Total**	Material	Transportation	**Total**
Hydro MJ	317,272	114	**317,386**	0	570	**570**
Coal MJ	3,738,533	1,659	**3,740,191**	0	8,314	**8,314**
Diesel MJ	355,631	240,307	**595,938**	156,606	1,291,169	**1,447,776**
Feedstock MJ	5,258,434	0	**5,258,434**	0	0	**0**
Gasoline MJ	1,532	0	**1,533**	0	0	**0**
Heavy Fuel Oil MJ	1,310,020	27,388	**1,337,408**	0	30,554	**30,554**
LPG MJ	8,658	248	**8,906**	0	1,244	**1,244**
Natural Gas MJ	4,490,818	10,132	**4,500,950**	0	50,781	**50,781**
Nuclear MJ	597,358	440	**597,798**	0	2,197	**2,197**
Wood MJ	0	0	**0**	0	0	**0**
Total Primary Energy Consumption MJ	16,078,256	280,287	**16,358,544**	156,606	1,384,830	**1,541,436**

	Manufacturing			*Construction*		
Summary Measures	Material	Transportation	**Total**	Material	Transportation	**Total**
Fossil Fuel Consumption (MJ)	15,163,626	279,734	**15,443,360**	156,606	1,382,063	**1,538,669**
Global Warming Potential (kg CO2 eq)	1,047,459	19,714	**1,067,173**	10,414	98,947	**109,361**
Acidification Potential (moles of H+ eq)	305,309	6,429	**311,738**	5,132	32,278	**37,410**
HH Criteria (kg PM10 eq)	3,105.94	8.36	**3,114.31**	3.01	41.99	**45.01**
Eutrophication Potential (kg N eq)	499.41	6.99	**506.40**	5.03	35.11	**40.14**
Ozone Depletion Potential (kg CFC-11 eq)	7.09E-03	7.89E-07	**7.09E-03**	0.00E+00	3.95E-06	**3.95E-06**
Smog Potential (kg O3 eq)	37,177	3,449	**40,626**	2,893	17,316	**20,208**

A.2.16 I2: Heavy Industrial

Base data source: RS Means 2008 Square Foot costs, M.210 model: Factory, 1 story

(RSMeans 2009)

Dimensions: 36,000 ft^2, 1 floor, 360'x100'

Project

Material	Quantity	Unit
#15 Organic Felt	2,238.62	100sf
24 Ga. Steel Roof (Commercial)	52,800.00	sf
Aluminum	7.52	Tons
Ballast (aggregate stone)	403,933.06	lbs
Blown Cellulose	44,679.60	sf(1")
Concrete 20 MPa (flyash av)	734.78	yd³
Concrete Blocks	30,134.06	Blocks
EPDM membrane (black, 60 mil)	1,005.19	lbs
Galvanized Decking	36.50	Tons
Galvanized Sheet	8.49	Tons
Glazing Panel	0.34	Tons
Modified Bitumen membrane	16,443.92	lbs
Mortar	753.47	yd³
Nails	2.46	Tons
Open Web Joists	33.23	Tons
Rebar, Rod, Light Sections	221.27	Tons
Roofing Asphalt	270,576.18	lbs
Screws Nuts & Bolts	0.04	Tons
Solvent Based Alkyd Paint	1,057.94	US Gallon
Standard Glazing	10,088.46	sf
Type III Glass Felt	4,477.24	100sf
Welded Wire Mesh / Ladder Wire	3.33	Tons

	Manufacturing			***Construction***		
	Material	Transportation	**Total**	Material	Transportation	**Total**
Hydro MJ	388,338	90	**388,428**	0	589	**589**
Coal MJ	3,680,387	1,310	**3,681,698**	0	8,588	**8,588**
Diesel MJ	362,067	190,710	**552,777**	167,635	1,327,204	**1,494,839**
Feedstock MJ	5,533,058	0	**5,533,058**	0	0	**0**
Gasoline MJ	1,715	0	**1,715**	0	0	**0**
Heavy Fuel Oil MJ	1,181,863	21,279	**1,203,142**	0	32,555	**32,555**
LPG MJ	9,011	196	**9,207**	0	1,285	**1,285**
Natural Gas MJ	4,323,196	8,003	**4,331,199**	0	52,455	**52,455**
Nuclear MJ	4,490,734	347	**4,491,081**	0	2,269	**2,269**
Wood MJ	0	0	**0**	0	0	**0**
Total Primary Energy Consumption MJ	19,970,369	221,936	**20,192,304**	167,635	1,424,944	**1,592,580**

	Manufacturing			Construction		
Summary Measures	Material	Transportation	**Total**	Material	Transportation	**Total**
Fossil Fuel Consumption (MJ)	15,091,297	221,499	**15,312,795**	167,635	1,422,087	**1,589,722**
Global Warming Potential (kg CO2 eq)	977,912	15,570	**993,482**	11,172	102,205	**113,376**
Acidification Potential (moles of H+ eq)	304,020	5,090	**309,110**	5,372	33,246	**38,617**
HH Criteria (kg PM10 eq)	3,269.88	6.62	**3,276.51**	3.13	43.25	**46.38**
Eutrophication Potential (kg N eq)	495.53	5.54	**501.07**	5.23	36.16	**41.40**
Ozone Depletion Potential (kg CFC-11 eq)	6.63E-03	6.23E-07	**6.63E-03**	0.00E+00	4.08E-06	**4.08E-06**
Smog Potential (kg O3 eq)	35,407	2,732	**38,139**	3,021	17,827	**20,848**

A.2.17 Athena Modifications

To validate Athena's output, concrete, aluminum and steel components were compared to literature values. Minor differences were found a few steel/metal components, but a major discrepancy was found with Athena's estimated energy value for aluminum production, with the Athena output being almost 27 times greater than the published value (U.S. DOE 2007). In the Athena output, this large increase is always due to high reported amounts of nuclear energy. This is potentially an error in the Athena estimates.

Table 17: Athena modifications

	Energy (MJ)		*GHG (kg CO_2eq)*	
	Athena	Literature	Athena	Literature
Aluminum	**1607.9**	**60**	6.81	10
Rebar, Rod, Light Sections	24.4	15.0	1.10	0.6
24 Ga. Steel Roof (Commercial)	178.2	60.0	13.03	3
Galvanized Decking	40.3	40.3	2.80	1

Energy values were reduced in proportion to the embedded energy use associated with aluminum manufacturing in each prototype.

A.2.18 Material Modifications

Modification factors were developed to calculate the increases in embedded energy use and GHG emissions associated with older material manufacturing technologies (Table 18). The upper three rows are literature values for energy use and GHG emissions, and the two modification factors (bottom rows) are the ratio between post-1990 emissions and the two earlier time periods. The modification factors were applied proportionally to energy use and GHG emissions attributed respectively to the manufacture each of these three materials in the original base Athena model.

Table 18: Material Modifications

	Energy			*GHG*		
	Steel	Concrete	Aluminum	Steel	Concrete	Aluminum
1900-1950	38	9	73	0.92	350	73
1950-1990	32.61	8	63	0.74	300	63
1990-2010	23.53	7	29	0.59	250	29
Modification Factor1	1.61	1.29	2.52	1.56	1.40	2.52
Modification Factor2	1.39	1.14	2.17	1.25	1.20	2.17

The final prototype factors modified for manufacturing changes and normalized by building area are presented below (Table 19).

Table 19: Prototype Factors.

Category	*Time Period*	*Energy (MJ/SF)*	*GWP (kg/SF)*	*Steel (kg/SF)*	*Wood (kg/SF)*	*Concrete (kg/SF)*
Single Family	Pre-1950	116.6	14.5	0.8	10.3	33.5
Single Family	1950 - 1990	110.3	12.3	1.0	10.7	34.7
Single Family	Post 1990	105.2	10.0	0.7	7.7	47.4
Multi-Family (Large)	Pre-1950	295.9	30.9	5.8	2.0	49.7
Multi-Family (Large)	1950 - 1990	262.6	27.0	5.8	2.0	49.7
Multi-Family (Large)	Post 1990	205.5	21.7	5.8	2.0	49.7
Multi-Family (Small)	Pre-1950	74.3	9.1	0.4	3.5	13.6
Multi-Family (Small)	1950 - 1990	69.1	8.2	0.4	3.5	13.6
Multi-Family (Small)	Post 1990	56.0	6.3	0.4	3.5	13.6
Condominium	Pre-1950	124.1	19.6	0.5	7.7	10.0
Condominium	1950 - 1990	110.3	17.2	0.5	7.7	10.0
Condominium	Post 1990	66.7	9.6	0.5	7.7	10.0
Hotel	Pre-1950	239.1	28.6	7.7	2.6	12.3
Hotel	1950 - 1990	213.1	25.0	7.7	2.6	12.3
Hotel	Post 1990	163.8	18.7	7.7	2.6	12.3
Department Store	Pre-1950	169.4	21.3	1.6	0.0	65.5
Department Store	1950 - 1990	155.3	18.8	1.6	0.0	65.5
Department Store	Post 1990	134.6	15.7	1.6	0.0	65.5
Neighborhood Store	Pre-1950	313.6	38.5	7.5	0.1	66.3
Neighborhood Store	1950 - 1990	280.3	33.9	7.5	0.1	66.3
Neighborhood Store	Post 1990	220.1	27.2	7.5	0.1	66.3
Low Office	Pre-1950	971.1	41.5	175.5	0.5	53.8
Low Office	1950 - 1990	835.3	33.6	175.5	0.5	53.8
Low Office	Post 1990	602.8	26.5	175.5	0.5	53.8
High Office	Pre-1950	81.2	15.7	2.0	0.0	51.8
High Office	1950 - 1990	71.8	13.5	2.0	0.0	51.8
High Office	Post 1990	53.3	10.2	2.0	0.0	51.8
Hospital	Pre-1950	402.5	53.0	12.1	0.0	110.6
Hospital	1950 - 1990	357.2	46.3	12.1	0.0	110.6
Hospital	Post 1990	281.8	37.8	12.1	0.0	110.6
Church	Pre-1950	257.0	49.8	8.8	3.7	59.6
Church	1950 - 1990	230.8	43.9	8.8	3.7	59.6
Church	Post 1990	174.0	31.8	8.8	3.7	59.6
School	Pre-1950	316.5	51.9	9.4	0.1	66.2
School	1950 - 1990	282.6	45.6	9.4	0.1	66.2
School	Post 1990	214.2	33.9	9.4	0.1	66.2
Warehouse	Pre-1950	575.7	40.4	10.3	0.1	91.9
Warehouse	1950 - 1990	510.5	34.9	10.3	0.1	91.9
Warehouse	Post 1990	410.3	29.8	10.3	0.1	91.9
Heavy Industrial	Pre-1950	349.8	32.3	8.3	0.1	52.6
Heavy Industrial	1950 - 1990	313.1	28.3	8.3	0.1	52.6
Heavy Industrial	Post 1990	251.0	23.5	8.3	0.1	52.6

A.3 Prototype Validation

Athena outputs were validated against building life cycle estimates in existing literature as well as literature on material components. Literature values for embedded building energy use and GHG emissions showed wide variability due to differences in boundary (included

building components), building material choice, building type, and location of building construction (Figure 27). With the exception of category R2, multi-family large (over 3 stories tall), all of the Los Angeles prototype factors fall within or just below the expected range. The factors generated with Athena are likely conservative estimates since only major building shell components were considered, and more detailed building finishes (HVAC, plumbing, flooring, etc.) were not included. For industrial buildings, no specific studies were found. In construction, industrial buildings likely resemble commercial buildings, and the prototype factors fall well within the commercial literature range.

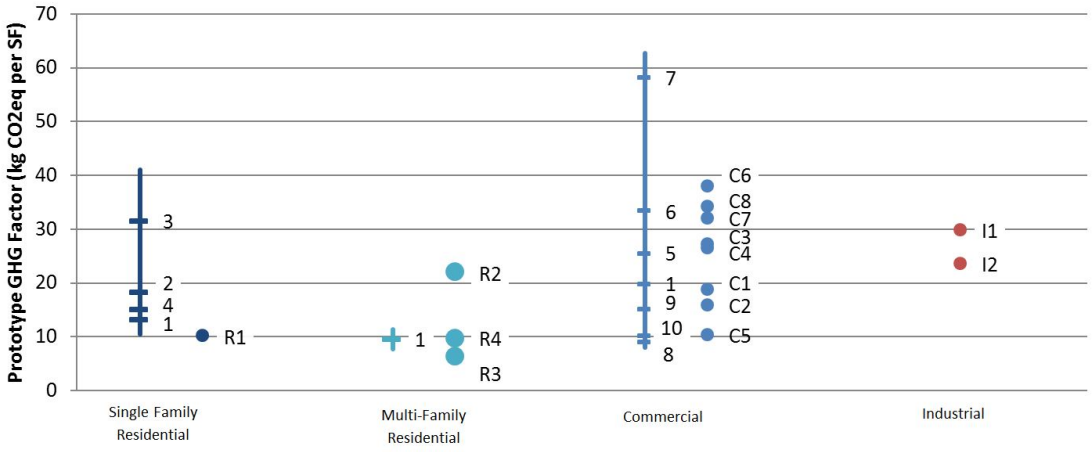


Figure 27: Embedded GHG Prototypes. The Athena results for Post-1990 construction were validated against existing literature studies. The circles are prototypes estimated for this study, the lines are the range of prototype values in the literature, and the dashes on the lines are averages from specific studies.

Table 20: Literature Comparison

No.	Study	Category	Energy (MJ)	GWP (kg CO2eq)	Location	Components Included	LC Included	Tools	Notes
1	Ochsendorf et al. 2011	SFD		14.5	Phoenix	Basic Shell	Man-Con	Process data	2 floors insulated concrete, 2400 ft2
1	Ochsendorf et al. 2011	SFD		10.6	Phoenix	Basic Shell	Man-Con	Process data	2 floors light-frame
1	Ochsendorf et al. 2011	SFD		11.5	Chicago	Basic Shell	Man-Con	Process data	2 floors insulated concrete, 2400 ft2
1	Ochsendorf et al. 2011	SFD		12.4	Chicago	Basic Shell	Man-Con	Process data	2 floors light-frame
1	Ochsendorf et al. 2011	MF		11.3	Phoenix	Basic Shell	Man-Con	Process data	4 floors insulated concrete
1	Ochsendorf et al. 2011	MF		7.8	Phoenix	Basic Shell	Man-Con	Process data	4 floors wood
1	Ochsendorf et al. 2011	MF		11.5	Chicago	Basic Shell	Man-Con	Process data	4 floors insulated concrete
1	Ochsendorf et al. 2011	MF		8.1	Chicago	Basic Shell	Man-Con	Process data	4 floors wood
1	Ochsendorf et al. 2011	Commercial		17.8	Phoenix	Basic Shell	Man-Con	Process data	12 floors cast-in-place concrete
1	Ochsendorf et al. 2011	Commercial		22.0	Phoenix	Basic Shell	Man-Con	Process data	12 floors steel
1	Ochsendorf et al. 2011	Commercial		17.8	Chicago	Basic Shell	Man-Con	Process data	12 floors cast-in-place concrete
1	Ochsendorf et al. 2011	Commercial		22.0	Chicago	Basic Shell	Man-Con	Process data	12 floors steel
4	Lippke et al. 2004	SFD	313.3	18.0	Minneapolis	Basic Shell	Man-Con (GWP + EOL)		Wood
4	Lippke et al. 2004	SFD	368.1	22.7	Minneapolis	Basic Shell	Man-Con (GWP + EOL)		Steel
4	Lippke et al. 2004	SFD	183.5	9.9	Atlanta	Basic Shell	Man-Con (GWP + EOL)		Wood
4	Lippke et al. 2004	SFD	211.8	13.0	Atlanta	Basic Shell	Man-Con (GWP + EOL)		Concrete
2	Ochoa Franco 2004	SFD	330.4	23.5	Ann Arbor	All components		EIO-LCA	RS Means + HES
2	Ochoa Franco 2004	SFD	320.6	22.8	San Antonio	All components		EIO-LCA	RS Means + HES
2	Ochoa Franco 2004	SFD	330.2	23.6	Pittsburgh	All Components		EIO-LCA	RS Means + HES
3	CWC 2011	SFD	467.1	23.1	Toronto	Basic Shell	Man-Con-Maint	Athena	Wood
3	CWC 2011	SFD	590.4	30.9	Toronto	Basic Shell	Man-Con-Maint	Athena	Steel
3	CWC 2011	SFD	732.5	41.8	Toronto	Basic Shell	Man-Con-Maint	Athena	Concrete
10	Chester et al. 2013	SFD	1012.5	8.2	Phoenix	Basic Shell	Man-Con-Maint	Athena	1600 sf
10	Chester et al. 2013	MF	2138.2	12.3	Phoenix	Basic Shell	Man-Con-Maint	Athena	4 floors mixed use
10	Chester et al. 2013	MF	1571.3	10.2	Phoenix	Basic Shell	Man-Con-Maint	Athena	6 floors mixed use
10	Chester et al. 2013	MF	1422.3	10.9	Phoenix	Basic Shell	Man-Con-Maint	Athena	12 floors mixed use
10	Chester et al. 2013	MF	1720.2	10.5	Phoenix	Basic Shell	Man-Con-Maint	Athena	3 floor apartments
10	Chester et al. 2013	Commercial	814.5	9.6	Phoenix	Basic Shell	Man-Con-Maint	Athena	1 floor strip mall
10	Chester et al. 2013	Commercial	1571.3	10.2	Phoenix	Basic Shell	Man-Con-Maint	Athena	6 floor commercial
5	Eaton and Amato 1998	Commercial	232-269	22.4-30.9	UK	Basic Shell	Man-Con	Process data	4 Story Office Building
5	Eaton and Amato 1998	Commercial		18.6-23.2	UK	Basic Shell	Man-Con	Process data	8 Story Office Building
6	Junnila and Horvath 2003	Commercial		33.5	Finland	All components (minus landscape)	Man-Con	Process Data	Office building
7	Guggemos and Horvath 2005	Commercial	771-882	53.6-62.7	Mid-West U.S.	All components (minus landscape)	Man-Con-EOL	Hybrid LCA	5 story office building
8	Jonsson et al. 1998	Commercial	65-88	7.3-10.5	Sweden	Basic Shell	Man-Con	Process data	Steel/Concrete office
9	Johnson 2006	Commercial		13.6-16.4	Boston	Basic Shell	Man-Con	ecoInvent	Office Building

A.4 Embedded versus Emergent t-Test

To test the possibility of relationship between embedded and emergent (use) energy use, a statistical test was performed using the 2011 American Housing Survey. Six variables were used from all of the Los Angeles metropolitan statistical area households included in the survey (Table 21).

Table 21: AHS Variables

Variable Name	***Definition***
AMTE	Average monthly cost of electricity
AMTG	Average monthly cost of natural gas
BUILT	Year of unit construction
NUNIT2	Type of unit (single family, mobile home, etc.)
NUNITS	Number of units in structure
UNITSF	Size of the unit

If an individual Los Angeles household had a non-response for any one of these six variables it was removed from the test records. From the remaining 2,029 records two additional variables were calculated: embedded energy use and annual energy use.

Embedded energy was calculated using the appropriate residential prototype factors developed in this research. The final prototype factors modified for manufacturing changes and normalized by building area are presented below. It should be noted, therefore that embedded energy, in this instance, is a linear combination of unit size and classification (age + type). Annual energy use was calculated using average electricity and natural gas costs for 2011 published by the U.S. Bureau of Labor Statistics[1]. These costs are approximately $0.05 and $0.01 per MJ, respectively.

[1] http://www.bls.gov/ro9/cpilosa_energy.htm

A simple linear model was constructed between embedded energy use and use phase (annual) energy use using least squares. The model was: $E\{E_{emb}\} = 27{,}175 + 39.172 * E_{use}$ A t-test was performed on the second coefficient to determine if it could be zero, signifying no relationship between E_{emb} and E_{use}. The test was defined as follows:

$H_0: \beta_1 = 0; H_a: \beta_0 \neq 0$ with $\alpha = 0.01$

If $t^* > t(0.99, 2028)$ I will reject the null hypothesis and conclude that the correlation between the two variables is non-negligible.

$$t^* = \frac{b_1}{s\{b_1\}} = \frac{39.172}{1.667} = 23.52$$

$$t(0.99{,}2028) = 2.33 < t^*$$

Therefore I reject the null hypothesis and conclude that the coefficient of E_{use} is significant.

A.4.1 Test Discussion

The physical structure of a building can influence its energy efficiency throughout its lifetime (Thormark 2006), and embedded impacts should be weighed against use phase impacts. Recent studies suggest that higher initial energy investments in buildings could lead to lifetime energy savings over the life of the building (Nahlik and Chester 2014; Kimball et al. 2013; Chester et al. 2013). To evaluate the link between embedded and emergent emissions, a statistical analysis was developed. Using Los Angeles data from the 2011 American Housing Survey (~2,000 households sampled), embedded emissions for each dwelling unit were calculated using the aforementioned methods and the reported size and classification of buildings from AHS. A simple linear regression model was fit for the embedded versus use phase emissions and a t-test was performed on the slope. At the 99% confidence level, the slope of this line is not equal to zero, indicating that some correlation

between embedded and emergent energy use exists. Although this test alone is not comprehensive (I have not included other important factors influencing energy consumption), it underscores the importance of further research to characterize the relationship between embedded and emergent emissions in the building stock.

A.5 Supplementary Discussion: Socio-institution Infrastructure Drivers

Los Angeles has undergone four major eras of rapid development of land use, largely driven by flip-flopping densification policies and pressured zoning practice (Whittemore 2012). The first era of growth began in 1921 with the advent of zoning in the city of Los Angeles. It was characterized by rampant speculation on commercial properties, and a general trend of "over-zoning" or creating dwelling unit densities in excess of the official plans. The transition to the second phase of growth coincided with the collapse of property values at the start of the Great Depression in 1929 and the federally insured mortgages through the Federal Housing Administration (FHA) which favored low-density single family development and homogeneity of socio-ethnic groups (Whittemore 2012; Fairfield 2010). As the readily developable land in the region dwindled in the late 1950s, developers began to infill existing areas with multi-family units and higher density single family units. This provoked a backlash from established single family residents who favored preserving suburban ideals (Davis 1990), and thus beginning the third era of land-use. This "slow-growth" movement realized many of its goals in the late 1970s and 1980s with the passing of multiple regulations which lowered property taxes, limited density of commercial development, and instituted massive "down-zoning" or lowering of building density in the official zoning plans. By the 1990s this had coalesced into a massive housing shortage (estimated at 300,000 units by 2000) and soaring land prices (Whittemore 2012). Between 2000 and 2010 there were efforts to balance housing shortages through growth-limitations

and infilling, with efforts such as California State Assembly Bill 1866 in 2003 which allowed the addition of secondary units on single family properties (State of California 2003). Under current regulations, Los Angeles appears to be "locked-in", meaning that large amounts of new construction and building stock growth are unlikely. The future of land-use regulation in Los Angeles is uncertain, but it will likely involve adapting the current urban structures for more intensive future use.

A.6 References

Canadian Wood Council. (2011). *Energy and the Environment in Residential Construction. Environmental monitoring and assessment*, 1–4.

Chavez, S., and Quinn, J. (1987). "Substandard Housing Garages: Immigrants In, Cars Out." *Los Angeles Times*, 24 May.

Chester, M. V, Nahlik, M. J., Fraser, A. M., Kimball, M. a, and Garikapati, V. M. (2013). "Integrating Life-cycle Environmental and Economic Assessment with Transportation and Land Use Planning." *Environmental science & technology*, 47(21), 12020–8

CSBE (California State Board of Equalization). 2010. *Assessors' Handbook, Section 531: Residential Building Costs*. http://www.boe.ca.gov/proptaxes/pdf/ah53110.pdf. Accessed March 2014.

Davis, M. 1990. Ch 3 Homegrown Revolution. In *City of Quartz.* London: Vintage.

Guggemos, A. and A. Horvath. 2005. Comparison of Environmental Effects of Steel-and Concrete-Framed Buildings. *ASCE Journal of Infrastructure Systems.* 11:93-101.

Lippke, B., Wilson, J., Perez-Garcia, J., Bowyer, J., and Meil, J. (2004). "CORRIM : Life-Cycle Environmental Performance of Renewable Building Materials." *Forest Products Journal*, 54(6), 8–19.

Johnson,T.J. 2006. Comparison of environmentla impacts of steel and concrete as building materials using the life cycle assessment method. Master's thesis, Massachusetts Institute of Technology, Cambridge, MA, U.S.

Jonsson, A., Bjorklund, T., and A.M. Tillman. 1998. LCA of Concrete and Steel Building Frames. *International Journal of LCA.* 3(4):216-224.

Junnila, S., and A. Horvath. 2003. Life-Cycle Environmental Effects of an Office Building. *ASCE Journal of Infrastructure Systems.* 9:157-166.

Kimball, M., M. Chester, C. Gino, and J. Reyna. 2013. Assessing the Potential for Reducing Life- Cycle Environmental Impacts through Transit-Oriented Development Infill along Existing Light Rail in Phoenix. *Journal of Planning Education and Research* 33(4): 395–410.

Nahlik, M. and M. Chester. 2014. Transit-oriented smart growth can reduce life-cycle environmental impacts and household costs in Los Angeles. *Transport Policy*. 35:21-30.

Ochoa Franco, L.A. 2004. *Life cycle assessment of residential buildings*. Ph.D. dissertation, Carnegie Mellon University, Pittsburgh.

Ochsendorf, J., L.K. Norford, D. Brown, H. Durschlag, S.L. Hsu, A. Love, N. Santero, O. Swei, A. Webb, and M. Wildnauer. 2011. Methods, Impacts, and Opportunities in the Concrete Building Life Cycle. *Research Report R11-01, Concrete and Sustainability Hub, Department of Civil and Environmental Engineering, Massachusetts Institute of Technology* (August): 119. http://www.greenconcrete.info/downloads/MITBuildingsLCArep ort.pdf. Accessed October 2014.

RSMeans. 2009. *2008 Square foot costs: residential, commercial, industrial, institutional*. 15th ed. Kingston, MA, U.S.: R.S. Means Company.

State of California. 2003. *Assembly Bill 1866*. http://www.hcd.ca.gov/hpd/hpd_memo_ab 1866.pdf. Accessed February 2014.

Thormark, C. 2006. The effect of material choice on the total energy need and recycling potential of a building. *Building and Environment* . 41(8): 1019–1026.

U.S. Census Bureau. 2000. *Chapter 8: Accuracy of the Data.* http://www.census.gov/prod/cen2000/doc/sf3chap8.pdf. Accessed March 2014.

U.S. Department of Energy. (2007). *U . S . Energy Requirements for Aluminum Production.*

USC (University of Southern California), Southern California Studies Center, and Brookings Center on Urban and Metropolitan Policy. 2001. Sprawl Hits the Wall: Confronting the Realities of Metropolitan Los Angeles. *The Atlas of Southern Califronia* .

Whittemore, A.H. 2012. Zoning Los Angeles: a brief history of four regimes. *Planning Perspectives*. 27(3): 393-415.

APPENDIX B

SUPPLEMENTARY INFORMATION FOR CHAPTER 3

B.1 General Profile of LA and NYC

Table 22: Energy Profiles of LA and NYC. LA and NYC use energy in different ways due to the differences in heating and cooling. I detail the year of my two energy datasets, the weather parameters for that year, and the average household (HH) use of energy and electricity in that year.

	LA (LADWP)	*NYC*
Accounts	1,305,759	3,834,461
CBG	2,503	6,497
CT	1,003	2,166
Accounts/CBG	521	590
Heating Degree Days	1,278	4,877
Cooling Degree Days	905	891
Annual HH Elec. Use	5,523 kWh	6,515 kWh
Annual HH Energy Use	5,922 kWh	15,816 kWh
Year	2011	2009

B.2 Data Sources and Processing

I obtained the technical, social and energy data for this project in a variety of formats: shapefiles, CSVs, DBFs, etc. Most of the processing and synthesis of these data was in an iPython notebook with some shapefile operations in ArcMap. Table A2 summarizes data sources for the clustering. I now briefly describe the processing for each dataset.

Table 23: Source Data Summary

Dataset	***Location***	***Type***	***Format***	***Resolution***
ACS	LA / NYC	Social	CSV	Blk Groups
NYC Electricity /PLUTO	NYC	Electricity/Technical	Shapefile / DBF	Tax Lot
RECS	NYC	Technical	CSV	Account
LADWP Electricity	LA	Electricity	Shapefile /DBF	Blk Group
RASS	LA	Technical	CSV	Account
LA Assessor	LA	Technical	Access DB	Building

B.2.1 American Community Survey (ACS)

The ACS is available from the US Census Bureau at the census block group (CBG) scale. I downloaded a CSV of the ACS data for all the block groups in Los Angeles County. After filtering and processing the social variables of interest, I joined these data to the geographies of the CBGs in the LADWP service area (for LA). I also appended the number of accounts from the LADWP Electricity data and processed the GeoPLUTO database, respectively. I used this prepared shapefiles directly for the social clustering with the *maxp* function of the PySal module in my iPython notebook.

B.2.2 NYC Electricity / GeoPLUTO

I obtained the energy data underlying the Howard et al. 2012 publication and the related NYC electricity map as a shapefile. The DBF of the shapefile also contained the full, publicly available, geoPLUTO dataset. The resolution of this data was the tax lot level. There are approximately 1-2 buildings per tax lot. In this file, the energy data were not segregated by building classification (i.e. residential, commercial, industrial), so I used the methods and factors described in the Howard paper to calculate electricity and fuel use only for residential buildings based upon the building classification and residential floor area in SPSS. I created a separate shapefile with only electricity and the number of residential accounts on each tax lot. I aggregated these data in ArcMap to the CBG level. I used this prepared file for the electricity-only clustering, and to calculate end statistics for the other clustering formulations. I also used the GeoPLUTO data to develop technical data for NYC. This is described in more detail in B.3 Technical Prototypes.

B.2.3 LADWP Electricity Data

I obtained the LADWP Electricity data at the CBG level from researchers at the California Center for Sustainable Communities at UCLA (Pincetl et al. 2015). These are metered data from fiscal year 2011 at LADWP. Some of the CBGs in the LADWP service area had been removed prior to my acquisition of the data for privacy reasons. These data were in a prepared shapefile that I used directly in the clustering algorithm.

B.2.4 LA Assessor's Database

The Los Angeles Assessor's Office has a publicly available database on every building in Los Angeles County including information such as use code, floor area, classification, and year of construction. These data are similar to what's available for the GeoPLUTO database, and I used these data in the development of the prototypes.

B.2.5 RECS / RASS

Both of these survey datasets informed my development of the technical prototypes. I describe the processing of these in Technical Prototypes.

B.3 Technical Prototypes

There are no available geospatial datasets of building technical characteristics beyond the basic information in the LA Assessor and GeoPLUTO databases that I are aware of, so I estimate technical characteristics from the Residential Appliance Saturation Survey (RASS) in LA and the Residential Energy Consumption Survey (RECS) in NYC. Both of these surveys include household-level data, which I subdivide into several prototype categories based on year of construction and floor area. Table A3 gives the number of sample points in each prototype category for LA. I collapsed some prototype categories to ensure a minimum

sample of 10 for each category. In NYC, the sample size is smaller than in LA, so I collapse the categories further (Table A4)

Table 24: Sample Size by Prototype Category in Los Angeles from the RASS.I subdivide prototypes by time period of construction (ranges given in RASS) and type of building: single family detached (SFD), single family attached (SFA), multifamily large (MFL - includes 5+ units), and multifamily small (MFS - < 5 units).

Time	*SFD*	*SFA*	*MFL*	*MFS*
Pre-1940	251	40	55	38
1940-1949	232	14	40	26
1950-1959	398	12	69	26
1960-1969	174	13	103	25
1970-1982	106	53	181	31
1983-1992	48	19	65	13
1993-1997	40	5	29	7
2001-2008	33	17	60	8

Table 25: Sample Size by Prototype Category in New York from the RECS. I subdivide prototypes by time period of construction (ranges given in RECS) and type of building: single family detached (SFD), single family attached (SFA), multifamily large (MFL - includes 5+ units), and multifamily small (MFS - < 5 units).

Time	*SFD*	*SFA*	*MFL*	*MFS*
Pre-1950	38	11	102	43
1950-1959	55	8	27	15
1960-1969	28	10	33	18
1970-1979	16		19	
1980-1989	14	10		6
1990-1999			22	
2000-2009				

For each prototype category, I calculate the technical profile. This is summarized in the following Tables.

Table 26: Technical Variables for LA Prototypes

	T_Sqft	*T_BDL Age*	*T_ExtIns*	*T_CeilIns*	*T_Double Pane*	*T_Pool*	*T_ElecHeat*	*T_NGT herms*	*T_ACTy pe_CAC*	*T_ACTy pe_Mixed*	*T_ACTy pe_None*	*T_ACTy pe_RAC*	*T_ACTy pe_Evap*	*T_NumTV*	*T_NumFridge*	*T_NumComp*
SFD1	1678	73	0.50215	1.941	0.39	0.12	0.01	483.67	0.24	0.06	0.52	0.18	0.00	2.330677	1.33	1.59
SFD2	1583	63	0.50233	2.739	0.49	0.14	0.01	447.74	0.32	0.09	0.42	0.17	0.01	2.512931	1.35	1.63
SFD3	1771	53	0.57609	2.732	0.51	0.26	0.02	502.45	0.51	0.11	0.21	0.15	0.01	2.648241	1.39	1.73
SFD4	1995	43	0.7044	2.8	0.58	0.36	0.01	438.37	0.61	0.13	0.18	0.08	0.01	2.764368	1.4	1.77
SFD5	2331	32	0.84211	2.533	0.53	0.34	0.01	1264.18	0.72	0.10	0.13	0.04	0.01	2.698113	1.42	1.94
SFD6	2868	21	0.88372	5.27	0.75	0.30	0.00	750.43	0.79	0.08	0.10	0.02	0.00	3.166667	1.56	2.13
SFD7	2740	11.3	0.92105	3.13	0.89	0.16	0.00	3407.52	0.83	0.05	0.13	0.00	0.00	1.827586	1.43	2.4
SFD8	2486	3.3	1	4.72	0.84	0.14	0.00	363.34	0.79	0.12	0.09	0.00	0.00	2.727273	1.42	2.09
SFA1	1320	73	0.30556	0.763	0.30	0.03	0.00	445.97	0.18	0.03	0.55	0.25	0.00	2.2	1.2	1.38
SFA2	701.8	63	0.38462	0.958	0.14	0.00	0.00	219.53	0.14	0.07	0.64	0.14	0.00	2.142857	1.21	0.86
SFA3	1035	53	0.2	0.6	0.30	0.00	0.00	287.53	0.08	0.00	0.33	0.58	0.00	1.5	1.08	1.25
SFA4	1227	43	0.4	0.25	0.25	0.00	0.00	334.97	0.23	0.08	0.46	0.23	0.00	1.923077	1.23	1.85
SFA5	1422	31.62	0.58537	1.456	0.47	0.00	0.08	600.02	0.72	0.09	0.11	0.08	0.00	2.207547	1.17	1.53
SFA6	1421	21	0.75	1.75	0.32	0.00	0.00	1534.16	0.68	0.05	0.26	0.00	0.00	2.263158	1.32	1.53
SFA7	1533	9.8	0.75	1.25	0.80	0.00	0.00	295.39	0.60	0.20	0.20	0.00	0.00	2	1.6	1.6
SFA8	1816	2.41	1	3.357	0.88	0.00	0.00	255.53	0.82	0.06	0.06	0.06	0.00	2.705882	1.35	2.29
MFS1	1130	73	0.24242	0.592	0.30	0.03	0.03	308.56	0.05	0.13	0.55	0.26	0.00	2	1.13	1.29
MFS2	982.7	63	0.44	0.385	0.16	0.04	0.04	254.55	0.00	0.04	0.54	0.42	0.00	1.5	1.04	1.15
MFS3	689.7	53	0.47826	0.5	0.28	0.00	0.00	2635.19	0.12	0.04	0.50	0.35	0.00	1.769231	1.04	1.08
MFS4	852.7	43	0.3	0.786	0.20	0.00	0.12	1543.15	0.04	0.08	0.72	0.16	0.00	1.92	1.08	0.96
MFS5	885.2	32	0.55556	0.948	0.33	0.00	0.03	1969.52	0.39	0.10	0.29	0.23	0.00	1.870968	1.1	1.03
MFS6	1019	21	0.6	1.792	0.42	0.08	0.08	135.37	0.39	0.15	0.15	0.31	0.00	2.153846	1.08	1.23
MFS7	951.2	11.29	0.83333	0.833	0.80	0.00	0.00	2988.85	0.43	0.14	0.29	0.00	0.14	3.6	1	1.14
MFS8	1125	2.5	1	2.5	0.71	0.00	0.00	221.31	0.38	0.00	0.63	0.00	0.00	2.625	1.25	1.5
MFL1	797.2	73	0.52083	0.637	0.31	0.04	0.04	4938.49	0.18	0.11	0.40	0.31	0.00	1.381818	1.02	1.31
MFL2	860.5	63	0.3125	0.297	0.17	0.03	0.03	825.45	0.03	0.08	0.55	0.35	0.00	1.775	1.05	1.23
MFL3	762.1	53	0.51667	0.6	0.25	0.05	0.00	1407.18	0.09	0.13	0.35	0.44	0.00	1.565217	1.07	1.19
MFL4	930.7	43	0.58667	0.387	0.27	0.02	0.06	2801.66	0.18	0.14	0.32	0.36	0.00	1.650485	1.04	1.04
MFL5	1058	32.44	0.66892	0.733	0.30	0.02	0.10	7059.29	0.47	0.15	0.19	0.19	0.01	1.856354	1.04	1.32
MFL6	1006	21	0.73469	0.633	0.19	0.02	0.00	4957.3	0.66	0.05	0.19	0.11	0.00	1.846154	1.03	1.4
MFL7	980.7	11.62	0.76923	1.589	0.40	0.00	0.00	1006.07	0.52	0.24	0.21	0.03	0.00	3.125	1	1.41
MFL8	1013	2.53	0.88	1.365	0.63	0.02	0.02	3549.86	0.78	0.15	0.05	0.02	0.00	1.766667	1.05	1.58

Table 27: Technical Variables for NYC Prototypes

	T_AC	*T_ADQINS*	*T_BDLAge*	*T_DoublePane*	*T_ExtSiding*	*T_NUMFRIG*	*T_NumComp*	*T_NumTV*	*T_Pool*	*T_ElecHeat*
SFD1	0.84	0.76	1930.87	0.90	0.68	1.29	1.80	3.26	0.11	0.00
SFD2	0.86	0.80	1952.76	0.73	0.73	1.27	1.57	3.07	0.24	0.05
SFD3	0.89	0.89	1964.86	0.82	0.86	1.36	1.88	2.57	0.18	0.04
SFD4	0.07	0.81	1974.50	0.69	0.75	1.38	1.43	3.63	0.25	0.06
SFD5	0.00	0.93	1994.36	0.93	0.86	1.29	0.00	2.79	0.36	0.07
SFA1	0.73	0.73	1925.27	0.64	0.36	1.18	1.50	2.00	0.00	0.00
SFA2	0.75	1.00	1952.38	0.75	0.13	1.25	1.70	3.38	0.00	0.00
SFA3	1.00	0.80	1965.90	0.80	0.20	1.50	1.60	2.90	0.10	0.10
SFA4	0.84	0.90	1990.30	0.90	0.60	3.27	1.50	3.00	0.10	0.00
MFS1	0.58	0.81	1930.19	0.40	0.28	1.02	0.87	1.72	0.00	0.05
MFS2	0.73	0.73	1951.20	0.73	0.20	1.00	0.89	1.73	0.00	0.00
MFS3	0.78	0.89	1968.44	0.56	0.17	1.06	0.33	2.17	0.00	0.28
MFS4	0.67	0.50	1995.67	0.50	0.33	1.17	1.82	1.83	0.00	0.17
MFL1	0.71	0.80	1930.72	0.64	0.01	1.02	0.99	1.73	0.00	0.06
MFL2	0.93	0.93	1952.59	0.67	0.00	1.00	1.19	1.93	0.00	0.07
MFL3	0.73	0.82	1962.55	0.36	0.00	1.03	0.89	2.00	0.00	0.00
MFL4	0.58	0.90	1979.63	0.68	0.00	0.95	1.18	1.79	0.00	0.21
MFL5	0.82	0.91	1999.68	0.73	0.05	1.00	1.09	1.45	0.00	0.09

I then classified all of the use codes from the LA Assessor's database and the geoPLUTO database to one of these prototype categories. I then applied a prototype category to every building or tax lot in LA and NYC, respectively. From here, I aggregate the buildings and tax lots to the CBG level to get a count of each prototype per CBG. I then use the factors in Table A5 and Table A6 to calculate an average technical profile for that CBG. I create a shapefile by linking the technical characteristics by CBG to the geography.

B.4 Subset Selection and Weighting

I use regression analysis in python and R to identify significant social and technical variables and to compute weights for the weighted clustering. I provide the R regression results for the three analyses in each city.

B.4.1.1 Los Angeles

I first run the regression in R from the iPython notebook using the full socio-technical dataset. Initially I tried forwards stepwise regression, and the results were nearly identical to the variables which showed significant from this run. I retain "Age, Composition, Education, Income, Ethnicity, Rental, Building Age, Pool, Floor Area, and Employment" from the first regression. I use the coefficients from the full regression as weights for the clustering on the full socio-technical dataset.

Output 1: Regression on full set of socio-technical characteristics in LA

```
Call:
lm(formula = y ~ x)

Residuals:
   Min     1Q Median     3Q    Max
 -9621   -763    -27    588  41964

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  2765.49     860.60   3.213  0.00133 **
xAge         1298.18     621.70   2.088  0.03689 *
xFamily       694.25     390.33   1.779  0.07543 .
xGender      -841.45     631.17  -1.333  0.18260
xHH_Size     -895.55     720.98  -1.242  0.21431
```

```
xHS_or_Less   705.87     333.94   2.114  0.03463 *
xIncome     11233.04     489.34  22.956  < 2e-16 ***
xNon_White  -1023.63     208.80  -4.902 1.01e-06 ***
xRental     -1343.64     289.40  -4.643 3.61e-06 ***
xT_ACTYPE_C  4582.27    4627.60   0.990  0.32217
xT_ACTYPE_E   -98.09     553.29  -0.177  0.85930
xT_ACTYPE_M  1429.39    1345.24   1.063  0.28809
xT_ACTYPE_N   853.31    3274.16   0.261  0.79441
xT_ACTYPE_R  -161.27    1895.95  -0.085  0.93222
xT_BDLAGE    2600.35    1312.79   1.981  0.04773 *
xT_CEILINS  -1188.71    2233.47  -0.532  0.59462
xT_DOUBLEPA -2459.67    2397.42  -1.026  0.30501
xT_ELECHEAT -1008.04     783.46  -1.287  0.19833
xT_EXTINS    2260.72    2742.58   0.824  0.40985
xT_NGTHERMS -1151.51    1202.94  -0.957  0.33854
xT_NUMCOMP   2103.08    3413.66   0.616  0.53790
xT_NUMFRIDG -6787.89    5584.72  -1.215  0.22431
xT_NUMTV    -5724.93    4328.62  -1.323  0.18610
xT_POOL      3117.11    1116.04   2.793  0.00526 **
xT_SQFT      6628.26    3133.30   2.115  0.03449 *
xUnemployed   824.10     306.77   2.686  0.00727 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1936 on 2477 degrees of freedom
Multiple R-squared:  0.653,      Adjusted R-squared:  0.6495
F-statistic: 186.4 on 25 and 2477 DF,  p-value: < 2.2e-16
```

I re-run the regression on the new subset. I retain Age, Income, Ethnicity, Rental, Building Age, and Pool in the second subset. I use the coefficients from this regression to weight the clustering on the first subset of socio-technical characteristics.

Output 2: Regression on first subset of socio-technical characteristics in LA

```
Call:
lm(formula = y ~ x)

Residuals:
   Min     1Q Median     3Q    Max
 -9733   -748     -5    599  42210

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   1213.4      673.6   1.801 0.071777 .
xAge          1880.2      540.2   3.480 0.000509 ***
xFamily        137.7      323.6   0.426 0.670425
xHS_or_Less    650.4      287.9   2.259 0.023971 *
xIncome      11509.6      476.5  24.156  < 2e-16 ***
xNon_White    -833.9      203.5  -4.097 4.32e-05 ***
xRental      -1255.9      256.0  -4.906 9.87e-07 ***
xT_BDLAGE    -1200.9      240.9  -4.984 6.66e-07 ***
xT_POOL       3110.4      340.9   9.124  < 2e-16 ***
xT_SQFT       1883.3      761.2   2.474 0.013425 *
xUnemployed    806.9      307.1   2.628 0.008648 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

```
Residual standard error: 1950 on 2492 degrees of freedom
Multiple R-squared:  0.6458,     Adjusted R-squared:  0.6444
F-statistic: 454.4 on 10 and 2492 DF,  p-value: < 2.2e-16
```

Irun the final regression on the smallest LA subset to obtain the weights for clustering.

Output 3: Regression on second subset of socio-technical characteristics in LA

```
Call:
lm(formula = y ~ x)

Residuals:
   Min     1Q Median     3Q    Max
 -9505   -787     18    603  42640

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   3194.2      448.8   7.118 1.43e-12 ***
xAge          1120.4      479.6   2.336  0.01958 *
xIncome      10838.9      405.1  26.758  < 2e-16 ***
xNon_White    -641.3      196.6  -3.263  0.00112 **
xRental      -1540.0      233.6  -6.593 5.26e-11 ***
xT_BDLAGE    -1165.0      229.2  -5.083 4.00e-07 ***
xT_POOL       3762.4      262.1  14.357  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1958 on 2496 degrees of freedom
Multiple R-squared:  0.6425,     Adjusted R-squared:  0.6416
F-statistic: 747.7 on 6 and 2496 DF,  p-value: < 2.2e-16
```

B.4.2 New York City

As for LA, I first run the regression in R from the iPython notebook using the full socio-technical dataset. Initially I tried forwards stepwise regression, and the results were nearly identical to the variables which showed significant from the full socio-technical run. I retain "Household Size, Rental, Electric Heat, Air Conditioning, Number of Refrigerators, Number of Computers, Number of TVs, Floor Area, and Pool" from the first regression. I use the coefficients from the full regression as weights for the clustering on the full socio-technical dataset.

Output 4: Regression on full set of socio-technical characteristics in NYC

```
Call:
lm(formula = y ~ x)

Residuals:
     Min       1Q   Median       3Q      Max
```

```
-0.28621 -0.06484 -0.01111  0.04620  0.60202

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.0231996  0.4456904   0.052 0.958509
xS_AGE      -0.0410185  0.0331164  -1.239 0.216129
xS_FAMILY    0.0161179  0.0125152   1.288 0.198451
xS_FEMALE    0.0008981  0.0107139   0.084 0.933230
xS_HHSIZE    0.1998118  0.0559557   3.571 0.000394 ***
xS_HSORLESS  0.0032885  0.0122705   0.268 0.788819
xS_INCOME   -0.0034079  0.0210992  -0.162 0.871758
xS_NONWHITE -0.0015678  0.0117843  -0.133 0.894221
xS_RENTAL   -0.0481047  0.0141308  -3.404 0.000723 ***
xS_UNEMPLOY  0.0085929  0.0124023   0.693 0.488759
xT_AC        0.0221640  0.0133916   1.655 0.098602 .
xT_ADQINS   -0.0183854  0.0140405  -1.309 0.191043
xT_BDLYR     0.0212389  0.4613499   0.046 0.963302
xT_DBLPANE   0.0151780  0.0115668   1.312 0.190116
xT_ELECHEAT  0.0895257  0.0222645   4.021 6.79e-05 ***
xT_EXTSIDIN  0.0248198  0.0134765   1.842 0.066170 .
xT_FT3NG    -0.0435001  0.0319797  -1.360 0.174430
xT_NUMFRIG   0.1945011  0.0500018   3.890 0.000115 ***
xT_NUMPC     0.1681360  0.0444860   3.780 0.000178 ***
xT_NUMTV     0.2743210  0.0422390   6.495 2.20e-10 ***
xT_POOL      0.1010898  0.0221612   4.562 6.54e-06 ***
xT_SQFT      0.1415525  0.0609443   2.323 0.020640 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.1114 on 453 degrees of freedom
Multiple R-squared:  0.5521,     Adjusted R-squared:  0.5313
F-statistic: 26.59 on 21 and 453 DF,  p-value: < 2.2e-16
```

I re-run the regression on the new subset. I retain Household Size, Rental, Electric Heat, Number of Refrigerators, Number of TVs, Number of Computers, and Pool in the second subset. I use the coefficients from this regression to weight the clustering on the first subset of socio-technical characteristics.

Output 5: Regression on first subset of socio-technical characteristics in NYC

```
Call:
lm(formula = y ~ x)

Residuals:
     Min       1Q   Median       3Q      Max
-0.29735 -0.06064 -0.01270  0.04967  0.60427

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.008941   0.024893   0.359 0.719634
xS_HHSIZE    0.232674   0.046278   5.028 7.10e-07 ***
xS_RENTAL   -0.043811   0.013351  -3.281 0.001110 **
xT_AC        0.024334   0.012741   1.910 0.056756 .
xT_ELECHEAT  0.098143   0.021485   4.568 6.32e-06 ***
xT_EXTSIDIN  0.025620   0.013220   1.938 0.053222 .
xT_NUMFRIG   0.179318   0.048659   3.685 0.000256 ***
xT_NUMPC     0.182204   0.038905   4.683 3.71e-06 ***
```

```
xT_NUMTV      0.276396   0.041502   6.660 7.77e-11 ***
xT_POOL       0.105839   0.021689   4.880 1.46e-06 ***
xT_SQFT       0.153585   0.060172   2.552 0.011016 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.111 on 464 degrees of freedom
Multiple R-squared:  0.5442,     Adjusted R-squared:  0.5344
F-statistic:  55.4 on 10 and 464 DF,  p-value: < 2.2e-16
```

I run the final regression on the smallest NYC subset to obtain the weights for clustering.

Output 6: Regression on second subset of socio-technical characteristics in NYC

```
Call:
lm(formula = y ~ x)

Residuals:
     Min       1Q   Median       3Q      Max
-0.28782 -0.06746 -0.01367  0.04808  0.58175

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.04875    0.02265   2.152   0.0319 *
xS_HHSIZE    0.24640    0.04653   5.295 1.83e-07 ***
xS_RENTAL   -0.07019    0.01159  -6.058 2.84e-09 ***
xT_ELECHEAT  0.09536    0.02174   4.387 1.42e-05 ***
xT_NUMFRIG   0.20441    0.04891   4.179 3.49e-05 ***
xT_NUMPC     0.19785    0.03910   5.060 6.04e-07 ***
xT_NUMTV     0.30700    0.04135   7.424 5.41e-13 ***
xT_POOL      0.11821    0.02157   5.481 6.92e-08 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.1125 on 467 degrees of freedom
Multiple R-squared:  0.5284,  Adjusted R-squared:  0.5214
F-statistic: 74.76 on 7 and 467 DF,  p-value: < 2.2e-16
```

I provide a summary of the subsets for both cities in Table 28.

Table 28: Regression Subsets.

	LA		*NYC*	
	Set 1 (10)	Set 2 (6)	Set1 (10)	Set2 (7)
T_BDL Age	x	x		
T_NumFridge			x	x
T_Pool	x	x	x	x
T_SqFt	x		x	
T_AC			x	
T_Electric Heat			x	x
T_ExtSiding			x	
T_NumPC			x	x
T_NumTV			x	x
S_Rental	x	x	x	x
S_HSorLess	x			
S_Age	x	x		
S_Family	x			
S_Income	x	x		
S_Unemployed	x			
S_NonWhite	x	x		
S_HHSize			x	x

B.5 New York City Total Energy Heterogeneity

I run the same clustering formulations for NYC total energy use, including natural gas and other heating fuels. I find that all of the clustering formulations are have statistically lower formulation heterogeneity than the census tracts, implying that my conclusions are valid for all types of energy use and not just electricity. I do not perform the full analysis on LA, as comparable data on fuel use are not available.

Table 29: Average Formulation Heterogeneity and Formulation Standard Deviation for Total Energy Use in NYC

	NYC			
	Heterogeneity	St. Dev.	t-value	p value
Electricity	2557.2	25.0	323.3	1E-21
Social	2704.8	26.6	321.4	2E-21
Technical	2605.9	33.4	246.6	3E-20
Socio-Technical Full-set	2634.3	27.3	305.0	3E-21
Socio-Technical Subset 1	2626.9	37.0	224.6	7E-20
Socio-Technical Subset 2	2693.3	33.3	255.6	2E-20
Tracts	3456.1	-		

B.6 References

Pincetl, Stephanie, Robert Graham, Sinnott Murphy, and Deepak Sivaraman. 2015. "Analysis of High-Resolution Utility Data for Understanding Energy Use in Urban Systems: The Case of Los Angeles, California." *Journal of Industrial Ecology*, June, n/a – n/a. doi:10.1111/jiec.12299.

APPENDIX C

METHODS FOR CHAPTER 4

C.1 Introduction

Under current climate change projections, many regions of the United States (U.S.) will experience increased annual average temperatures, which may have significant implications for building energy use. Air conditioning in residential buildings constitutes approximately 5% of total electricity use in the U.S. (U.S. Energy Information Administration 2014a; Lawrence Berkeley National Laboratory 2016). This proportion will likely increase with projected temperature increases, creating additional costs for homeowners and environmental burdens. Forecasting how climate change will impact space cooling as well as strategies for meeting or mitigating increased demand is exceedingly important, especially as climate change could also decrease the output of electricity generation facilities (Bartos and Chester 2015a; van Vliet et al. 2016).

C.2 Model Calibration

To quantify the relationship between electricity consumption and climate change, I develop a model for forecasting residential energy use through 2060 in Los Angeles County (LAC) using a calibrated engineering building prototype ensemble. Under this approach, I model 84 building prototypes to represent all of the residential building stock of LAC, simulate energy use in each of these prototypes, categorize all LAC buildings into prototype categories, and compare my simulated energy use for LAC to real-world data. In this section, I discuss the data acquisition, base model development, and calibration. As part of the mitigation strategies, I test a series of building and appliance energy efficiency measures. In order to understand and target sub-urban energy consumption patterns, the model needs to i) maintain spatial resolution, ii) subdivide end use consumption, and iii) be based on the physical properties of the building.

Multiple models exist for energy simulation and forecasting. According to Swan and Ugursal (2009), in the residential sector these fall into one of two larger categories: bottom-up or top-down (Figure 28). Under this categorization, top down models are based upon historic, high-level variables such as macroeconomic parameters. The advantages to this modeling approach are availability of data, simplicity of the model, and ability to rely upon historic trends in developing a forecast. Top-down models, however, have difficulty forecasting long time horizons or when dramatic changes to the input parameters occur (e.g. rapidly accelerating population growth). Furthermore, top-down models do not subdivide end use types, which makes it difficult to identify areas for improvement or to understand the physical and behavioral drivers of energy consumption. In contrast, bottom-up models utilize data at the sub-sector level to calculate the energy consumption of a sub-group of buildings and then extrapolate these models trends to represent the entire building sector. Statistical bottom-up models utilize historic relationships between energy consumption and building end uses to develop mathematical relationships among the parameters, whereas engineering bottom-up models calculate the energy consumption of the end uses based on the equipment in the buildings without any historic information (Kavgic et al. 2010). The advantage to bottom-up approaches is that end uses can be directly predicted and targeted for improvement, at the disadvantage of having much greater complexity, data requirements, and computation time. Within the engineering bottom-up classification, using building "archetypes" is a common technique for simulating the electricity use within a city or a city sector (H. Akbari et al. 1993; Huang et al. 1991; Huang et al. 1999; Opitz et al. 1997; Sezgen et al. 1995; Yamaguchi, Shimoda, and Mizuno 2007; Jones, Patterson, and Lannon 2007; Carlo, Ghisi, and Lamberts 2003; Shimoda et al. 2004), but it has rarely been used for long-term forecasting, as most of the models are not calibrated. For example, Shimoda et al.

(2004) find discrepancies of 18% for residential energy consumption from their model to actual values, but do not attempt to correct the values (Shimoda et al. 2004). Many prototype models do not even attempt to compare totals from the model to a real-world value. Kavgic et al. (2010) underscore the lack of available data for identifying technical and behavior trends for developing quality bottom-up models (Kavgic et al. 2010). To avoid this limitation, most models used for long-term forecasts employ a top-down approach (Esteves et al. 2015).

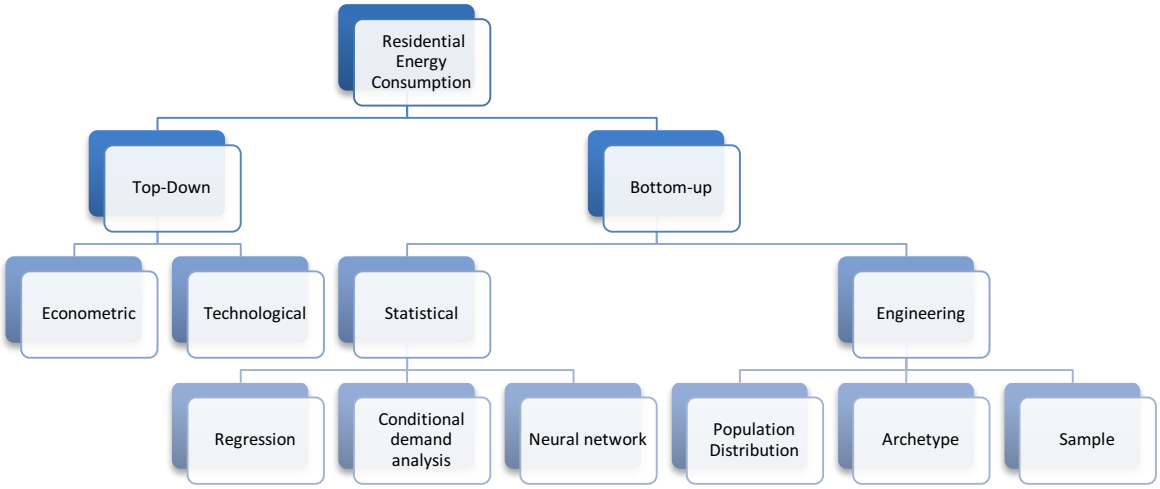


Figure 28: Models of Residential Energy Consumption. Under this schema, the present study is classified as an "Archetype" model.

Adapted from: Swan, Lukas G, and V Ismet Ugursal, 2009. "Modeling of End-Use Energy Consumption in the Residential Sector: A Review of Modeling Techniques." *Renewable and Sustainable Energy Reviews* 13 (8): 1819–35. doi:10.1016/j.rser.2008.09.033.

C.2.1 Methodology

For this study, I develop prototype (archetype) - based bottom-up engineering models to forecast energy consumption between 2020 and 2060 in the residential sector. This type of modeling creates a group of building energy simulations which represent the

entire building stock. This is the most appropriate model for the project goals as a prototype model 1) is not bounded by historic data trends, 2) allows transparency and manipulation of end use types, and 3) allows for the customization of the model to LAC. A drawback to this approach is the high computational resources required to run the building simulation ensemble as well as the detailed data input requirements. I overcome this by simplifying the simulation where possible and utilizing the rich variety of data sources available for LAC. A bottom-up model is necessary to maintain end use consumption detail which I then modify in future years to investigate the impact of energy efficiency improvements across the building stock. First, I develop the 84 building simulation models in BEopt, and for each I include 21 heating and 13 cooling technologies. In BEopt, I utilize EnergyPlus, a state-of-the-art building simulation software developed by the U.S. Department of Energy, as the main simulation engine. Next, I scale electricity and natural gas consumption to the county level, while maintaining spatial detail by census block group (CBG). I then calibrate the model using the subset of CBGs which fall within the Los Angeles Department of Water and Power's (LADWP) service area. A fundamental assumption of the model is that patterns of use are correlated to building type, for example that homeowners in similar vintage homes in the same climate zone will use similar set temps within their homes. The major dataset I use is median and average monthly residential electricity for the LADWP service area, aggregated by CBG. The University of California, Los Angeles (UCLA) obtained these data as part of a research project with the California Energy Commission (CEC) (Pincetl et al. 2015). UCLA has removed some census block groups which might validate the confidentiality of the account holders. In total, there are 2501 CBGs in the dataset that can be used. This is a uniquely detailed set of electricity data.

C.2.2 Development of Prototypes

In developing the prototypes, I utilize three major sources of information: the Residential Appliance Saturation Survey, the Los Angeles County Assessor database, and the California Assessor's Handbook. The Residential Appliance Saturation Survey (RASS) is a California-specific appliance survey conducted by the California Energy Commission which captures a diverse set of variables on building thermal properties and appliance use. The most recent RASS survey, from 2008, contains approximately 6500 survey responses for LAC, and I used these responses to inform appliance distribution within each prototype and some material properties of the buildings (Table 30). The Los Angeles County Assessor's office maintains a database of every building standing in LAC (Los Angeles County Assessor Office 2009). This database is maintained primarily for tax purposes, and I utilize information on building size, classification, location, and quality in developing the prototypes. The California Assessor's Handbook provides "typical" characteristics of buildings in different quality classes, and it exists as a reference for assessing property value in the state of California. I used the handbook to add in additional details on thermal properties for each prototype if they were not available from the other sources. I give a summary of the data I obtain from each source (Table 30).

Table 30: Variables for Prototype Definition and Sources

Variable	*Source*
Building Size (sqft)	Assessor DB
Building Age	Assessor DB/ RASS
Number of Stories	RASS
Number of Bedrooms	RASS
Presence of Garage	RASS
Cooling Technology & Age	RASS
Heating Technology & Age	RASS
Window Quality	RASS
Framing and Foundation	Assessor Handbook
Exterior Finishes	Assessor Handbook
Interior Finishes	Assessor Handbook
Ceiling Fans	RASS
Temperature Set Point	RASS
Water Heater Technology & Age	RASS
Insulation (Walls & Attic)	RASS
Quality Class Code	Assessor DB
Lighting Type	RASS
Refrigerator Type, Size, & Age	RASS
Ranges & Ovens	RASS
Washer & Dryer	RASS
TVs & PCs	RASS
Pool Presence	Assessor DB
Pool Pump/Heater Fuel	RASS

In Los Angeles County, the climate varies greatly between coastal and inland regions, so I differentiated my prototypes based upon five climate zones. The California Energy Commission developed these zones specifically for buildings for the purposes of compliance with California Title 24 Building Energy Efficiency Standards (Figure 29). Climate Zone 6 includes coastal beaches and low lying coastal land along the southern California coast. The ocean regulates temperature in the summer and winter, keeping the climate mild. Climate Zone 8 is further inland, but is regulated by marine air, keeping the high and low temperatures more moderate than further inland zones. Summers are generally warmer and winters cooler than on the coast, so more heating and cooling are necessary. Climate Zone 9

has influence of both coastal and interior weather patterns. Cool moist air arrives from the ocean and hot dry air from further inland. Climate Zone 14 is a high desert climate characterized by large temperature swings without the mediating influence of the ocean. Climate Zone 16 is about 5,000 feet in elevation and semi-arid. This is a colder climate than the other four in LAC. A summary of the heating degree days (HDD) and cooling degree days (CDD) is given below (Table 31). These numbers are the summation of degrees above or below the reference temperature (80˚F or 65 ˚F, respectively) per day. Climate information is adapted from the Pacific Energy Center's Guide to California Climate Zones and Bioclimatic Design (Pacific Energy Center 2006).

Table 31: LAC Climate Zones – Heating Degree Days and Cooling Degree Days

Climate Zone	*HDD*	*CDD*
6	1460	730
8	1290	1300
9	1150	1540
14	2704	1998
16	4300	1040

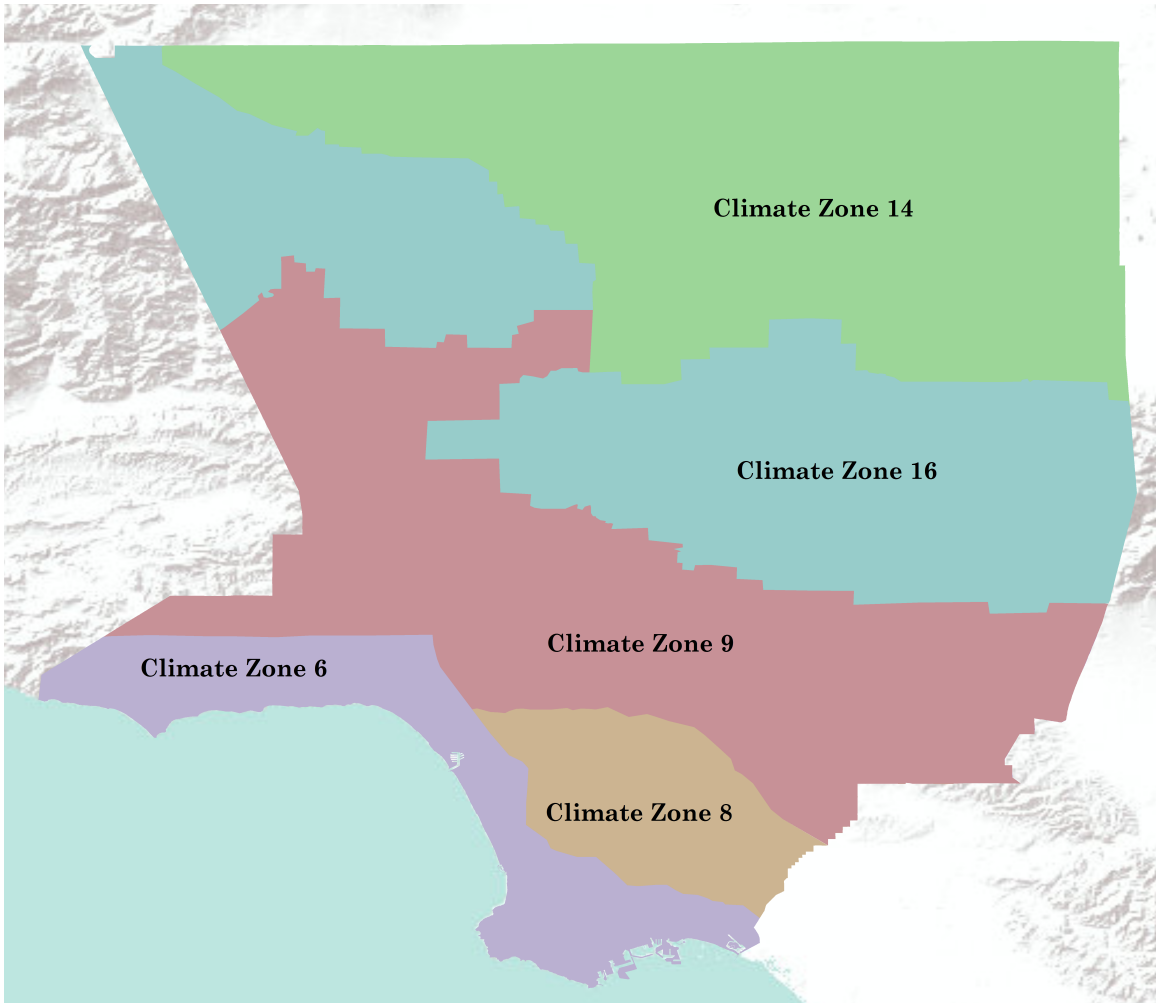


Figure 29: LAC Climate Zones

I develop custom building prototypes based upon my previous work (Reyna and Chester 2015) which were then subdivided by climate zone, period of construction, and residential building type. There are 140 potential prototype categories, as I consider seven

major time periods, five climate zones, and four building types (7 × 5 × 4 = 140), but I aggregate this further to ensure sufficient survey responses in RASS for each prototype. This results in a total of 84 prototypes for the simulation (Table 32).

Table 32: Core Prototype Divisions and Names

	Apartment or Condo (2-4 Units)					*Apartment or Condo (5+Units)*				
	CZ 6	CZ 8	CZ 9	CZ 14	CZ 16	CZ 6	CZ 8	CZ 9	CZ 14	CZ 16
<1940	6MFS1	8MFS1	9MFS1	14MFS1-7	16MFS1-4	6MFL1	8MFL1-2	9MFL1	14MFL1-5	16MFL1-7
1940-1949	6MFS2-3	8MFS2-3	9MFS2			6MFL2		9MFL2		
1950-1959			9MFS3			6MFL3	8MFL3	9MFL3		
1960-1969	6MFS4	8MFS4	9MFS4			6MFL4	8MFL4	9MFL4		
1970-1982	6MFS5-7	8MFS5	9MFS5		16MFS5-7	6MFL5	8MFL5	9MFL5		
1983-1997		8MFS6-7	9MFS6-7			6MFL6	8MFL6	9MFL6	14MFL6-7	
1998-2008						6MFL7	8MFL7	9MFL7		

	Single Family Detached					*Townhouse, Duplex, or Row House*				
	CZ 6	CZ 8	CZ 9	CZ 14	CZ 16	CZ 6	CZ 8	CZ 9	CZ 14	CZ 16
<1940	6SFD1	8SFD1	9SFD1	14SFD1-3	16SFD1-3	6SFA1-4	8SFA1-2	9SFA1	14SFA1-7	16SFA1-7
1940-1949	6SFD2	8SFD2	9SFD2					9SFA2		
1950-1959	6SFD3	8SFD3	9SFD3				8SFA3-4	9SFA3-4		
1960-1969	6SFD4	8SFD4	9SFD4	14SFD4	16SFD4					
1970-1982	6SFD5	8SFD5	9SFD5	14SFD5	16SFD5	6SFA5	8SFA5-7	9SFA5		
1983-1997	6SFD6-7	8SFD6-7	9SFD6	14SFD6	16SFD6	6SFA6-7		9SFA6		
1998-2008			9SFD7	14SFD7	16SFD7			9SFA7		

I next group all of the residential buildings of LAC in the Los Angeles Assessor database into each of the 84 categories. I use characteristics from the Assessor database as specifications for the prototypes (e.g. average building size), and the grouping also allows for

the final simulation results to be scaled to the county-level. For each of the 84 categories, I compiled a profile of the typical building shape (perimeter to area ratio), predominate material in the framing, average size, and quality class from the Assessor database. California assessors use the quality class designation to indicate greater quality and home value. In some cases, this means improved thermal properties as well. For prototypes that are in the same climate zone that have the same predominant quality class and similar floor areas, I combine them to save on computation time. I maintain all 84 prototypes for appliance assessment, but for the building simulations, I use a condensed 51 simulation models (Table 33).

Table 33: Simulation Prototype Divisions and Names

<table>
<tr><td></td><td colspan="5">Apartment or Condo (2-4 Units)</td><td colspan="5">Apartment or Condo (5+Units)</td></tr>
<tr><td></td><td>CZ 6</td><td>CZ 8</td><td>CZ 9</td><td>CZ 14</td><td>CZ 16</td><td>CZ 6</td><td>CZ 8</td><td>CZ 9</td><td>CZ 14</td><td>CZ 16</td></tr>
<tr><td><1940</td><td rowspan="3">6MFS D-5</td><td>8MFS D-4</td><td rowspan="2">9MFS D-5</td><td rowspan="5">14MFS D-5</td><td rowspan="3">16MFS D-4</td><td rowspan="2">6MFL D-5</td><td rowspan="2">8MFL D-5</td><td>9MFL D-5</td><td rowspan="3">14MFL D-5</td><td rowspan="6">16MFL D-4</td></tr>
<tr><td>1940-1949</td><td rowspan="2">8MFS D-5</td><td rowspan="4">9MFL D-6</td></tr>
<tr><td>1950-1959</td><td rowspan="3">9MFS D-6</td><td rowspan="3">6MFL D-6</td><td rowspan="3">8MFL D-6</td></tr>
<tr><td>1960-1969</td><td rowspan="3">16MFS D-6</td></tr>
<tr><td>1970-1982</td><td rowspan="3">6MFS D-6</td><td rowspan="3">8MFS D-6</td><td rowspan="3">14MFL D-6</td></tr>
<tr><td>1983-1997</td><td rowspan="2">6MFL D-7</td><td rowspan="2">9MFL D-7</td></tr>
<tr><td>1998-2008</td></tr>
</table>

<table>
<tr><th></th><th colspan="5">Single Family Detached</th><th colspan="5">Townhouse, Duplex, or Row House</th></tr>
<tr><th></th><th>CZ 6</th><th>CZ 8</th><th>CZ 9</th><th>CZ 14</th><th>CZ 16</th><th>CZ 6</th><th>CZ 8</th><th>CZ 9</th><th>CZ 14</th><th>CZ 16</th></tr>
<tr><td><1940</td><td rowspan="2">6SFD D-5C</td><td>8SFD D-5C</td><td>9SFD D-5C</td><td rowspan="3">14SFD D-5C</td><td rowspan="6">16SFD D-7 (Mtn.)</td><td rowspan="3">6SFA D-6C</td><td>8SFA D-6C</td><td>9SFA D-6C</td><td rowspan="6">14SFA D-6M</td><td rowspan="6">16SFA D-7 (Mtn.)</td></tr>
<tr><td>1940-1949</td><td>8SFD D-6C</td><td>9SFD D-6C</td></tr>
<tr><td>1950-1959</td><td>6SFD D-5M</td><td>8SFD D-6M</td><td>9SFD D-6M</td><td rowspan="2">8SFA D-8M</td><td rowspan="4">9SFA D-7M</td></tr>
<tr><td>1960-1969</td><td rowspan="2">6SFD D-7M</td><td rowspan="2">8SFD D-7M</td><td rowspan="3">9SFD D-7M</td><td rowspan="3">14SFD D-7M</td></tr>
<tr><td>1970-1982</td><td>6SFA D-7M</td><td rowspan="3">8SFA D-7M+</td></tr>
<tr><td>1983-1997</td><td rowspan="2">6SFD D-8M+</td><td rowspan="2">8SFD D-7M+</td><td rowspan="2">6SFA D-6M+</td></tr>
<tr><td>1998-2008</td><td>9SFD D-8M+</td><td>14SFD D-8M+</td><td>16SFD D-8 (Mtn.)</td><td>9SFA D-8M+</td></tr>
</table>

For these 51 categories, I develop models BEopt using data from three sources on the thermal properties of the building (Table 30). For HVAC technologies, I use 21 different heating technologies and 13 different cooling technologies within each prototype (Table 34). I do this to obtain a more representative "weighted average" for HVAC end use energy consumption. For example, in RASS, the survey responses indicated that the main heating technology across most prototypes is a natural gas furnace of 78% efficiency. However, if I only simulate this one technology for all prototypes, I would fail to capture the true variability in heating technologies (and associated energy use) which exists. Instead, I run all of the technologies in BEopt and weight the energy consumption by prototype category based on the RASS survey responses.

Table 34: Base Model HVAC Technologies

	Category	*Efficiency*
	Furnace	Electric 100% AFUE
	Furnace	Gas 64% AFUE
	Furnace	Gas 68% AFUE
	Furnace	Gas 80% AFUE
	Furnace	Propane 64% AFUE
	Furnace	Propane 68% AFUE
	Furnace	Propane 80% AFUE
	Boiler	Electric
	Boiler	NG, Forced Draft, 72% AFUE
	Boiler	NG, Forced Draft, 76% AFUE
	Boiler	NG, Forced Draft, 80% AFUE
	Boiler	Propane, Forced Draft, 72% AFUE
	Boiler	Propane, Forced Draft, 76% AFUE
	Boiler	Propane, Forced Draft, 80% AFUE
	Electric Baseboard	100% Efficiency
	Air-Source Heat Pump	SEER 8, 6 HSPF
	Air-Source Heat Pump	SEER 10, 6.2 HSPF
	Air-Source Heat Pump	SEER 13, 7.7 HSPF
	Air-Source Heat Pump	SEER 14, 8.2 HSPF
	Air-Source Heat Pump	SEER 15, 8.5 HSPF
	Mini-Split Heat Pump	SEER 14
	Central A/C	SEER 8
	Central A/C	SEER 10
	Central A/C	SEER 13
	Central A/C	SEER 14
	Central A/C	SEER 15
	Room A/C	EER 8.5
	Room A/C	EER 9.8

To save on computation time, I model appliances independently of HVAC and building shell, but with a similar weighted approach to capture the range of technologies for

each appliance. I list the appliance levels from BEopt in Table 35. Since the presence of appliances in buildings impacts thermal loading, I included a typical set of appliances which remained constant across all the HVAC simulations, but utilized only the heating and cooling end-use consumption from the HVAC simulations.

Table 35: Appliance Levels in Prototypes

Category	*Efficiency*
Water Heater	Electric Standard
Water Heater	Electric Tankless
Water Heater	Natural Gas Standard
Water Heater	Natural Gas Tankless
Water Heater	Natural Gas Premium
Water Heater	Propane Standard
Water Heater	Propane Tankless
Water Heater	Heat Pump
Water Heater	Solar Water Heating
Refrigerator	25 cu ft, EF=6.5, side freezer
Refrigerator	18 cu ft, EF=6.9, top freezer
Refrigerator	21 cu ft, EF=6.7, bottom freezer
Refrigerator	25 cu ft, EF=13.8, side freezer
Refrigerator	18 cu ft, EF=14.1, top freezer
Refrigerator	21 cu ft, EF=13.6, bottom freezer
Refrigerator	25 cu ft, EF=4.4, side freezer
Refrigerator	18 cu ft, EF=4.4, top freezer
Refrigerator	21 cu ft, EF=4.5, bottom freezer
Refrigerator	25 cu ft, EF=10.8, side freezer
Refrigerator	18cu ft, EF=10.5, top freezer
Refrigerator	21 cu ft, EF=10.2, bottom freezer
Refrigerator	25 cu ft, EF=15.7, side freezer
Refrigerator	18 cu ft, EF=15.9, top freezer
Refrigerator	21 cu ft, EF=15.9, bottom freezer
TVs	Standard TVs
TVs	Plasma TVs
TVs	Large LCD TVs
TVs	Small LCD TVs
Computers	Desktop
Computers	Laptop
Pool	No Heat Pool
Pool	Electric Pool
Pool	Natural Gas Pool
Freezer	16 cu ft. EF=13, chest, 11-20 years
Freezer	18 cu ft. EF=9, upright, 11-20 years
Freezer	16 cu ft. EF=24, chest, 2-7 years
Freezer	18 cu ft. EF=16, upright, 2-7 years
Freezer	16 cu ft. EF=10, chest, 21+ years
Freezer	18 cu ft. EF=6, upright, 21+ years
Freezer	18 cu ft. EF=18, chest, 8-10 years
Freezer	16 cu ft. EF=12, upright, 8-10 years

Freezer	16 cu ft. EF=27, chest, <2 years
Freezer	18 cu ft. EF=18, upright, <2 years
Microwave	0-5 years
Microwave	6-10 years
Microwave	11-15 years
Microwave	15+ years
Cooking Range / Oven	Electric
Cooking Range / Oven	Conventional Gas
Cooking Range / Oven	Conventional Propane

C.2.3 Calculation of ensemble totals / Aggregation to the County Scale

BEopt output is in hourly increments (as is the BEopt core simulation engine, EnergyPlus), and I aggregate this to yearly resolution for the calibration to be consistent with the LADWP data. To get the total consumption for the residential building stock, I normalize HVAC end use consumption per square foot by prototype, and multiply the square footage of each prototype category within each CBG. The RASS survey reports the frequency of use of HVAC equipment by time of day, and in many prototype categories, a non-negligible percentage of inhabitants own HVAC equipment, but left it off the majority of the time. I utilize this "non-use" percentage to adjust the typical energy consumption of the prototypes. Additionally, I simulate lighting with the 51 simulation prototypes and normalize per square foot, but I maintain appliances at the per prototype level. In the aggregation, appliance types were maintained so that end use could be ascertained in the final model and tracked in the forecast.

C.2.4 Calibration

I run the simulation ensemble for FY 2011-2012, and to be commensurate with the climatic conditions of the LADWP, I develop my own custom weather files. The LADWP data is for fiscal year 2011-2012, so the data range starts July 2011 through the end of June

2012. BEopt utilizes an EPW file, which includes a range of climatic variables such as temperature, humidity, solar radiation, snow cover, precipitation, and rainfall (Table 36). I developed a custom EPW for each of the five climate zones for this time period, utilizing climatic inputs from local weather stations (Iowa Environmental Mesonet 2015) and publically available solar radiation databases (Clean Power Research 2015).

Table 36: EPW Parameters and Data Sources (Note: Fields marked "N/A" are currently not used in EnergyPlus calculations)

EPW Name	*EPW Parameter*	*Data Sources*
N1-N5	Year, month, day, hour minute	Self-Produced
A1	Uncertainty Flags	N/A
N6	Dry bulb temperature (°C)	IEM ASOS
N7	Dew point temperature (°C)	IEM ASOS
N8	Relative humidity (%)	IEM ASOS
N9	Atmospheric pressure (Pa)	IEM ASOS
N10	Extraterrestrial horizontal radiation (Wh/m^2)	N/A
N11	Extraterrestrial direct normal radiation (Wh/m^2)	N/A
N12	Horizontal infrared radiation from sky (Wh/m^2)	SolarAnywhere
N13	Global horizontal radiation (Wh/m^2)	N/A
N14	Direct normal radiation (Wh/m^2)	SolarAnywhere
N15	Diffuse horizontal radiation (Wh/m^2)	SolarAnywhere
N16	Global horizontal illuminance (lux)	N/A
N17	Direct normal illuminance (lux)	N/A
N18	Diffuse horizontal illuminance (lux)	N/A
N19	Zenith luminance (Cd/m^2)	N/A
N20	Wind direction (degrees)	IEM ASOS
N21	Wind speed (m/s)	IEM ASOS
N22	Total sky cover (tenths of sky)	N/A
N23	Opaque sky cover (tenths of sky)	N/A
N24	Visibility (km)	IEM ASOS
N25	Ceiling height	N/A
N26	Present weather observation	Self-Produced
N27	Present weather codes	Self-Produced
N28	Precipitable water (mm)	N/A
N29	Aerosol optical depth	N/A
N30	Snow depth	Not Used
N31	Days since last snowfall	N/A
N32	Albedo	N/A
N33	Liquid Precipitation Depth	IEM ASOS
N34	Liquid Precipitation Quantity	N/A

Once I run the ensemble with the appropriate weather data and scale it to county level, I are able to extract the subset of CBGs which exist within the LADWP service area. The goals of the calibration are to 1) have the total modeled electricity consumption be equivalent to the LADWP reported consumption and 2) to have the end use consumption percentages in the model similar to those reported in RASS. To identify prototypes where thermal properties need to be adjusted, I compare normalized heating and cooling electricity consumption by prototype from the model to the end use consumption reported by RASS for that prototype. RASS models rather than measures end use consumption, but this is still useful for identifying which prototypes are above or below the expected value. To prioritize which prototypes to modify, I then weight the deviation from RASS by the average total floor area of all buildings mapped to that prototype. Priority is given first to prototypes with high coverage since they have the largest influence on the model. Once I identify the prototypes for modification, I modify thermal properties of the shell within the uncertainty bounds of the input data sources, for example changing duct efficiency, changing flooring, or increasing insulation. For appliances, rather than adjusting the distribution of types within homes, I use linear scaling factors to adjust consumption towards the expected end use breakdown. The entire calibration procedure is based upon electricity consumption since that is the data that I have for validation, but natural gas comprises a significant amount of energy use in Los Angeles County residential consumption, mostly in water and space heating. Natural gas data are not available for calibration, but I maintain natural gas results to compliment the electricity modeling.

C.2.5 Calibration Results

The final calibrated model predicts total annual electricity use for LADWP within 2% of the expected value (Table 37). Some uncertainty does exist due to the quality of the inputs, but this calibration represents the best research effort to-date to create a calibrated bottom-up model.

Table 37: Model End-Use and Total Compared to LADWP Data

End-Use	*Model*	*LADWP*	*Variation*
Other	24.1%	24.7%	-0.6%
Lighting	15.2%	15.0%	0.2%
Fridge	13.7%	13.9%	-0.2%
TV	13.5%	12.6%	0.9%
PC	9.0%	9.1%	-0.1%
Pool	6.2%	6.3%	-0.1%
Cooling	5.8%	6.0%	-0.3%
2nd Fridge	4.3%	4.4%	0.0%
Heating	0.2%	0.1%	0.2%
Freezer	2.0%	2.1%	-0.1%
Microwave	1.9%	2.0%	-0.1%
Water Heating	1.6%	1.6%	0.0%
Range	1.3%	1.2%	0.0%
Fans	1.1%	1.1%	0.0%
Total (GWh)	7,270	7,190	80
Percent in model	101.1%	100.0%	

C.3 Creating Forecasting Weather Files

I develop custom EPW files for each of the five climate zones in LAC in order to forecast changes in building performance under GCM temperature changes. These files are the weather data input for the building simulation software, BEopt. In traditional (i.e. non-forecasting) applications, EPW files represent a "typical" year of meteorological activity for a location, by combining historic weather data (often up to 30 years). This can then be used as

a standard for predicting and comparing building performance in a single location, given the assumption that the climate of the location is not changing. In order to use EPWs for forecasting, a unique EPW file must be developed for each forecast and year.

To maintain spatial differentiation between the climate zones, I utilize statistically downscaled CMIP5 (via bias correction with constructed analogues) projections for temperature. For California, these data are available at 12 km x 12 km resolution every day for the years 1950-2099 from the U.S. Bureau of Reclamation (U.S. Department of the Interior and U.S. Bureau of Reclamation 2013). To obtain a representative temperature forecast for each model run and climate zone, I take all grid points from that run within a climate zone and average them at every point in time. I then "morph" the daily trajectories to obtain hourly temperature profiles. To be included in my simulation, each climate model must accurately predict the average number of cooling degree days between 1970 and 2000 within plus or minus 10%. I include the following number of models from each GCM, 10 total for each RCP (Table 38).

Table 38: Number of Runs Utilized from Each Climate Model

Model ID	*Project Code*	*RCP2.6*	*RCP 4.5*	*RCP 6.0*	*RCP8.5*
Access1-0	ACC	-	1	-	1
BCC-CSM1-1	BCC	1	-	1	-
CCSM4	CCS	2	2	2	2
CESM1-BGC	CES	-	-	-	-
CNRM-CM5	CNR	-	1	-	1
GFDL-CM3	GFC	1	-	1	-
GFDL-ESM2M	GFG	1	1	1	1
GFDL-ESM2M	GFM	-	-	1	-
INMCM4	INM	-	1	-	1
IPSL-CM5A-LR	IPL	-	-	1	-
IPSL-CM5A-MR	IPM	1	-	1	-
MIROC5	MIR	1	1	-	1
MPI-ESM-LR	MPL	3	3	-	3
MRI-CGCM3	MRI	-	-	1	-
NORESM1-M	NOR	-	-	1	-

Belcher et al. 2005 first proposed "morphing" as a method for taking a temporally less resolute climate forecast and creating a more detailed hourly profile as is necessary for building simulation software(Belcher, Hacker, and Powell 2005). I morph the temperature trajectories for each model run, using Sailor 2014's modification to Belcher's originally proposed method (Sailor 2014):

$$T_{i,EPW,future} = \frac{DTR_{GCM}}{DTR_{EPW}} * \left(T_{i,EPW} - T_{EPW,min}\right) + T_{GCM,min}$$

where $T_{i,EPW,future}$ is the temperature at any hour in the future, DTR_{GCM} and DTR_{EPW} are the diurnal temperature range (difference in the daily maximum and minimum temperatures) for the model and the base file, respectively, $T_{i,EPW}$ is the temperature of the base file at that hour, $T_{EPW,min}$ is the minimum for that day in the base file, and $T_{GCM,min}$ is that daily minimum value in the climate model. For my study, the base weather files are the EPWs developed by the CEC for each of the sixteen climate zones in the state of California and available as default files for BEopt. Effectively, this morphing transformation matches the maximum and minimum daily temperatures from the GCM and scales the intermediate hours based on the EPW pattern. For each morphed temperature trajectory, I use a four hour weighted average to smooth discontinuities between days. In total, I create 1,640 EPW files (10 GCMs × 4 RCPs × 41 years) for each of the five climate zones. These files can then be run with my 51 calibrated prototypes.

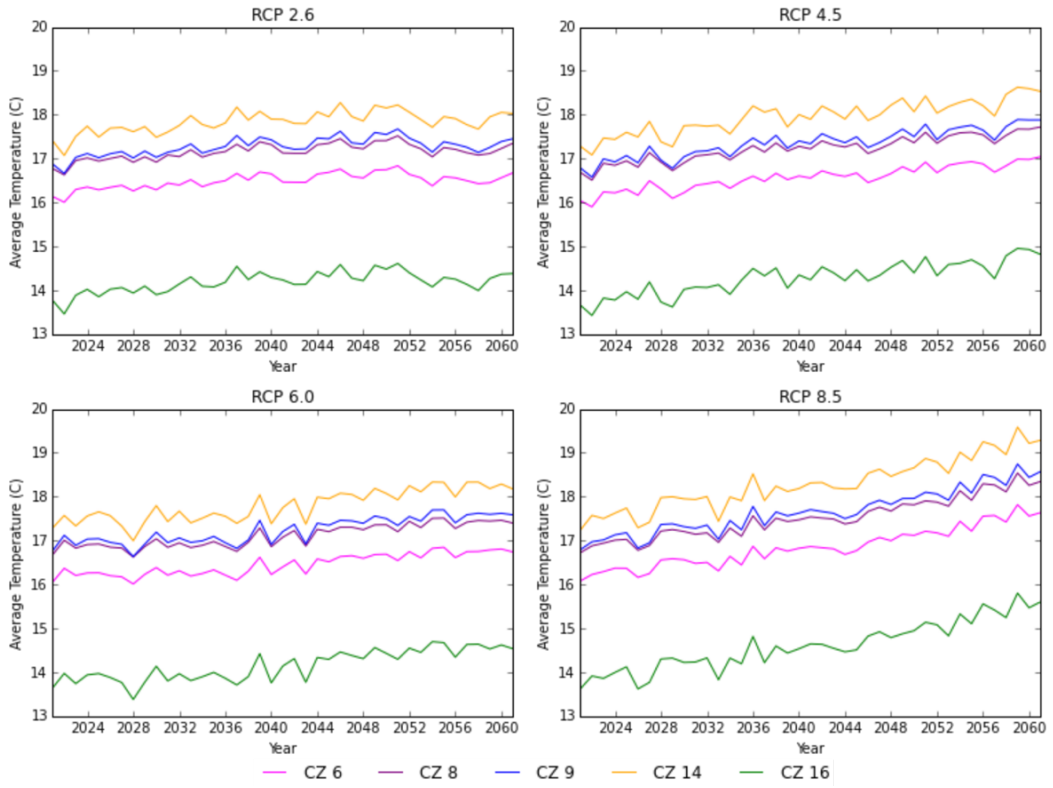


Figure 30: Projected Temperature Increases. For each RCP I graph the average annual temperature from the GCMs by climate zone.

C.4 Developing the Forecasting Ensemble

Utilizing the custom weather files I developed for each of the GCM runs, I simulate my 51 prototype models using batch processing for EnergyPlus. EnergyPlus is the main simulation engine for BEopt, so once I create the models, I can customize the EnergyPlus input files and directly run them in EnergyPlus. This saves on processing time and allows us to customize the simulation output format. I perform a total of 83,640 simulations: 10 GCMs × 4 RCPs × 41 years × 51 prototypes. With the model output, I post-process the data with Python and store it in a SQLite database.

In the prototype calibration, I run the models with 28 different heating and cooling technologies, and for the forecasting I included an additional 11 technologies (Table 39). To run the full ensemble, this would result in 3,261,960 building simulations, which is

computationally limiting. To capture the differences in heating and cooling technologies without running this many simulations, I run the full set of technologies for a single GCM and develop a linear relationship between heating/cooling load of the building and the resulting energy consumption by that technology within that prototype category. In my testing, this method captures the actual amount of energy used by the technology within +/- 4%. I utilize these factors in post-processing to compute energy consumption for each of the 3,261,960 cases without having to run each of the simulations.

Table 39: Additional HVAC Technologies for Forecasting

Category	*Efficiency*
Furnace	Gas 90% AFUE
Furnace	Gas 98% AFUE
Boiler	NG, Forced Draft, 85% AFUE
Boiler	NG, Forced Draft, 98% AFUE
Air-Source Heat Pump	SEER 19
Air-Source Heat Pump	SEER 22
Mini-Split Heat Pump	SEER 26
Central A/C	SEER 17
Central A/C	SEER 18
Central A/C	SEER 21
Room A/C	EER 10.7

Similar to the calibration phase, I calculate a weighted average of HVAC technologies based on the number of dwelling units and the prevalence of the technology within each prototype category. The main difference is that these factors are temporally dynamic in the forecast since technology adoption and the number of dwelling units change over time. To obtain run totals, I average electricity and natural gas forecasts for all GCM runs within an RCP. The maximum and minimum energy values across all the models for each year are the uncertainty bounds for that RCP.

C.5 Validation

I validate my model results by developing a regression relationship between max daily temperature and electricity sales, and comparing a forecast of the regression model against my prototype model. For the regression model, I utilize daily maximum temperatures for downtown Los Angeles (weather station CQT) from between 2006 and 2010, downloaded from the Iowa Environmental Mesonet (Iowa Environmental Mesonet 2015). The Federal Energy Regulatory Commission (FERC) Form 714 provides total hourly electricity demand for LADWP over the same time period. I then use monthly totals of residential electricity sales from U.S. Energy Information Administration Form 826 to get a fraction of sales each month that are residential, and then apply this ratio to the hourly FERC electricity sales. I sum the estimated hourly sales to daily sales for equal temporal comparison to the temperature data. When I fit a regression curve to predict electricity consumption from daily maximum temperature, I find that a quadratic relationship provides the best correlation coefficient without over-fitting the data (Figure 31).

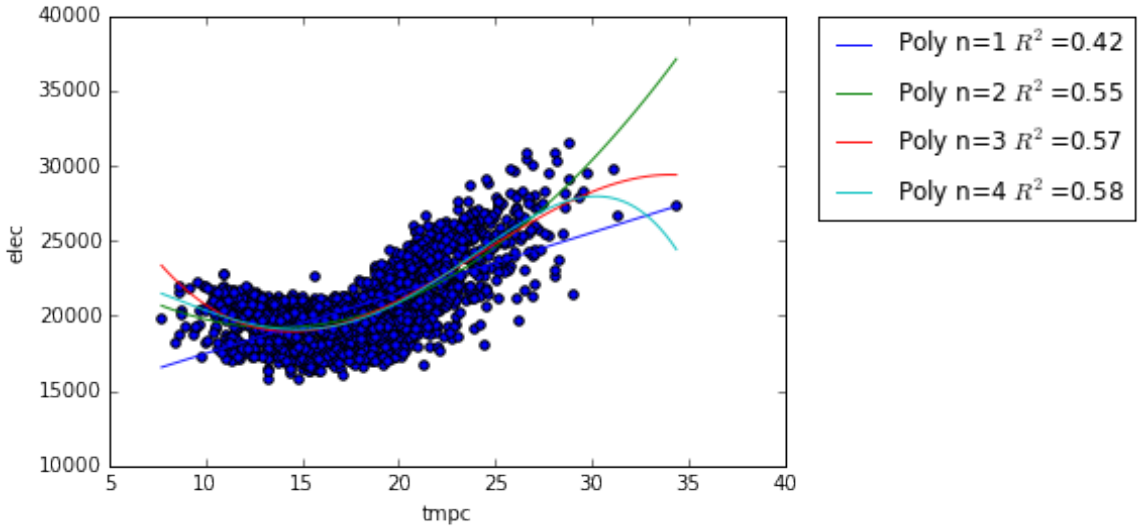


Figure 31: Scatterplot and Regression Models

In order to compare the prototype model to the regression model, I remove the dynamic elements (population, appliance mix, building turnover, etc.), changing only the weather files between 2020 and 2060. Additionally, the prototype model is only run for the CBGs within the LADWP service area in order to be comparable to the validation data. I then project the regression model with a 95% confidence interval along with the prototype forecasts with GCM temperature averages for each RCP (Figure 32).

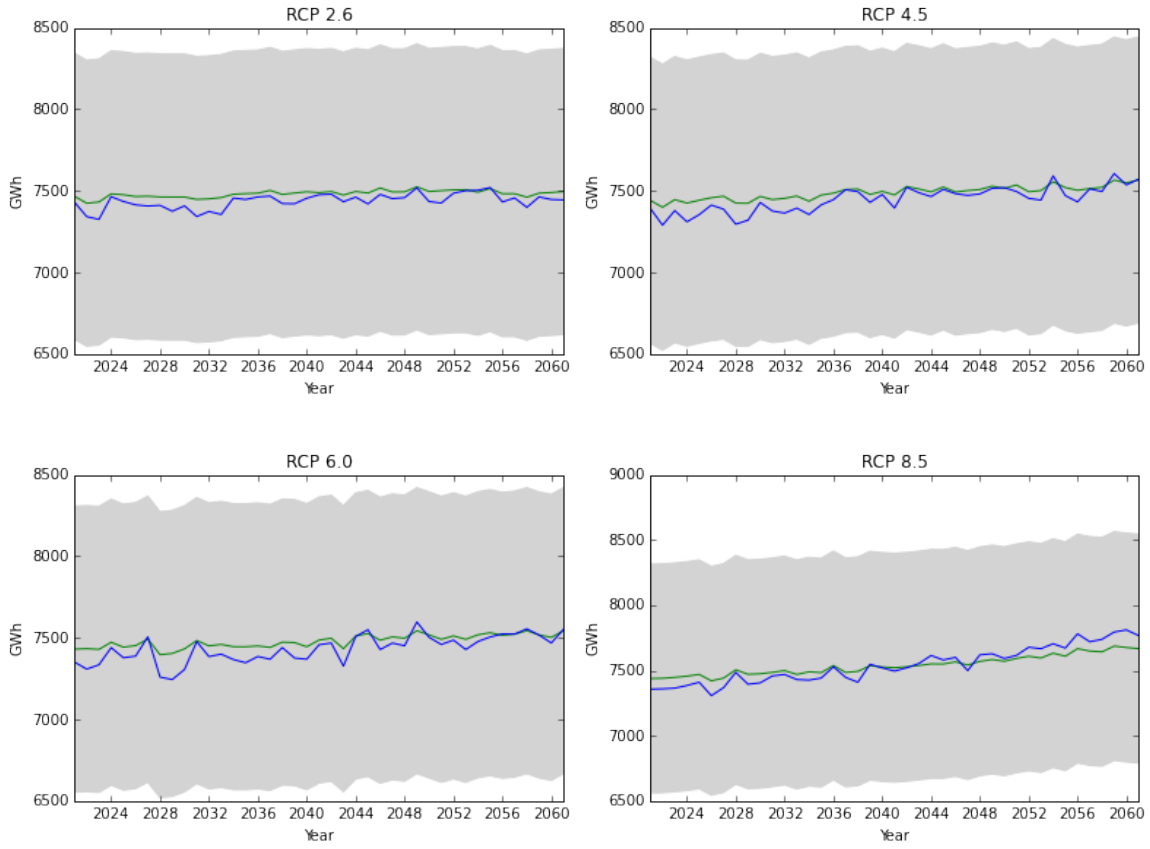


Figure 32: Regression vs Prototype Model. The regression model forecasts are in green with a grey 95% confidence interval, and the prototype forecasts are blue.

C.6 Scenario Development

In this section I provide an overview of the assumptions underlying each scenario including the current policies and publications that support the development of these assumptions.

C.6.1 Population Growth and Building Turnover

The California Department of Finance forecasts that the population of LAC will grow from 9,824,194 in 2010 to 11,489,127 in 2060 (Department of Finance 2013), and this will necessitate the construction of new dwelling units to accommodate the additional inhabitants. Tracking the population growth with Southern California Association of Government's housing forecast through 2030, I develop bi-decadal housing growth rates for LAC (Table 40). I apply these housing growth rates based on population to all the scenarios, starting with the building stock from the LAC Assessor's database.

Table 40: Housing Growth in LAC

Year	*Growth*
2010	0.0%
2015	3.3%
2020	9.5%
2025	12.3%
2030	15.9%
2035	17.9%
2040	20.0%
2045	21.4%
2050	22.2%
2055	22.5%
2060	22.5%

In a previous study, I studied historic building turnover trends in LAC, and developed a model of building turnover based upon initial year of construction (Reyna and Chester 2015). In addition to housing growth, I include these building turnover rates in the

stock model by replacing having the rates of older vintages replaced by newer vintages of the same classification and climate zone. For Scenarios 1 and 2 I utilize the same rates as in my previous paper, and in Scenarios 3 and 4 I augment the turnover to be 10 times the natural rate to represent an incentivization of building turnover and upgrades (Table 41).

Table 41: Building Turnover Rates

Building Vintage	*Annual Turnover Rate (%) Scenarios 1 & 2*	*Annual Turnover Rate (%) Scenarios 3 & 4*
<1940	0.04%	0.4%
1940-1949	0.02%	0.2%
1950-1959	0.01%	0.1%
1960-1969	0.03%	0.3%
1970-1982	0.07%	0.7%
1983-1997	0.3%	3%
1998+	N/A	N/A

In applying the population growth and building turnover, I spatially distribute the changes based upon the location of existing dwelling units. For population growth, in reality, new construction might be more likely to occur in less populated CBGs rather than densifying existing areas.

C.6.2 Heating and Cooling Equipment

I turnover existing heating and cooling equipment within each prototype category using a distribution based on the age of the equipment (ex: 80% of a technology by 2020, 90% by 2030, etc.). These turnover timeframes are constant for all scenarios. I then create a replacement matrix that gives a distribution of technologies that replaces any retired equipment of each category. For example, a 76% efficient natural gas boiler might be replaced 10% of the time by an electric furnace, 30% of the time by an 80% efficient natural gas furnace, 10% of the time by an 85% efficient natural gas furnace, 10% of the time by a SEER 14 Air-Source Heat Pump, 10% of the time by a SEER 15 Air-Source Heat Pump,

and 10% of the time by a SEER 19 Air-Source Heat Pump. In Scenario 1, I base these replacement rates on purchase trends reported in the U.S. Department of Energy's Building Energy Databook (U.S. Department of Energy 2015). In Scenario 2, I also use the purchase trends, but remove natural gas and propane as choices for new appliance replacement and instead distribute new purchases only among electric technologies. In Scenario 3, I restrict all heating replacements to be only heat pumps, and in Scenario 4 all heating and cooling equipment is replaced by only the most efficient heat pumps in the model.

C.6.3 Air Conditioning Adoption

In addition to the retirement of aging HVAC equipment, I also add in additional cooling equipment based upon previous studies on saturation rates of air conditioning and temperature. Sailor and Pavlova (2003) developed an empirical relationship between cooling degree days (CDD) and percent saturation of air conditioning based upon data from cities throughout the United States (Sailor and Pavlova 2003).

$$S_y = S_{2010} + (0.00349)\exp\left(-0.00298 * CDD_y\right) * (CDD_y - CD_{2010})$$

In this equation, S_y is percent air conditioning saturation in a given year, S_{2010} is the initial saturation, CDD is the cooling degree days of the future year, and CDD_{2010} is the initial number of cooling degree days. I apply this relationship for every climate zone and every year for all four average RCPs to obtain saturation rates for every year. Since CDD can be somewhat variable from year to year in the forecasts, I forward fill saturation rates so that an air conditioning saturation rate in a future year cannot be less than in a previous year. For example, if 2034 projects fewer CDD than 2033, I apply the 2033 saturation rate to 2034 since those who purchased air conditioners in 2033 will not discard them the next year. I then apply the saturation rates to prototypes for that climate zone in that year.

C.6.4 Appliances and Plug Loads

With the exception of lighting and plug loads, I assume the number of appliances utilized is linearly proportional to the number of dwelling units. I do not alter the distribution of appliances throughout the scenarios, only the energy consumption, with the exception of the "plug loads" category which captures use by miscellaneous appliances in homes (e.g. cell phones, electronics, blenders, etc.). This section discusses the *per unit* changes in appliances, not to the total amount consumed by each category.

C.6.4.1 Lighting

In 2012, the lighting portion of the Energy Independence and Security Act went into effect regulating the power consumption of incandescent light bulbs in the United States (110th U.S. Congress 2007). Beyond increasing the efficiency of incandescent light bulbs, this has driven down the cost of alternative light bulbs such as compact fluorescent lighting (CFLs) and light-emitting diodes (LEDs). The U.S. Department of Energy forecasts that these changes, particularly the adoption of LEDs, will reduce residential electricity consumption from lighting by 53% below 2013 levels by 2030 (Navigant Consulting 2014). Extrapolating market penetration of LEDs and other future lighting technologies I apply lighting electricity consumption reductions of 80% per household by 2060 for Scenarios 1 and 2, 90% for Scenario 3, and 95% for Scenario 4 (Table 42).

C.6.4.2 Televisions and Computers

The CEC has proposed regulations on computers and monitors that would take effect in 2017 and 2018. This rule would set performance standards for laptops, desktops, and monitors as well as target standby energy consumption (California Energy Commission 2015). The CEC projects that this rule would reduce consumption of desktop computers by

60% and laptops by 10%. In my forecasts, I assume a computer and television energy reduction of 30% by 2060 for Scenarios 1 and 2, of 50% for Scenario 3, and 70% for Scenario 4.

C.6.4.3 Water Heating

I include nine different types of water heaters with four different fuels (electric, gas, propane, and solar). In the scenario development, energy consumption could be changed within a prototype category by 1) switching to another type of water heater or 2) changing the efficiency of the nine classifications. For type switching in Scenario 1, I utilize purchase profiles of the domestic hot water market(Verinnovation 2012), and for Scenarios 2 utilize the same distribution, but restrict purchases to include only electric and solar product types. In Scenario 3, I increase the proportion of heat pumps and solar water heaters to 30% of the total replacement stock by 2060, and in Scenario 4, these technologies comprise 70% of the stock with electric tankless systems making up the remaining 30%. In 2015, Department of Energy efficiency standards went into effect for hot water heaters. For small residential water heaters (< 55 gallons), these regulations will improve efficiency by ~4%. For larger units, efficiency will improve by at least 25% (DiMascio 2015). For all water heater types, I extrapolated the efficiency savings to 20% of the total by 2060 for Scenarios 1 and 2, 40% for Scenario 3, and 60% for Scenario 4.

C.6.4.4 Refrigerators and Freezers

In fall 2014, new DOE efficiency standards on refrigerators and freezers went into effect, and these standards are anticipated to lead to savings of approximately 20-30%. For scenarios 1 and 2, I set refrigerators and freezers to be 30% more efficient by 2060, and for Scenarios 3 and 4 I augment these savings to 50% and 70%, respectively.

C.6.4.5 Plug Loads/Miscellaneous Electronics

In my calibrated base model, for each unit I use the equation employed in the U.S. Department of Energy's Building America program for miscellaneous plug load estimation:

$$E_y = 1108.1 + 180.2 * n_b + 0.278 * a$$

Where E_y is the annual electricity use from plug loads, n_b is the number of bedrooms in the dwelling unit, and a is the finished floor area of the unit. During calibration, I find that in LAC, the miscellaneous category needs to be scaled 50% to represent consumption as reported in RASS. Scaling the Building America equation to the county level is:

$$E_{a,LAC} = 1.5 * (N_u * (1108.1 + 180.2 * N_b) + 0.278 * A)$$

Where $E_{a,LAC}$ is the total annual electricity consumption for LAC, N_u is the number of dwelling units, N_b is the total number of bedrooms (from the Assessor), and A is the total finished floor area for all dwelling units.

The change in miscellaneous plug loads over the next 40-50 years is uncertain, but the CEC predicts that they will increase 63.9% for the LADWP service area between 2013 and 2026 (Gorin 2015). This is growth of nearly 5% per year. As miscellaneous plug loads in the base model are approximately 30% of total use, extrapolating this trend through 2060 yields an electricity consumption profile dominated by plug loads. For Scenarios 1 and 2, I instead include more conservative forecasts of 1% per year. In Scenarios 3 and 4, I assume efficiency improvements in miscellaneous appliances offsets some of this growth to be 0.5% and 0.25% per year for each scenario respectively.

C.6.4.6 Microwaves

Standards regulating microwave standby efficiency will go into effect in 2016, and they will reduce standby consumption by 75% (U.S. Department of Energy 2013). Based on

this, I include energy savings of 50% for microwaves by 2060 in Scenarios 1 and 2, 75% in Scenario 3, and 80% in Scenario 4.

Table 42: Summary of Appliance Efficiency Changes

	Scenario 1	*Scenario 2*	*Scenario 3*	*Scenario 4*
Lighting	-80% by 2060	-80% by 2060	-90% by 2060	-95% by 2060
TV/Computer	-30% by 2060	-30% by 2060	-50% by 2060	-70% by 2060
Water Heating	-20% by 2060, shift to electric from purchase trends	-20% by 2060, shift to electric for all new DWH	-40% by 2060, shift to electric for all new DWH	-60% by 2060, shift to electric for all new DWH
Refrigerators	-30% by 2060	-30% by 2060	-50% by 2060	-70% by 2060
Plug Loads	+1% per year	+1% per year	+0.5% per year	+0.25% per year
Freezer	-30% by 2060	-30% by 2060	-50% by 2060	-70% by 2060
Microwave	-50% by 2060	-50% by 2060	-75% by 2060	-80% by 2060

C.6.5 Rebound Calculation

In real-world application, improvements in energy efficiency in homes can lead to the rebound effect – where expected savings energy are partially offset by changes in inhabitant behavior. For example, if a homeowner upgrades to a more efficient air conditioning unit, they might end up using the air conditioning in the home more frequently, as it is less expensive to operate. To capture some of these potential behavioral changes in my model I include a 10% elasticity efficiency penalty as the rebound effect. Estimates on the appropriate elasticity of residential energy demand vary widely (Kenneth Gillingham et al. 2013), but a review of recent studies suggests that around 10% demand elasticity is appropriate (Kenneth Gillingham, Rapson, and Wagner 2016). For HVAC, this penalty is applied by comparing the energy savings between years due to equipment turnover and reducing the savings to be 90% of what was anticipated. For appliances, I reduce the total expected savings by 10% of what was expected (i.e. Table 42).

C.7 End Use Results and Cost Analysis

Below I provide a breakdown of electricity and natural gas use in each scenario and RCP in 2020 and 2060. These values are the total difference in savings for the scenarios.

Table 43: RCP 8.5 - Electricity End Use Results Summary by Scenario (PetaJoules)

	Base - 2020	*Scenario 1 - 2060*	*Scenario 2 - 2060*	*Scenario 3 - 2060*	*Scenario 4 - 2060*
Heating/Cooling	10.1	25.0	39.7	33.7	25.9
Water Heating	1.0	0.7	7.5	4.6	1.1
Main Fridge	9.7	7.9	7.9	6.0	4.1
TV	9.8	8.0	8.0	5.9	4.1
Computer	6.8	5.7	5.7	4.4	3.0
Pool	5.3	5.6	5.6	5.2	5.2
2nd Fridge	3.9	3.3	3.3	2.6	1.8
3rd Fridge	0.2	0.1	0.1	0.1	0.1
Freezer	1.9	1.6	1.6	1.2	0.8
Microwave	1.4	0.9	0.9	0.5	0.5
Oven/Range	1.0	1.3	1.3	1.1	1.1
Lights	11.5	7.7	7.7	7.3	6.7
Exterior Lights	6.0	4.5	4.8	4.2	3.8
Miscellaneous	8.3	35.0	35.0	33.2	34.2
Total	**76.8**	**107.2**	**129.1**	**110.2**	**92.4**

Table 44: RCP 8.5 – Natural Gas End Use Results Summary by Scenario (PetaJoules)

	Base - 2020	*Scenario 1 - 2060*	*Scenario 2 - 2060*	*Scenario 3 - 2060*	*Scenario 4 - 2060*
Heating/Cooling	13.5	19.3	3.1	0.3	0.5
Water Heating	14.0	2.5	9.3	6.4	2.9
Oven/Range	8.0	2.2	2.2	2.0	2.0
Pool	2.7	5.2	5.3	4.9	4.9
Miscellaneous	1.7	1.7	1.7	1.7	1.7
Total	**39.9**	**31.0**	**21.6**	**15.3**	**12.1**

Table 45: RCP 6.0 - Electricity End Use Results Summary by Scenario (PetaJoules)

	Base - 2020	*Scenario 1 - 2060*	*Scenario 2 - 2060*	*Scenario 3 - 2060*	*Scenario 4 - 2060*
Heating/Cooling	10.0	21.3	34.4	29.2	22.3
Water Heating	1.0	0.7	7.5	4.6	1.1
Main Fridge	9.7	7.9	7.9	6.0	4.1
TV	9.8	8.0	8.0	5.9	4.1
Computer	6.8	5.7	5.7	4.4	3.0
Pool	5.3	5.6	5.6	5.2	5.2
2nd Fridge	3.9	3.3	3.3	2.6	1.8
3rd Fridge	0.2	0.1	0.1	0.1	0.1
Freezer	1.9	1.6	1.6	1.2	0.8
Microwave	1.4	0.9	0.9	0.5	0.5
Oven/Range	1.0	1.3	1.3	1.1	1.1
Lights	11.5	7.7	7.7	7.3	6.7
Exterior Lights	6.0	4.5	4.8	4.2	3.8
Miscellaneous	8.3	35.0	35.0	33.2	34.2
Total	**76.7**	**103.5**	**123.7**	**105.6**	**88.8**

Table 46: RCP 6.0 – Natural Gas End Use Results Summary by Scenario (PetaJoules)

	Base - 2020	*Scenario 1 - 2060*	*Scenario 2 - 2060*	*Scenario 3 - 2060*	*Scenario 4 - 2060*
Heating/Cooling	14.1	21.1	3.1	0.3	0.5
Water Heating	14.0	2.5	9.3	6.4	2.9
Oven/Range	8.0	2.2	2.2	2.0	2.0
Pool	2.7	5.2	5.3	4.9	4.9
Miscellaneous	1.7	1.7	1.7	1.7	1.7
Total	**40.5**	**32.8**	**21.6**	**15.3**	**12.1**

Table 47: RCP 4.5 - Electricity End Use Results Summary by Scenario (PetaJoules)

	Base - 2020	*Scenario 1 - 2060*	*Scenario 2 - 2060*	*Scenario 3 - 2060*	*Scenario 4 - 2060*
Heating/Cooling	10.4	21.7	34.9	29.6	22.7
Water Heating	1.0	0.7	7.5	4.6	1.1
Main Fridge	9.7	7.9	7.9	6.0	4.1
TV	9.8	8.0	8.0	5.9	4.1
Computer	6.8	5.7	5.7	4.4	3.0
Pool	5.3	5.6	5.6	5.2	5.2
2nd Fridge	3.9	3.3	3.3	2.6	1.8
3rd Fridge	0.2	0.1	0.1	0.1	0.1
Freezer	1.9	1.6	1.6	1.2	0.8
Microwave	1.4	0.9	0.9	0.5	0.5
Oven/Range	1.0	1.3	1.3	1.1	1.1
Lights	11.5	7.7	7.7	7.3	6.7
Exterior Lights	6.0	4.5	4.8	4.2	3.8
Miscellaneous	8.3	35.0	35.0	33.2	34.2
Total	**77.2**	**103.9**	**124.3**	**106.1**	**89.2**

Table 48: RCP 4.5 – Natural Gas End Use Results Summary by Scenario (PetaJoules)

	Base - 2020	*Scenario 1 - 2060*	*Scenario 2 - 2060*	*Scenario 3 - 2060*	*Scenario 4 - 2060*
Heating/Cooling	14.5	20.0	3.1	0.3	0.5
Water Heating	14.0	2.5	9.3	6.4	2.9
Oven/Range	8.0	2.2	2.2	2.0	2.0
Pool	2.7	5.2	5.3	4.9	4.9
Miscellaneous	1.7	1.7	1.7	1.7	1.7
Total	**40.9**	**31.7**	**21.6**	**15.3**	**12.1**

Table 49: RCP 2.6 - Electricity End Use Results Summary by Scenario (PetaJoules)

	Base - 2020	*Scenario 1 - 2060*	*Scenario 2 - 2060*	*Scenario 3 - 2060*	*Scenario 4 - 2060*
Heating/Cooling	10.9	19.5	31.7	26.9	20.5
Water Heating	1.0	0.7	7.5	4.6	1.1
Main Fridge	9.7	7.9	7.9	6.0	4.1
TV	9.8	8.0	8.0	5.9	4.1
Computer	6.8	5.7	5.7	4.4	3.0
Pool	5.3	5.6	5.6	5.2	5.2
2nd Fridge	3.9	3.3	3.3	2.6	1.8
3rd Fridge	0.2	0.1	0.1	0.1	0.1
Freezer	1.9	1.6	1.6	1.2	0.8
Microwave	1.4	0.9	0.9	0.5	0.5
Oven/Range	1.0	1.3	1.3	1.1	1.1
Lights	11.5	7.7	7.7	7.3	6.7
Exterior Lights	6.0	4.5	4.8	4.2	3.8
Miscellaneous	8.3	35.0	35.0	33.2	34.2
Total	**77.6**	**101.7**	**121.1**	**103.3**	**87.0**

Table 50: RCP 2.6 – Natural Gas End Use Results Summary by Scenario (PetaJoules)

	Base - 2020	*Scenario 1 - 2060*	*Scenario 2 - 2060*	*Scenario 3 - 2060*	*Scenario 4 - 2060*
Heating/Cooling	14.3	20.6	3.1	0.3	0.5
Water Heating	14.0	2.5	9.3	6.4	2.9
Oven/Range	8.0	2.2	2.2	2.0	2.0
Pool	2.7	5.2	5.3	4.9	4.9
Miscellaneous	1.7	1.7	1.7	1.7	1.7
Total	**40.7**	**32.3**	**21.6**	**15.3**	**12.1**

C.7.1 Cost of Conserved Energy

Using my modeled results, I can estimate the average cost savings to consumers using a concept known as cost of conserved energy (CCE). CCE quantifies the amount of money that needs to be spent on a specific intervention to save a unit of electricity:

$$CCE = \frac{I * d}{(1 - (1 + d)^{-n}) * S}$$

CCE = Cost of conserved energy ($/kWh)

I = Incremental Cost ($)

d= Discount Rate

S = Annual energy savings (kWh/yr)

n=lifetime of mitigation option (yrs)

I develop CCE estimates for each of the 10 end uses in Table 56 based on the difference in energy consumption between Scenario 2 and Scenario 4 under RCP 8.5. These CCE values can then be used to calculate the cost to homeowners of the efficiency differences between the two scenarios. For the highest contributing end uses to the total savings (HVAC, water heating, and refrigerators/freezers), I develop my own CCE estimates. These end uses comprise ~70% of the energy savings. For the other end uses, I use CCEs developed for a National Academy of Sciences energy efficiency study (National Academy of Sciences 2010). In the following sections, I discuss the development of the incremental cost estimates for heating, cooling, water heating, and refrigerators/freezers.

C.7.1.1 Heating and Cooling

For heating and cooling I develop a weighted average cost of a heating or cooling unit for Scenarios 2 and 4. The difference in the scenarios within the RCP is the incremental cost needed for the CCE calculation. I pull the cost of purchasing and installing each type of unit from www.homeadvisor.com which contains user-reported data on home repairs. I weight the cost based upon the count of each type of HVAC system in 2060.

Table 51: Incremental Cooling Cost

Type	*Cost (2015$)*	*S4_8.5*	*S2_8.5*	*S4_6.0*	*S2_6.0*	*S4_4.5*	*S2_4.5*	*S4_2.6*	*S2_2.6*
ASHP - SEER8	$5,266	0	0	0	0	0	0	0	0
ASHP - SEER10	$5,266	0	0	0	0	0	0	0	0
ASHP - SEER13	$5,266	0	0	0	0	0	0	0	0
ASHP - SEER14	$5,266	0	369,191	0	369,191	0	369191	0	369191
ASHP - SEER15	$5,266	1	277,593	1	277,593	1	277593	1	277593
ASHP - SEER19	$5,266	0	185,014	0	185,014	0	185,014	0	185,014
ASHP - SEER22	$5,266	3,547,753	371,380	3,490,265	311,541	3,501,361	323,101	3,463,156	283,110
MSHP - SEER14	$5,266	0	36,315	0	36,315	0	36,315	0	36,315
MSHP - SEER26	$5,266	0	36,315	0	36,315	0	36,315	0	36,315
CAC - SEER8	$5,240	0	0	0	0	0	0	0	0
CAC - SEER10	$5,240	0	0	0	0	0	0	0	0
CAC - SEER13	$5,240	0	0	0	0	0	0	0	0
CAC - SEER14	$5,240	0	513,204	0	513,204	0	513,204	0	513,204
CAC - SEER15	$5,240	146	550,543	146	550,543	146	550,543	146	550,543
CAC - SEER17	$5,240	0	370,036	0	370,036	0	370,036	0	370,036
CAC - SEER18	$5,240	0	189,668	0	189,668	0	189,668	0	189,668
CAC - SEER21	$5,240	0	180,368	0	180,368	0	180,368	0	180,368
RAC - EER8.5	$2,400	0	0	0	0	0	0	0	0
RAC - EER9.8	$2,400	512	219,855	512	219,855	512	219,855	512	219,855
RAC - EER10.7	$2,400	0	219,287	0	219,287	0	219,287	0	219,287
Average Cost		**$5,265**	**$4,895**	**$5,266**	**$4,889**	**$5,266**	**$4,890**	**$5,266**	**$4,885**

Table 52: Incremental Heating Cost

Type	*Cost (2015$)*	*S4*	*S2*
Furnace - Electric	$2,600	11,646	476,215
Boiler - Electric	$5,104	3,257	70,859
Electric Baseboard	$637	73,723	274,436
ASHP - SEER8	$5,266	0	0
ASHP - SEER10	$5,266	0	0
ASHP - SEER13	$5,266	0	0
ASHP - SEER14	$5,266	0	977,730
ASHP - SEER15	$5,266	2	734,222
ASHP - SEER19	$5,266	0	489,173
ASHP - SEER22	$5,266	3,578,435	244,740
MSHP - SEER14	$5,266	0	183,981
MSHP - SEER26	$5,266	0	183,981
Average Cost		**$5,164**	**$4,564**

C.7.1.2 Water Heating

Similar to HVAC, for water heating, I develop a weighted cost of equipment for each scenario. The source of the cost data for this portion is a 2009 market analysis from the U.S. Department of Energy (U.S. Department of Energy 2009b).

Table 53: Incremental Cost Water Heating

Type	*Cost (2009$)*	*Scenario 4*	*Scenario 2*
Electric Standard	$650	0	3,089,743
Electric Tankless	$1,255	1,078,256	277,178
50 gal HP @ 125F	$1,500	1,437,674	154,649
Solar Water Heating (2)	$3,200	1,078,256	72,615
Average Cost		**$1,937**	**$785**

C.7.1.3 Refrigerators and Freezers

In my model for refrigerators and freezers, I do not change the count of each type of appliance in the future forecast. Instead, I make the average electricity consumption of each

appliance end use category systematically more efficient. As a proxy for the cost difference of this efficiency improvement, I use the difference in cost between standard refrigerators and freezers from 2007 with the Energy Star models of that same year, based upon a report from the U.S. Department of Energy (U.S. Department of Energy 2007a).

Table 54: Incremental Cost Refrigerators

	Standard (2007$)	*Energy Star (2007$)*	*Count*
Side Freezer	$1,128	$1,336	2,001,626
Top Freezer	$660	$663	1,709,038
Bottom Freezer	$1,285	$1,254	391,541
Weighted Difference			**$100**

Table 55: Incremental Cost Freezers

	Standard (2007$)	*Energy Star (2007$)*	*Count*
Upright	$495	$602	190,613
Chest	$352	$473	90,841
Weighted Difference			**$112**

C.7.1.4 Cost Calculation

I use the CCE for each of the end use types to estimate the average savings to each household in LAC in 2060, based upon a method in the National Academy of Sciences study (National Academy of Sciences 2010). I calculate the total cost to the consumer by multiplying the CCE for each end use by the electricity savings in 2060, and then compare this to the amount that that electricity would have cost had it been purchased from the utility company. All costs are adjusted with inflation to 2010$, as this is the base year of the model. I use a discount rate of 7% to remain consistent with the CCE values from the National Academies study. In February 2015, the average price of electricity in Los Angeles County was 21.6 ¢/kWh (U.S. Bureau of Labor Statistics 2016). Converting this to 2010 dollars, the

equivalent price would be 19.6 ¢/kWh. I assume that the cost of electricity remains constant through 2060. This is approximately $300 (2010$) per household savings for that year comparing between Scenarios 4 and 2. This means that including the cost of equipment upgrades, households will save money on average from installing more efficient appliances in the home. With current electricity prices, all efficiency upgrades are cost savings with the exception of water heaters. In my model, the CCE is 23.8 2010¢/kWh, which is greater than the current electricity price of 19.6 2010¢/kWh. This is driven by the high cost of solar water heating and heat pumps relative to standard electric water heaters, and the high penetration of these technologies in my model. If subsidies were employed, it could make these cost-neutral for the consumer, and greater market share of these alternate water heating technologies might also decrease the cost.

Table 56: Efficiency Savings Between Scenarios 2 and 4 in 2060, RCP 8.5. The demand difference in the year 2060 subdivided by end use consumption to identify the sources of the efficiency savings.

	Change GWh	*Savings Percentage*	*Cost to Conserve (2010 ¢/kWh)*	*Estimated Savings (2010 $)*
Heating/Cooling	-3845.9	38.5%	6.6	-$499,813,541
Water Heater	-1770.1	17.7%	23.8	$74,937,468
Refrigerators	-1507.8	15.1%	2.7	-$254,275,236
TV	-1078.0	10.8%	0.9	-$201,435,311
Computer	-749.6	7.5%	4.5	-$113,313,268
Lights	-556.8	5.6%	1.4	-$101,359,332
Freezer	-206.3	2.1%	1.4	-$37,627,345
Pool	-114.9	1.2%	2.5	-$19,691,366
Microwave	-107.8	1.1%	1.8	-$19,161,662
Oven/Range	-48.1	0.5%	7.1	-$6,014,756
Total	**-9985.3**	**100.0%**		**-$1,177,754,349**

C.8 Model Uncertainty

There are multiple sources of uncertainty in my model which fall into either the category of 1) data uncertainty or 2) trend uncertainty. The sources of data uncertainty include elements within the base model or other projections that I use in my forecasts. Trend uncertainty includes the variability in future trends compared to what we've asserted in the model.

A primary source of data uncertainty is the GCM models. Variability exists from model to model within an RCP, and this variability in my forecast is captured in the figures presented in the main manuscript. Additionally, although my model is calibrated and validated, there is uncertainty in the prototype energy models due to 1) the internal uncertainty from the EnergyPlus model itself, and 2) the variability of buildings within a prototype category in LAC and the potential for a prototype to poorly represent some of those buildings. Another source of data uncertainty are the population projections for LAC.

A primary source of trend uncertainty is consumer behavior. In this model, I assume that energy consumption in buildings is primarily linked to the building type, equipment, and weather conditions. I do not account for changes in behavior beyond my inclusion of 10% rebound, although there potentially could be significant shifts in energy consuming behavior, particularly around plug loads as small electronics use increases. Additionally, I assume that energy prices are stable relative to inflation, and therefore include no changes in consumption or fuel switching in response to market forces. The rates of technology adoption and saturation in my scenarios are based upon current market trends, but this could change significantly over the next 50 years.

C.9 References

110th U.S. Congress. 2007. *Energy Independence and Security Act of 2007*.

Akbari, H., J. Eto, S. Konopacki, A. Afzal, K. Heinemeier, and L. Rainer. 1993. "Integrated Estimation of Commercial Sector End-Use Load Shapes and Energy Use Intensities in the PG&E Service Area, LBL-34263." Berkeley, CA. doi:10.2172/10140911.

Bartos, Matthew D., and Mikhail V. Chester. 2015. "Supplementary Information: Impacts of Climate Change on Electric Power Supply in the Western United States." *Nature Climate Change* 5 (8): 748–52. doi:10.1038/nclimate2648.

Belcher, S. E., J. N. Hacker, and D. S. Powell. 2005. "Constructing Design Weather Data for Future Climates." *Buildind Services Engineering Research & Technology* 1 (26): 49–61. doi:10.1191/0143624405bt112oa.

California Energy Commission. 2015. "Computer, Computer Monitors, and Electronic Displays: Docket Number 14-AAER-2." http://docketpublic.energy.ca.gov/PublicDocuments/14-AAER-02/TN203854_20150312T094326_Staff_Report__FINAL.pdf.

Carlo, Joyce Correna, Enedir Ghisi, and Roberto Lamberts. 2003. "The Use of Computer Simulation to Establish Energy Efficiency Parameters for a Building Code of a City in Brazil." *8 International IBPSA Conference*, 131–38.

Clean Power Research. 2015. "SolarAnywhere Radiation Data."

Department of Finance. 2013. "New Population Projections: California To Surpass 50 Million in 2049," 2.

DiMascio, Marianne. 2015. "Water Heaters Get an Efficiency Makeover Courtesy of the Department of Energy." *American Council for an Energy-Efficient Economy*. http://aceee.org/blog/2015/02/water-heaters-get-efficiency-makeover.

Esteves, Gheisa R. T, Bruno Q. Bastos, Fernando L. Cyrino, Rodrigo F. Calili, and Reinaldo C. Souza. 2015. "Long Term Electricity Forecast: A Systematic Review." *Procedia Computer Science* 55 (Itqm). Elsevier Masson SAS: 549–58. doi:10.1016/j.procs.2015.07.041.

Gillingham, Kenneth, Matthew J. Kotchen, David S. Rapson, and Gernot Wagner. 2013. "Energy Policy: The Rebound Effect Is Overplayed." *Nature* 493 (7433): 475–76. doi:10.1038/493475a.

Gillingham, Kenneth, David Rapson, and Gernot Wagner. 2016. "The Rebound Effect and Energy Efficiency Policy." *Review of Environmental Economics and Policy* 10 (1): 68–88. doi:10.1093/reep/rev017.

Gorin, Tom. 2015. "Plug Loads in the Residential and Commercial Forecasts." http://docketpublic.energy.ca.gov/PublicDocuments/15-IEPR-05/TN205066_20150618T095153_Plug_Loads_in_the_Residential_and_Commercial_Forecasts.pptx.

Huang, Joe, Hashem Akbari, Leo Rainer, and Ron Ritschard. 1991. "481 Prototypical Commerical Buildings for 20 Urban Market Areas, LBL-29798." Berkeley, CA.

Huang, Joe, Ellen Franconi, Environmental Energy, Technologies Division, and Lawrence Berkeley. 1999. "Commercian Heating and Cooling Loads Component Analysis, LBL-37208." Berkeley, CA.

Iowa Environmental Mesonet. 2015. "Automated Surface Observing System Historical Data." http://mesonet.agron.iastate.edu/ASOS/.

Jones, Phil, Joanne Patterson, and Simon Lannon. 2007. "Modelling the Built Environment at an Urban scale—Energy and Health Impacts in Relation to Housing." *Landscape and Urban Planning* 83 (1): 39–49. doi:10.1016/j.landurbplan.2007.05.015.

Kavgic, M, A Mavrogianni, D Mumovic, A Summerfield, Z Stevanovic, and M. Djurovic-Petrovic. 2010. "A Review of Bottom-up Building Stock Models for Energy Consumption in the Residential Sector." *Building and Environment* 45 (7). Elsevier Ltd: 1683–97. doi:10.1016/j.buildenv.2010.01.021.

Lawrence Berkeley National Laboratory. 2016. "Estimated U.S. Energy Use in 2014." Accessed January 5. https://flowcharts.llnl.gov/content/assets/images/energy/us/Energy_US_2014.png.

Los Angeles County Assessor Office. 2009. "Los Angeles County Database."

National Academy of Sciences. 2010. *Real Prospects for Energy Efficiency in the United States*. Washington, D.C.: National Academies Press. doi:10.17226/12621.

Navigant Consulting. 2014. "Energy Savings Forecast of Solid-State Lighting in General Illumination Applications." *U.S. Department of Energy Report*.

Opitz, M W, L K Norford, Yu A Matrosov, and I N Butovsky. 1997. "Energy Consumption and Conservation in the Russian Apartment Building Stock." *Energy and Buildings* 25: 75–92.

Pacific Energy Center. 2006. "Pacific Energy Center's Guide to California Climate Zones and Bioclimatic Design." http://www.pge.com/includes/docs/pdfs/about/edusafety/training/pec/toolbox/arch/climate/california_climate_zones_01-16.pdf.

Pincetl, Stephanie, Robert Graham, Sinnott Murphy, and Deepak Sivaraman. 2015. "Analysis of High-Resolution Utility Data for Understanding Energy Use in Urban Systems: The Case of Los Angeles, California." *Journal of Industrial Ecology*, June, n/a – n/a. doi:10.1111/jiec.12299.

Reyna, Janet L, and Mikhail V Chester. 2015. "The Growth of Urban Building Stock:

Unintended Lock-in and Embedded Environmental Effects." *Journal of Industrial Ecology* 19 (4): 524–37. doi:10.1111/jiec.12211.

Sailor, David J. 2014. "Risks of Summertime Extreme Thermal Conditions in Buildings as a Result of Climate Change and Exacerbation of Urban Heat Islands." *Building and Environment* 78. Elsevier Ltd: 81–88. doi:10.1016/j.buildenv.2014.04.012.

Sailor, David J., and A.A. Pavlova. 2003. "Air Conditioning Market Saturation and Long-Term Response of Residential Cooling Energy Demand to Climate Change." *Energy* 28 (9): 941–51. doi:10.1016/S0360-5442(03)00033-1.

Sezgen, Osman, Ellen M Franconi, Jonathan G Koomey, Steve E Greenberg, Asim Afzal, and Leslie Shown. 1995. "Technology Data Characterizing Space Conditioning in Commercial Buildings: Application to End-Use Forecasting with Commend, LBL-37065."

Shimoda, Yoshiyuki, Takuro Fujii, Takao Morikawa, and Minoru Mizuno. 2004. "Residential End-Use Energy Simulation at City Scale." *Building and Environment* 39 (8): 959–67. doi:10.1016/j.buildenv.2004.01.020.

Swan, Lukas G, and V Ismet Ugursal. 2009. "Modeling of End-Use Energy Consumption in the Residential Sector: A Review of Modeling Techniques." *Renewable and Sustainable Energy Reviews* 13 (8): 1819–35. doi:10.1016/j.rser.2008.09.033.

U.S. Bureau of Labor Statistics. 2016. "Average Energy Prices, Los Angeles-Riverside-Orange County February 2016." http://www.bls.gov/regions/west/news-release/averageenergyprices_losangeles.htm.

U.S. Department of Energy. 2007. "Final Rule, Techincal Supporting Document Residential Refrigeration."

———. 2009. "Water Heater Market Profile 2009."

https://www.energystar.gov/ia/partners/prod_development/new_specs/downloads/water_heaters/Water_Heater_Market_Profile_Sept2009.pdf.

———. 2013. "New Energy Efficient Standards for Microwave Ovens to Save Consumers on Energy Bills." http://energy.gov/articles/new-energy-efficiency-standards-microwave-ovens-save-consumers-energy-bills.

———. 2015. "Building Energy Databook." http://buildingsdatabook.eren.doe.gov/.

U.S. Department of the Interior, and U.S. Bureau of Reclamation. 2013. "Downscaled CMIP3 and CMIP5 Climate and Hydrology Projections: Release of Downscaled CMIP5 Climate Projections, Comparison with Preceding Information, and Summary of User Needs." Denver. http://gdo-dcp.ucllnl.org/downscaled_ cmip_projections.

U.S. Energy Information Administration. 2014. "Annual Energy Outlook 2015." http://www.eia.gov/forecasts/aeo/index.cfm.

van Vliet, Michelle T. H., David Wiberg, Sylvain Leduc, and Keywan Riahi. 2016. "Power-Generation System Vulnerability and Adaptation to Changes in Climate and Water Resources." *Nature Climate Change*, no. January (January). doi:10.1038/nclimate2903.

Verinnovation. 2012. "NEEA Water Heater Market Update 2011 Report #12-234." Seattle, WA. http://neea.org/docs/reports/2011WaterHeaterMarketUpdateA273DBB87CA3.pdf?sfvrsn=6.

Yamaguchi, Y, Y Shimoda, and M Mizuno. 2007. "Proposal of a Modeling Approach Considering Urban Form for Evaluation of City Level Energy Management." *Energy and Buildings* 39 (5): 580–92. doi:10.1016/j.enbuild.2006.09.011.