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Integrated Urban Metabolism Analysis Tool (IUMAT)

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Integrated Urban Metabolism Analysis Tool (IUMAT)

A Dissertation Presented

by

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(IUMAT)

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To Mom, Dad and Grandpa

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ABSTRACT

INTEGRATED URBAN METABOLISM ANALYSIS TOOL
(IUMAT)

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A number of tools are available today for simulating different aspects of urban activity. But these efforts are fragmented and do not effectively reflect the interrelationships between very diverse groups of urban sectors and resource flows. There is a critical need for robust and reliable urban metabolism analysis tools that integrate socio-economic elements of urbanization and physicality of the built environment into evaluating sustainability in cities.

This dissertation outlines the development of an Integrated Urban Metabolism Analysis Tool (IUMAT) that dynamically measures the environmental impacts of land cover, transportation, and consumption of energy, water and materials by employing a holistic framework. It includes examination of the existing scholarship on urban metabolism as well as description of the calculative framework for IUMAT. The scope of work is establishment of the Residential Energy Model that would serve as a template for the larger Energy, Water and Materials (EWM) Model. The EWM model takes a bottom-up approach to generate spatial resource demand profiles based on building and neighborhood characteristics. The Residential Energy Consumption Survey (RECS) 2009 data is used to explain how the proposed framework makes use of actual data to find

determinants of resources' demand and unravel correlations between environmental consequences and myriad of urban variables. Quantile regression is explored as a robust method for large-scale energy modeling that is a prototype for resource use projection within other urban sectors.

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INTRODUCTION

More than half of the world's population live in cities, contributing to more than 70% of the global GHG emissions (Feng et al., 2013). Cities are rapidly growing especially in developing economies of Asia and Africa, extending their environmental footprint beyond their official municipal borders. Accordingly, development and dissemination of reliable urban planning and policy tools that can address environmental concerns is a grand challenge of the future. Quantifying and predicting the effectiveness of urban sustainability initiatives and the environmental impacts of growth scenarios are crucial for the urban designers and city planners. One of their major concerns over the past decades has been to establish new development practices and visions towards building sustainable new communities and lowering the environmental footprint of the existing building stock. Hampering the growing consequences of urban sprawl has triggered a wide range of practice and policy adaptation, from national and regional climate action plans to specific building energy requirements or transportation demand reduction mandates. These efforts are considered to effectively push in a positive direction, however, their partial or aggregate influence on the overall sustainability of urban regions cannot be precisely indexed. In addition, due to the location based nature of the proposed plans, effective solutions for a specific region could be entirely fruitless for another.

"Metabolic" analysis has been a popular term for referring to efforts that aim at quantifying the flows of mass and energy through urban areas. Recent studies on analyzing the metabolism of cities underline the importance of integrating both physical and socio-economic factors that govern the patterns of change and their environmental impacts. Understanding the big picture of metabolism in cities could significantly benefit urban design and planning disciplines, especially for incorporations of sustainability principles in the processes of analysis, design and policy making. Productive harvesting of the benefits associated with a metabolic analysis approach, requires development of urban scale simulation software tools, in addition to defining the indicators of urban sustainability. The puzzling interconnectedness of urban subsystems requires simulation approaches that simultaneously consider social, economic and environmental aspects of urban life. However, most of the urban resource consumption modeling packages in use today, focus on particular urban sectors with very specific simulation objectives. The Integrated Urban Metabolism Analysis Tool (IUMAT) aims to create a large-scale sustainability modeling framework that considers and integrates various urban subsystems and is capable of handling the overlapping features of urban activity and life.

Research Objectives

Integrating the implications and impacts of built and natural forms, open space, transportation, sanitation and municipal services is essential to prioritizing how to best conserve natural resources and reduce GHG emissions for each unique urban area. This Ph.D. project aims to address this need by developing an Integrated Urban Metabolism Analysis Tool (IUMAT), a modeling structure that quantifies the “metabolism” of urban spaces in terms of inlet and outlet flows of energy, water, materials and waste. Principally, urban metabolism has been defined as ‘the sum total of the technical and socio-economic processes that occur in cities resulting in growth, production of energy and elimination of waste’ (Kennedy et al., 2007, p.44). This projects aims to enable a comprehensive analytical understanding of city scale metabolism for urban design and policy making, and as a result, lay out foundations for developing simulation tools for sustainability evaluation in urban regions; a quantitative basis for understanding the environmental impacts caused from collaborative decisions made by a population of human beings within municipal borders of a city.

We have series of objectives that accomplishment of each is starting point for the proceeding. The ultimate sustainability aid tool goal for IUMAT requires environmental impacts evaluation by reporting sewage and waste production, atmospheric emissions, energy consumption breakdown, transportation demand and land use change. This would require:

a. Prioritizing urban sustainability indicators into a hierarchical setup of net sustainability index calculative module as the first objective. Our primary goal is to integrate interrelated features of urban dynamics in order to figure out the system-wide repercussions resulting from any occurrence of change or disturbance in different attributes of urban life.

b. Creating an evaluative/calculative structure in order to enable useful calculative integration among intertwined sectors of urban activity.

c. Developing a framework for intensive collection and use of actual data in the process of simulation and forecasting. We aim to provide researchers and planners a compact set of essential information needed for understanding and analyzing metabolism of metropolitan areas based on consumption of resources and negative environmental impacts associated with it, as well as setting an actual example on how real data can be used to understand and improve metabolic performance of cities.

Dissertation Outline

This dissertation includes an exhaustive review of the literature on simulation of sustainability at large scales to better define the achievements and gaps in the existing research in Chapter 1 (written by myself as the lead author, with co-authorship of Mohamad Farzinmoghadam, Benjamin Weil and Simi Hoque). The next chapter is dedicated to defining an evaluative/calculative structure for integration of urban subsystems and the interrelations between different sectors of urban activity/life by incorporating socio-economic factors (written by myself as the lead author, with co-authorship of Mohamad Farzinmoghadam and Simi Hoque). Chapter 3 details the development of IUMAT's residential energy model using actual energy consumption data that functions as a prototype for commercial and manufacturing energy models (written by myself as the lead author, with co-authorship of Mohamad Farzinmoghadam and Simi Hoque). The residential model also provides groundwork for calculating the environmental footprint of urban water and material use. Chapter 4 addresses some of the data collection and availability challenges for bottom-up urban modeling structures, and hints at possible future steps towards accomplishing models other than the residential energy model.

CHAPTER 1

INTEGRATED URBAN METABOLISM ANALYSIS TOOL (IUMAT)

The following chapter is published in the Urban Policy and Research Journal, Volume 32(1), October 2013. Mohamad Farzinmoghadam, Dr. Simi Hoque (Corresponding Author), and Dr. Benjamin Weil are other co-authors of this chapter. To cite this chapter:

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1.1 Abstract

The determinant share of cities in global primary energy use and greenhouse gas emissions highlights the importance of dissemination and development of reliable urban planning and policy tools. To reach sustainable urban development, having a comprehensive understanding of the concept of urban metabolism is critical. This work is the first step toward the development of an Integrated Urban Metabolism Analysis Tool (IUMAT) that seeks to consider all three social, economic and environmental capitals of an urban region in a multidisciplinary context. This tool is intended to provide a quantitative approach to assessing the sustainability indicators in a city. A literature review on the urban metabolism and urban-scale simulation tools is carried out to highlight the achievements as well as scientific gaps in the existing research, and to determine the objectives and functionalities that are expected from IUMAT.

1.2 Introduction

Cities are responsible for 67 per cent of the primary energy use and nearly 71 per cent of greenhouse gas (GHG) emissions on a global scale (International Energy Agency, 2008). The majority of the world's population resides in urban areas, and cities are expected to experience a

48 per cent growth by 2030, with the fastest rate of growth in the developing economies of Asia and Africa (UN Population Fund, 2007). Moreover, smaller cities and towns are expected to have a dominant role in urban population growth. This means that the development and dissemination of reliable urban planning and policy tools that address environmental concerns will be crucial in the decades ahead. To mitigate the consequences of this growth, city counsellors have initiated climate action plans, adaptation and mitigation policies, and energy conservation mandates to spur the development of high performance buildings, sustainable transportation, and increased green space. Although these efforts are assumed to have some positive impacts on the urban context, it is still unknown to what extent these actions can influence the overall sustainability of a city. A set of policy and planning options may be optimal for one city while counterproductive for another. Integrating the implications and impacts of built and natural forms, open space, transportation, sanitation and municipal services is essential to prioritizing how to best conserve natural resources and reduce GHG emissions for each unique city.

1.3 Background and Literature Review

Many different terms have been used to refer to the characterization, quantification and analysis of urban energy and mass flows, among which 'metabolic' analysis is the most popular. This section provides a review of studies useful in guiding the development of an urban metabolism analysis tool. The following does not completely cover the growing body of literature regarding the concept of urban metabolism analysis, but highlights key approaches and methods that have been adopted by researchers so far.

Forty years ago, in the wake of rapid urban expansion, Abel Wolman (1965) published a pioneering article on the metabolism of cities, which is regarded as a fundamental basis for researchers working on quantitative assessments of city energy and resource flows. The concept of urban metabolism was developed by Wolman as a response to deteriorating urban water and air quality in America, a trend that remains a challenge to urban sustainable development worldwide. He quantified the overall input and output flux of energy, water, materials and waste in a hypothetical American urban region with a population of 1 million. Since then, many researchers have conducted urban metabolism studies all around the world, using different perspectives, methodologies and frames.

Urban metabolism can be defined as “the sum total of the technical and socio-economic processes that occur in cities resulting in growth, production of energy and elimination of waste” (Kennedy et al., 2007, p. 44). Urban metabolism analysis is a way to qualify inlet and outlet flows of materials, water, energy and waste in an urban area (Sahely et al., 2003). The first studies of urban metabolism for actual cities were conducted in the 1970s on Tokyo (Hanya and Ambe, 1976), Brussels (Duvigneaud and Denayeyer-De Smet, 1977) and Hong Kong (Newcombe et al., 1978). The Brussels metabolism study was distinctive in that it included natural energy balances, going beyond quantification of human-activity induced energy flows (Kennedy et al., 2011). After these formative studies in the 1970s, interest in urban metabolism waned for almost a decade. During the last 20 years, the concept has gained traction, with tens of papers published on the subject.

Generally, there are two popular methodological frameworks used in metabolism studies. Some focus on qualitative methods categorized under a political science context (e.g. Heynen et al., 2006), while others are categorized under a quantitative or historical context (e.g. Tarr, 2002). Some researchers such as Swyngedouw and Heynen (2003) and Keil (2003) suggested the approach of urban political ecology to solve interconnected political, social, economic and ecological processes. Heynen et al. (2006) addressed the importance of regarding urbanization as a socio-ecological process of change. Tarr (2002) explored the use of land, water and air resources from 1800 to 2000 in the city of Pittsburgh. Lennox and Turner (2004) suggested long multi-decadal time-frames and regional context for temporal and spatial scales for settlement studies. Douglas et al. (2002) investigated changes in land use, material flows and river morphology in the Manchester urban area over the last two centuries.

A review of papers published in the last decade on urban metabolism shows that, within the quantitative context, two different analytical approaches are common. Metabolism has been described in terms of energy equivalents (e.g. Odum, 1983) or, in terms of mass flux with respect to a city's flows of water, materials and nutrients—also known as Material Flow Analysis (MFA). Odum applied his method for a case study on Paris using the data provided by Stanhill (1977). His approach has been used in a study on Miami, Florida by Zucchetto (1975) who studied the relationships between natural systems, energy data and economics. The introduction of the emergy concept in ecology and ecological economics provided a tool for analyzing natural systems and investigating the interface between natural and human systems. Odum (1996) clarified the fundamentals of an emergy theory, suggesting a thermodynamic approach to urban metabolism models which includes embodied energy or emergy (solar energy equivalents) flows. Some proposed that indices and ratios based on emergy flows can be calculated and used to evaluate different types of systems (Brown and Ulgiati, 1997). While Odum's method has not become main-stream, it was used by Huang and Hsu, for Taipei, Taiwan (Huang, 1998; Huang&Hsu, 2003), who studied the connection between ecological systems and urban economics. Zhang et al. (2009) used an emergy-based indicator system to evaluate metabolic factors of Beijing for the period 1990–2004.

Material flow analysis (MFA) of stocks and flows of resources is quantified in terms of mass, and is unlike Odum's approach, which concentrates on energy equivalents. These studies typically report energy flows in terms of joules, and a city's flows of water, materials and nutrients in terms of mass fluxes (Kennedy et al., 2011). Baccini and Brunner (2012) explained the use of MFA applications in examining metabolic characteristics of urban areas. They studied the metabolism of the anthroposphere by exploring effects of material fluxes on the biosphere. Using the MFA method, Warren-Rhodes and Koenig (2001) updated the Newcombe et al. (1978) study on urban metabolism of Hong Kong focusing on the trends in waste generation and resource consumption. Hendriks et al. (2000) illustrated MFA as a tool for environmental policy making, carrying out case studies of Vienna and the Swiss lowlands. Codoban and Kennedy (2008) employed MFA to explore flows of water, energy, food and waste in Toronto neighborhoods. Schulz (2007) used MFA to examine overall environmental effects of urban systems in Singapore. The challenge of implementing MFA is that the specific environmental impacts associated with material flows must also include consumption and post-consumption processes (disposal technologies for example). In addition, an ecosystem's vulnerability to urban processes is a function of geographic factors (Schulz, 2007). In response to this problem, some studies such as Wackernagel and Rees (1996) (for Vancouver, Canada) and Folke et al. (1997) (for cities in Baltic Europe) have assessed the urban metabolism using the application of ecological footprint techniques. Fischer-Kowalski and Hüttler (1998) analyzed characteristic features of MFA according to system level, frame of reference, and types of flows being studied. Barrett et al. (2002) applied the MFA method to the City of York, UK followed by ecological footprint analysis to understand the pressure on the environment by material flows. Niza et al. (2009) quantified the material balance of Lisbon for 2004. Zhang and Yang (2007) explored the efficiency of urban material metabolism for Shenzhen City in China regarding socio-economic development during 1998–2004. Browne et al. (2009) measured the change in total materials metabolic inefficiency for Limerick, Ireland from 1996 to 2002.

Some researchers, such as Sahely and Kennedy (2007), analyzed the urban metabolism by addressing water-related issues. Hermanowicz and Asano (1999) highlighted water metabolism in a city and investigated applications of wastewater reuse, correlating reuse application with patterns of water use. Gandy (2004) addressed the importance of water as a key dimension to the social production of urban space. Kane and Erickson (2007) explored water supply for New York City from an urban metabolism perspective considering interactions between urban cores and rural hinterlands. Baker et al. (2009) emphasized the importance of developing hydrologic balance for cities as a strong and fundamental tool for urban water managers. Thériault and Laroche (2009) studied hydrologic metabolism in the administrative boundaries of the Greater Moncton region, New Brunswick, by quantifying water input and output and carrying out a water balance for the period 1984–2004.

Studies based on nutrient flows are the least common, and most of them have focused on individual substances such as phosphorus and nitrogen, such as Færge et al. (2001) for Bangkok and Burström et al. (2003) for Stockholm. Færge et al. developed a nutrient balance model considering the nitrogen and phosphorous cycle for Bangkok province. Burström et al. explored the municipal material flow of nitrogen and phosphorus for the city of Stockholm. Barles (2007) studied flows of food and nitrogen in Paris for the period 1801–1914. Bohle (1994) studied the urban food metabolism by using an urban metabolism perspective to explore supply, production, consumption and distribution of food in developing countries. Forkes (2007) developed a nitrogen balance of the urban food cycle for the city of Toronto, Canada.

Some studies have taken approaches that cannot be categorized exactly under what was explained above. For instance, Bergbäck et al. (2001), Sörme et al. (2001) and Svidén and Jonsson (2001) studied the urban metal flows in Stockholm. Fung and Kennedy (2005) presented a macroeconomic model to link economic drivers with urban metabolism parameters. Deilmann (2009) studied the relationship between the surface of the cities and urban metabolism.

However, the conception of urban metabolism has not remained devoid of alterations over time. Newman and co-workers (Newman et al., 1996; Newman, 1999) studied the metabolism of Sydney proposing the inclusion of livability factors toward an extended metabolism model, by considering indicators of employment, health, housing, education, income, leisure and community activities. Inclusion of quality of life in urban metabolism is also mentioned by Stimson et al. (1999), who have emphasized the livability and long-term viability of cities in addition to environmental sustainability.

Kennedy et al. (2007) suggest that consequent impacts of growth and development of cities, such as water accumulation in urban aquifers, imported construction materials, trapped heat in rooftops and pavements, and nutrients deposited in the soil and waste dumps, gradually cause changes in the metabolism of cities. They used available data from previous urban metabolism studies in eight different cities across the world and analyzed four fundamental cycles of energy, materials, water and nutrients, and related the differences between the metabolism of the cities to cultural factors, stage of development and age in addition to urban population density and climate conditions.

Shimoda et al. (2004) simulated residential energy consumption by end use in Japan's Osaka City by summing up every one-hour energy use by 23 types of household and 20 dwelling types and multiplying the results by the number of households in each category based on weather data, set temperatures of heating and cooling, set temperature and amount of hot water supply, occupants' schedule of activities, appliances' energy performance and thermal properties of the buildings. They published a related paper in 2007 on quantitative evaluation of the effects of different energy conservation measures on residential energy consumption in Osaka City (Shimoda et al., 2007).

Ngo and Pataki (2008) conducted a metabolic study by analyzing input and output flows of energy, water, food and pollutants for Los Angeles County in California in 1990 and 2000. Their intent was to determine whether the urban development in Los Angeles County was moving toward environmental sustainability or away from it by comparing per capita input and output flows of energy, water, solid waste, food and GHG emissions for the study period 1990–2000. Baynes et al. (2011) addressed some of the contrasts between two different methodologies of an input–output consumption approach and a regional production method for urban energy consumption analysis of the metropolitan area of Melbourne, Australia.

Jin et al. (2009) suggested a policy-making platform for urban sustainability by incorporating system dynamics into the ecological footprint instead of snapshots, focusing on a case study of Wanzhou, China in 2005. Turner and West (2011) underlined the importance of capturing the long-term dynamics for strategic planning of infrastructural electricity generation for the state of Victoria, Australia. Huber and Nytsch-Geusen (2011) suggested some simplifications to accelerate largescale urban districts' simulation process via coupling building and plant simulation integrated with a three-dimensional (3D) computational energy analysis simulation for a case study of a new German–Iranian project of an urban area with 2000 planned residential buildings in northern Iran. Strzalka et al. (2011) developed a method for urban scale heating energy demand forecasting by 3D city modelling of a case study area with over 700 buildings in Ostfildern, Germany, outlining the feasibility of linking simulation tools with 3D geographical information system (GIS)/3D city models by making use of a GIS interface that provides inputs for a simulation model.

Some Canadian researchers incorporated an object- and agent-based micro-simulation framework called ILUTE for urban systems modelling that integrates demographics evolution, land use and transportation. In this framework, the system state that changes from initial base case to an end state is defined in terms of the agents as dwelling units, households, firms, individuals, etc. that together define the urban area which is to be modelled. ILUTE simulates the behavior of these agents (changes in labor force participation, residential location, travel and activity attributes, etc.) over specified time steps (Chingcuanco and Miller, 2011).

Howard et al. (2012) apportioned the energy consumption by end use in New York City's building sector using a spatial model for almost 860 000 tax lots. They performed a multiple linear regression method to develop annual end-use energy consumption by obtaining total fuel and electricity intensities for eight different building types.

1.4 Urban Metabolism and Sustainability

During the first years of the 20th century, city planners developed a utopian vision of an urban environment in which humans live in harmony with nature (Fishman, 1982). Although this vision disregarded social, economic and ecological differences between the communities, it was revived during a period of rapid urban renewal in Europe after the Second World War. As a short term consequence, cities faced noticeable social and economic conflicts due to daily life interactions between culturally and economically diverse communities. However, the ecological problems had a more long-term impact that designers, planners and researchers started responding to in the late 20th century by presenting climate action plans, adaptation and mitigation policies and other sustainable policies; efforts that can smooth the way toward development of urban sustainability.

After the 1987 report published by the Brundtland commission (United Nations (UN) World Commission of Environment and Development), the concept of sustainable development entered the lexicon of administrators, planners and community representatives. One of the most critical challenges is to introduce sustainable development into current urban activities by relevant stakeholders. This is a concern that requires ambitious strategies to better protect natural resources, limit energy consumption and reduce atmospheric pollution (NÆSS, 2001).

Conceptually, sustainability is related to improving or maintaining the integrated systems of the natural networks that collectively make up the life on this planet. The planet's capacity to support its population is decided by natural limitations and human behavior regarding environmental, economic, cultural and demographic variables. Sustainability deals with the level of impacts on the earth caused by the human population. It is not only concerned with the magnitude of the population, but also with the choices made by that population.

In the past two decades, the fundamental concepts of sustainable development have been applied to more and more sectors at different scales. For example, the growing awareness of the harmful impacts of the construction industry and its diverse features' contribution to environmental degradation has led to the establishment of building environmental assessment methods in different countries such as LEED (USA), LEED Canada (Canada), BREEAM (UK), CASBEE (Japan) and NABERS (Australia) (Papadopoulos and Giama, 2009).

Cities are undoubtedly the main sources of GHG emissions as they are major consumers of materials, energy, water and food. However, it may be important to include suburbs and peri-urban areas in some analyses (Lenzen and Peters, 2010), as these areas represent the interactions between the rural and urban regions, where land and landscape are being consumed as a food source (Lehmann, 2011). Today, many cities have extended their ecological footprint far beyond the lands they actually occupy, while the number of fast-growing cities in developing nations is increasing at an alarming rate. Given the consumption of resources and consequent generation of waste, cities should essentially evolve into more sustainable ecosystems (Kenworthy, 2006). This reduction in use of natural resources and waste generation should take place simultaneously with improvement of cities' livability in an extended model of urban metabolism (Newman, 1999). Simultaneous protection of the environment with increasing social equity in a steady state economy may be the most prominent challenge of urban sustainable development (Campbell, 1996).

The UN action plan for sustainable development, which was an outcome of the UNCED (United Nations Conference on Environment and Development) held in Rio de Janeiro in 1992, known as Agenda 21, outlines principal action plans toward sustainability (Doyle, 1998), but does not clearly demonstrate how those can be applied to cities (Newman, 1999). Although most of the challenging environmental arguments and debates were fought outside the circle of management of the cities in the past, governments, environmentalists and industry universally have recognized the need for coming back to cities today (Newman, 1999).

Sustainable urban development can be better understood by considering both notions of urban environmental sustainability and urban development simultaneously (Ravetz, 2000). Achieving a balance between human activities in a city and urban environmental resources must be viewed in a multidisciplinary context by socio-political, economic– industrial and resource–environmental systems. The familiar sustainable development triangular model with three vertices of environment, economy and society contains a multitude of combinations of strategies and targets that bring together socio-political issues with physical sciences (see Figure 1.1).

In the early 1990s, researchers such as Girardet (1992) began to investigate the connection between sustainable development and urban metabolism. Kennedy et al. (2011) proposed four practical applications of urban metabolism for planners and designers as defining sustainability indicators, urban GHG accounting, developing dynamic mathematical models for policy analysis and creation of design tools. Pivo (1996) suggested that the six basic principles for urban sustainable development are compactness, completeness, conservation, comfort, coordination, and collaboration. Krajnc and Glavic (2005) used a framework of sustainability indicators grouped into three categories of social, economic and environmental. Both positive and negative indicators were then normalized and weighted using an analytic hierarchy process and by summing up the values from sub-indices, a composite sustainable index was obtained. There are some other studies that have studied the impacts of technological methods such as water and waste management, low carbon emissions and air pollution control on sustainable urbanization and protection of the urban environment (Shen et al., 2012).

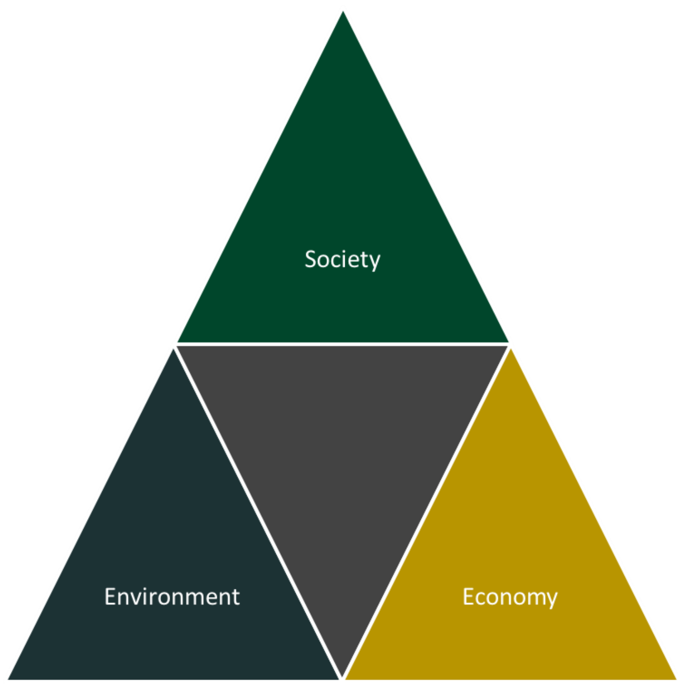

Figure 1.1: Triangular model of sustainable development

In the field of urban planning, designers and planners have presented different guidelines toward the goal of developing sustainable cities, but most generally addressed qualitative rather than quantitative features, which leaves many of the problems of the evaluation process unresolved. Urban metabolism studies have driven designers toward qualitative results, giving them a better perspective of urban ecology changes with design strategies. In terms of applications of urban metabolism, two different attitudes can be distinguished among contemporary studies on urban metabolism. The first outlook analyses the current data from different sources and summarizes the available data on usually one specific feature of urban metabolism. This approach mainly concentrates on data collection to be presented to policy makers, planners and designers. These kinds of studies do not present any quantitative methods for future prediction, or provide metrics for evaluating design sustainability. The other outlook focuses on one urban feature such as water, land use or transportation and suggests quantitative methods for further studies. None of these attitudes offers a comprehensive picture of the connections between the multiple interacting physio-morphological flows and stocks that characterize urban metabolism. Another challenge is that for some of the urban stocks, straightforward methods are not available for accurate quantifications of trajectory or state of flows and even disaggregating the different kinds of flows and stocks does not necessarily reduce the complexities. For example, urban green space can be measured in terms of area or number of trees, but to what level and how it affects the public wellbeing or amenity is difficult to quantify. In addition, ecosystems are exposed to continuous change even without human-related activities, which adds uncertainty in linking ecosystem evolutions to urban activities. A scientific measurement method to assess the pros and cons of a holistic urban design proposal has yet to be developed.

1.5 Urban Metabolism Simulation Tools

Indicators for measuring urban metabolism factors need to be defined and delimited based on the goals and objectives of the study. Intertwined environmental, technological, spatial, physical, cultural, ethical, political and economic features of urban life will result in a multidimensional urban metabolism assessment framework. Demographic transitions, growing urbanization and social disparities, loss of habitat and biodiversity, progressive increase in demand for resources, and growing energy and material-intensive industries in rapidly expanding cities should be understood by researchers who are trying to formulate urban responses (Lehmann, 2011).

There are a large number of tools available for simulating different aspects of urban activities, but these efforts are fragmented and do not reflect the interrelationships between different stocks and flows. In some cases, two or more of these tools are coupled and combined in order to simulate different scenarios, for example, a plant simulating tool with a building simulation tool (Huber and Nytsch-Geusen, 2011). For urban energy analysis as an example, disaggregate approaches have been popular historically, where only an individual static component of the urban system is investigated such as residential energy demand (e.g. Nesbakken, 1999) or urban transportation (e.g. Berkowitz et al., 1990). However, energy consumption in urban areas is the outcome of human decisions and activities, and energy demand of different interrelated urban sectors (commercial, residential and transportation) is connected through this system of human activity (Chingcuanco and Miller, 2011). Understanding the interactions between different sectors is critical to assessing or evaluating new policies. As an example for a city such as

Toronto, due to higher residential per capita energy demand in central areas compared to the suburbs as a result of looser construction codes and old infrastructure, higher heating demands can offset savings created by shorter commutes in the long term (Chingcuanco and Miller, 2011). The importance of a holistic approach to urban metabolism analysis can be realized from this simple example.

A modest number of tools have recently been developed for modelling in urban scale. Some of them such as iTEAM (Integrated Transportation and Energy Activity-Based Model), which is a tool for policy evaluation, employ agent-based micro-simulation to project and give a perspective of the future of the urban region's energy consumption. These tools model decisions taken by the agents and convert them into energy demands (Almeida et al., 2009).

Some other tools implement a normative methodology and concentrate on optimizing energy consumption within the urban system rather than drawing projections of the future state. As an example, CitySim has been conceived to simulate a building's energy flows with an engineering approach, aiming to develop a more comprehensive model by incorporating flows of materials, water and waste to optimize urban resource flows (Robinson et al., 2009).

SynCity is another toolkit for integrated modelling of urban energy systems. It has a layout model as the first component that seeks an optimal city design to minimize energy consumption, cost and carbon emissions. The agent activity micro-simulation model creates the demand for resources by simulating daily activities of the citizens in that layout. Afterwards a macro-level resource technology network model that takes available process types in addition to spatially and temporally distributed resource demands as inputs, is designed to interface with engineering models and provide technical end-use detailed maps (Keirstead et al., 2009).

UrbanSim is another micro-simulation discrete choice model of relationships between land use, transportation and the environment (Vanegas et al., 2009). It is an open source urban simulation system that takes a dynamic, disequilibrium approach for temporal basis in contrast to a cross-sectional, equilibrium approach (Waddell, 2002). The design of UrbanSim attempts to create models (demographic transition model, household location choice model, etc.) that represent behaviors of an essential set of agents (household, person, business, developer, market) (Waddell, 2011).

1.6 IUMAT

Despite the recent 30-year attention to the concept of urban metabolism, urban policymaking has been slow to use urban metabolism analysis as a decision aid. Although concerns about the environmental characteristics of cities have grown in the last decades, 'greening cities' has mainly been interpreted as improving the visual appearance of urban areas by creating more green spaces. However, cities not only should be environmentally pleasant, but also ecologically viable. The urgent need to develop accurate and effective sustainable policies is not well enough incorporated into urban planning tools, although the significance of sustainable urban development is understood by most city planners and urban managers (Yan et al., 2003).

The difficulties in simulating connections between variables of urban systems such as natural and built forms, network infrastructures and transportation, microclimate impacts and shading, waste management and water systems, and location and orientation make the process of sustainable urban design a complicated procedure. Hence, urban modelling tools often fail to give an accurate prediction and a robust quantification of relations between urban characterizing parameters (Noth et al., 2003). Most of the tools that are in use today apply an aggregate, cross-sectional, equilibrium approach. Simplifications that ignore continual dynamics of change in urban systems produce outcome results that deviate greatly from actuality.

An integrated analysis of the complicated and inextricably bound up global issues of environment–health and consumption–lifestyle, needs approaches and methods that go beyond traditional boundaries between familiar disciplines. A new methodology and modelling tool for urban metabolism analysis is needed, using an approach that identifies and integrates five major indicators of urban metabolism: land use, energy consumption, material flows, water and resources, and air quality. Furthermore, different sectors of urban area/activity must be classified as part of this matrix of indicators. These sectors are residential, commercial, industry, education, government, transportation and open space.

An accurate analysis of urban metabolism should address water and material consumption, sewage and waste production, energy use, emissions to the atmosphere and urban heat island effect in urban regions under alternative scenarios. Buildings, as indices of an urban area in addition to spaces that connect them together, are the recipients and transmitters of numerous flows and streams based on multiple sets of variables (see Figure 1.2). Robust and accurate results from any kind of simulation of an urban complex require all three capitals of social, economic and environmental be studied with rigor. To assess both morphological and psychological attributes of urban life, with a focus on the environmental/analytic side of urban metabolism assessment, the study will be stabilized on two linked axes of environmental–economy and environmental–society fragments. As shown in Figure 1.3, resource inputs to a city (land, energy, food, water, materials and resources) are used due to regular dynamics of settlement (transportation, economic and cultural priorities) and generate livability and the waste generation associated with that (sewage, solid and liquid waste, toxics and air pollutants, GHGs, waste heat and noise) (Newman, 1999).

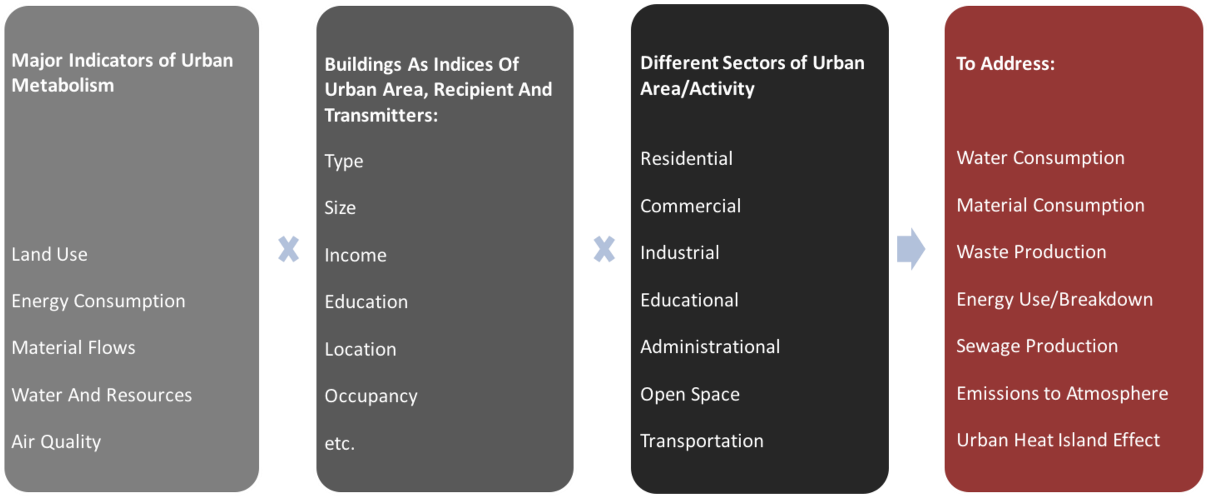

Figure 1.2: Variables and outcomes of the urban metabolism analysis tool

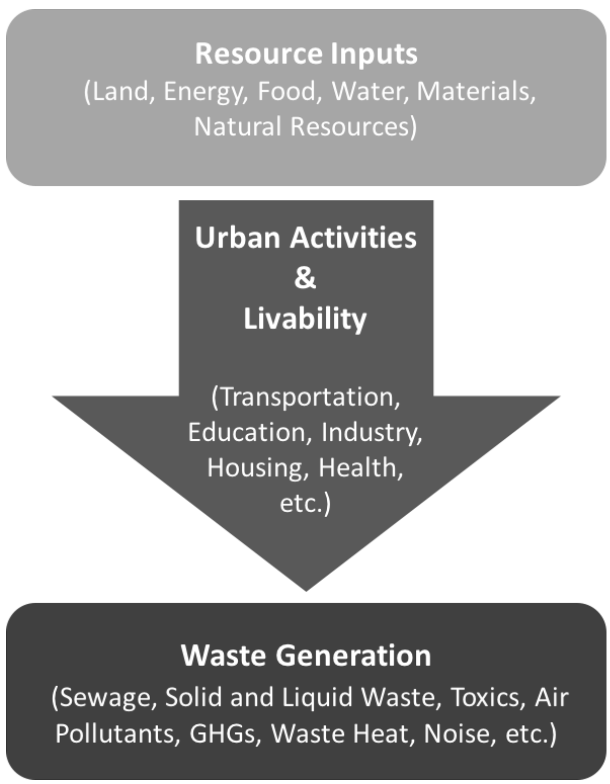

Figure 1.3: Trend from resources to livability and waste

Given most strategic urban planning tools are focused on energy use, transportation and land use, a new integrated urban metabolism analysis tool (IUMAT) should be designed with a framework that observes the interactions among quality of life, urban transformation processes, resource flows and waste streams (Rotmans and Van Asselt, 2000). Such an IUMAT will do the following:

1. Reconsider the urban footprint. Urban metabolism requires redefinition of the urban ecosystem and its borders and limits.

2. Assess current trends in a city. IUMAT provides possibilities to examine ongoing flows in a city such as energy, water and material consumption, waste and sewage production, and GHG emission rates.

3. Integrate interrelated features of urban dynamics. IUMAT creates more evaluative/calculative integration among intertwined sectors of urban life.

4. Increase urban efficiency and effectiveness. By addressing connections between the urban divisions, IUMAT can prepare a prolific ground toward more efficient utilization of natural resources and a more sustainable future.

5. Improve urban control and planning systems. IUMAT can provide a systematic and coherent structure for strategic planning in urban scale.

To achieve the objectives of IUMAT, five main functions can be expected from the tool:

1. Organizational function. Improvements that IUMAT can cause to control and planning systems, gives more flexibility to city planners in managing resource utilization and energy and material flows in an urban area.

2. Monitoring function. IUMAT enables effective and applied use of the available existing data. It simplifies harmonization of the data and points out were the data is scattered.

3. Evaluative/calculative function. IUMAT examines the current situation and alternative policies with regard to their social, economic and environmental consequences.

4. Comparative function. The tool enables comparison between alternative planning and design scenarios based on the evaluative assessments.

5. Policy function. IUMAT helps development of sustainable strategic planning toward reaching a balance between social, economic and environmental domains of an urban area and its surroundings.

IUMAT will take both normative and predictive approaches by taking advantage of positive features of both statistical and engineering methodologies, and making proper use of statistics in favor of engineering models.

With respect to the conceptual urban triangle, IUMAT's evaluative/calculative instrument will observe inter-flows within the environmental capital along with intra-flows in environmental–social and environmental–economic axes (see Figure 4). The evaluative/calculative instrument will include a calculative simulation model (linked to a GIS) to assess the quantitative trends for urban indices within specified geographic/ time borders, which is a mathematical approach to the conceptual triangular model. GIS improves the process of keeping records and enables better visualization of distributions in the urban area. IUMAT will use buildings as a reference point to indicate urban areas and will categories buildings and spaces between them as components of the urban area that are sources of different flows in the model, due to natural processes and human activities.

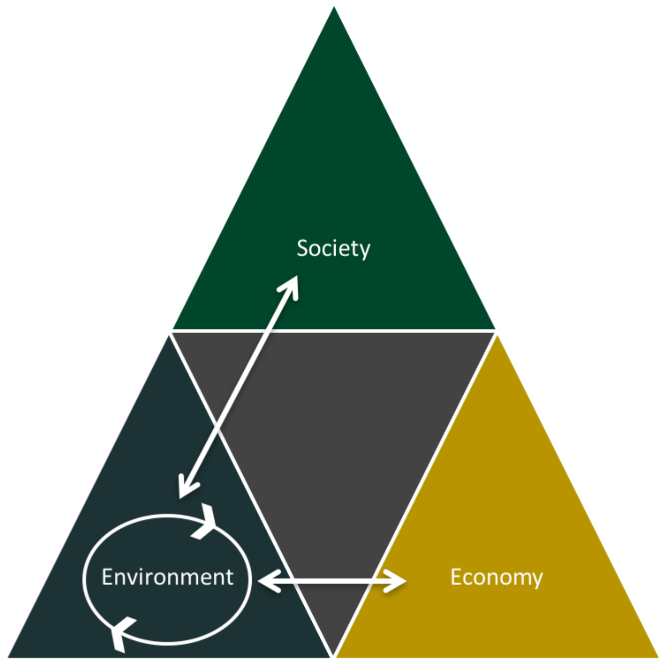

Figure 1.4: Inter-flows and intra-flows to be investigated by IUMAT

1.7 Conclusions

Environmental concerns associated with the worldwide growth of the urban sector outline the importance of development of reliable urban planning and policy tools. Although different guidelines have been presented by researchers and urban planners toward the goal of a sustainable urban ecosystem, qualitative features have been addressed most generally rather than quantitatively so far. The concept or urban metabolism can be applied as a basis for quantitative evaluation of the overall sustainability in a city. However, to carry out a realistic study, realms of the urban metabolic analysis should be extended as to integrate social, economic and environmental capitals of a city within the borders of the study. A holistic/integrative approach should be considered in the process of designing the tools that aim to simulate and analyze the intertwined physiological and morphological characteristics of the urban metabolism. Most of the available tools for simulation of different flows and streams in urban scale take a cross-sectional, equilibrium approach on usually one component of urban life such as land use, transportation and energy consumption. Development of tools such as IUMAT provides a ground for formulating urban responses that reflect the dynamics of natural and human-induced change in urban systems. The holistic design proposal employed by IUMAT will monitor/evaluate trajectory and state of interrelated urban flows and stocks in order to enable comparison between alternative planning scenarios in favor of sustainable urban design and strategic planning. Hence, IUMAT will have the capability to continually switch between normative and predictive frameworks, and statistical and engineering methodologies to enable effective use of available statistical data in the process of policy making. Buildings and spaces that connect them together are transmitters and recipients of different flows and streams that will be referred to by IUMAT as indices of an urban area. IUMAT will apply a matrix of variables that considers five major indicators of urban metabolism (land-use, energy consumption, material flows, water and resources, and air quality) within different sectors of the urban area/activity (residential, commercial, industry, education, government, transportation and open space) based on type, location, occupancy, etc. of the buildings and other indicators that are related to quality of life, such as level of income, education, etc. It will report sewage and waste production, atmospheric emissions, energy consumption breakdown and transportation (in terms of vehicle miles traveled), and will develop a basic framework for quantitative overall sustainability evaluation in cities. IUMAT applies a mathematical approach to the conceptual triangular model of sustainability and investigates inter-flows within the environmental capital along with intra-flows in environmental–social and environmental–economic axes. By connecting to GIS, IUMAT will enable designers and city planners to manipulate geographical/time borders of the analysis and provide an accessible structure for assessing ongoing trends and transformation processes in a city and improving urban control and planning systems. This will also ease the process of data harmonization and mapping the availability or absence of useful information.

CHAPTER 2

A FRAMEWORK FOR INTEGRATED URBAN METABOLISM ANALYSIS TOOL (IUMAT)

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2.1 Abstract

IUMAT (Integrated Urban Metabolism Analysis Tool) is a system-based sustainability analysis tool. It quantifies and aggregates the social, economic and environmental capitals of urban activity in an integrated framework focusing on the metabolic flows of urban development. This paper builds on previous work on urban metabolism and advances an analytical framework that defines how the consumption of resources and resulting environmental impacts are calculated as indices of sustainability in an urban region. The benefits of integrated urban modeling using the proposed framework as well as the data sources are detailed. The underlying analytical framework for the proposed tool applies the dynamics of choice, time, and scale towards dynamically interpreting demographic and economic factors. IUMAT's calculative modules for land cover, transportation, and energy/water/resource use are described as well as the modality of connections between the modules.

2.2 Introduction

Cities are on the front line of climate change. Government officials are aggressively targeting cities to reduce energy waste and cut carbon emissions. Today, cities are major consumers of resources and producers of waste having extended their ecological footprints far beyond their official borders. A secure plan for future global development will require cities to evolve into more sustainable ecosystems (Lenzen and Peters, 2010; Næss, 2001). However, due to their large size, socioeconomic structures and geopolitical attributes the patterns of change in cities are very complex (Hall, 1998). A comprehensive analysis of the dynamic of urban resource flows is critical to understand and address ecological challenges in the path towards a sustainable urbanized planet (Akimoto et al., 2008; Vera and Langlois, 2007). In this context, urban planning researchers have made great strides in developing methods to understand and model resource usage among different demographic populations (Pérez -Lombard et al., 2008). This knowledge base has extended to quantify how building type, location, and clustering impacts urban flows (Ratti et al., 2005). This paper describes the framework for an integrated urban metabolism analysis tool (IUMAT) to enable policymakers to assess the impact of changes to demographics, economics, land cover, transportation, energy and water and material resources. IUMAT is expected to promote greater understanding about the impact of environmental policies and development strategies at an urban scale, focusing on areas where sustainable urban planning and growth are critical to climate change mitigation and greenhouse gas reduction.

Urban metabolism is an analytical method for understanding the impact of urban development (Niza et al., 2009). It is a way of integrating and rationalizing the disciplinary boundaries between urban analysis, planning and policy (Gonz_alez et al., 2013). The use of urban metabolism in planning urban developments has the potential to greatly advance efforts to assess the overall sustainability in urban regions (Kennedy et al., 2011). A major challenge for policymakers and planners is to bridge the gap between field measurements and numerical studies (Park et al., 2012), associated with connecting and integrating the different functions and outputs to characterize the total urban system (Shen et al., 2013). While urban scale analytical tools exist for a wide range of applications, including land use/cover mapping, wind and solar analysis, traffic simulations, and building performance, integrated assessments of the aggregate environmental consequences of urban development remain a grand challenge (Mostafavi et al., 2014). This limitation may critically undermine our understanding of the benefits and tradeoffs of programs and policies intended to improve the overall sustainability of a city.

2.3 Background

There are a multitude of methods and tools available for analyzing urban processes and activities. In general, urban policymakers use BMPs, or Best Management Practices, rather than quantitative data to support policy decisions (Punter, 2007). Many BMPs are derived from singular case studies that have been scaled up for an urban region. For example, greening the roof of one building may alleviate storm water management for the building, improve the microclimate around the building, and reduce energy loads for the building. However, this does not mean that greening all the roofs on all the buildings will necessarily have the same benefits for an entire city.

The concept of simulating urban sectors to support design decisions is not new. In 1989, SimCity, a city management simulation environment was released for gamers to build houses, streets, factories, airports, and parks with metrics for crime, pollution, and economic stability. The most recent version, SimCity 4, offers sustainable design measures such as solar and wind power generation, sustainable transportation choices, and energy efficient building standards (SimCity, 2016). SimCity and others, such as ESRI's CityEngine, are mainly design tools that emphasize visualization and data reporting, and offer little opportunity for quantitative analyses. In the research community, tools to quantify urban performance measures are emerging.

UrbanSim, developed at the University of Washington, combines land use and transportation development with economic impacts, and has been applied to actual urban contexts (Patterson and Bierlair, 2010). The intended users are Metropolitan Planning Organizations (MPOs) and non-governmental organizations. UrbanSim calculates the effects of infrastructure and policy decisions with outcomes, such as motorized and non-motorized accessibility, housing affordability, greenhouse gas emissions, and the protection of open space and environmentally sensitive habitats. SUNtool is a European urban neighborhood-modeling tool that integrates building performance with its surrounding microclimate effects (Robinson et al., 2007). The focus of SUNtool is buildings, particularly predicting the optimal built form of an urban neighborhood with regard to optimizing pedestrian comfort and building energy efficiency. At the Massachusetts Institute of Technology, the Sustainable Urban Design Lab is developing an urban modeling tool that analyzes day-lighting potential, walkability, and operational energy use (Reinhart et al., 2007). UMI is a Rhino-based design environment that is intended to be used at the early stages of urban design and planning interventions to assess the environmental performance of urban neighborhoods. Mostafavi et al. (2014) present a comprehensive perspective of the characteristics of existing urban scale modeling tools.

UrbanSim, SUNtool, and UMI are important to understanding how targeted features within an urban environment perform. These urban simulation packages are designed for specific areas and with specific goals. Yet, the interdependence of subsystems in a city necessitates the application of methodologies that bring together the social, economic and environmental capitals of urban life to predict, analyze, and evaluate sustainability measures.

For most of the existing tools, singular static components of urban activity/life are the focus. In some cases, a few subsystems are combined (transportation and land use for instance), but the relationships within the flux of urban flows are not aggregately investigated. IUMAT aims to develop an integrated modeling structure that defines the urban area as a single system, rather than dividing it into different sectors to be solved separately. It is capable of handling overlapping features. The IUMAT integrative/analytical framework defines buildings and spaces that connect them as indicators of an urban area. In other words, the existence of building or land defines the study area for IUMAT. This perspective forecloses the rural-urban dichotomy in planning tools and approaches.

Developing a simulation framework for urban metabolism analysis is not trivial. The framework must include different scales of spatial interaction that dynamically influence how urban system parameters are affected. The resulting model must balance precision and accuracy, parsing the range of variables that characterize an urban area. Increased complexity may lead to loss of flexibility or unmanageable time steps. The boundaries of the system need to be well defined and the statistical dependences between random variables need to be meticulously tracked to minimize the chances of correlations being interpreted as causation patterns.

In self-organizing systems, dynamics will automatically drive the system toward a state of equilibrium. In cities that are large disordered systems, some properties can be reliably described by averaging over a sufficiently large population that can represent the whole system (Wilson, 2000). Quantities that are regarded as self-averaging produce a normal distribution of variations around a frequent mean, which itself is generated as the result of random interplays between factors from highly disordered subsystems. The challenge is where these borders should be drawn to make use of averaging techniques.

Buildings are complex systems and that complexity is intensified when combined with other urban systems such as transportation or land use. The major task in simulating complex systems is simulating the complexity itself. This may require maximizing the number of independent variables that affect the desired dependent variable. Moreover, the mathematical formulation must describe real world interdependency and nonlinearity. Designing an urban simulation methodology that can capture all the complexities of the real world examples is not possible. Even if it is assumed that the paths of change are governed by simple mechanisms in an urban region, complexity still exists due to the number of possible initial conditions the subsystems might have. In addition, due to the interdependence of subsystems in a city, the system is always oscillating between different possible equilibriums. Regional system mathematical models can be used as triggers that enable pointing out the separating leaps from one specific state of equilibrium to another. The IUMAT framework will determine these critical points for different states in different urban arrangements.

The format of results and visualizing techniques for the simulation outcomes need to be analyzed. The display of large collections of urban data should take aggregation approaches that combine city blocks and buildings into legible clusters without limiting the user's perspective on the data or obstructing their mental model of the urban region (Chang et al., 2007). The efforts toward urban modeling visualization are mostly independent, with graphics researchers focusing on visualizing spatial representations while the planning community focuses on quantifying urban dynamics and patterns (Vanegas et al., 2010). A participatory urban planning decision making platform can reasonably take advantage of improvements in visualization techniques (Drettakis et al., 2007) to produce complex spatial descriptions of the urban region that are consistent with cognitive insight. IUMAT will advance this further with coherent simulation results view models.

2.4 Overview of IUMAT framework

The IUMAT framework focuses on the urban region primarily as a collection of buildings, rather than an economic system. Therefore the urban dynamics are modeled in terms of any kind of change caused to these core elements of the city, whether it is variation in the number of existing buildings or changes in building program or demographic and economic factors inside the buildings. Any of these changes can affect the spatial distribution of transportation patterns and other urban flows or even the shape of urban development during the desired time intervals of study. The IUMAT framework simulates changes in demographics, economics, land cover, transportation, energy and water and material resources as reflected in the core urban elements. Three specific analytical models characterize the dynamics of choice, time, and scale in the IUMAT framework. The modeling structure is further defined by levels of resolution and associated methodologies.

2.4.1 Dynamics of Choice

Buildings, as core elements, effect changes to the surroundings as they go through phases of transformation. Aside from the impact of natural forces, patterns of change take place as urban agents take actions that can have repercussions throughout the entire system. Agents as producers and consumers of services and goods are expected to make choices about their locations and activities in a way that best serve their primary interests. The choices made by different types of agents are limited by the environment in which they act. Associations and inter-dependencies within the regional systems and urban agents impact the process of decision making over the course of time. In addition, the environment is itself not static. Understanding the behavior of the agents underpins much of regional and urban theory. This is done through discrete choice modeling of continuous variables by defining intervals (Hoyos, 2010). Engineering modeling techniques are used to analyze the boundary conditions within the borders of each interval.

2.4.2 Dynamics of Time

In addition to agent choice, associations and inter-dependencies within the regional systems and urban agents impact the process of decision-making (Tian and Qiao, 2014). Many parameters are defined or at least influenced by the joint decisions of agents in the past. These previous decisions create a backdrop against which new decisions are made. But how rapidly change occurs in the backdrop depends on the phase and stage of development.

2.4.3 Dynamics of Scale

A third issue is the scale at which the dynamics of choice and time should be introduced and simulated. To illustrate with an example, simulating the changes in population growth at the scale of a household or block, is meaningless in terms of overall urban environmental impacts. But at the scale of the county, it can offer insights into how the urban system may be influenced. By zoning the city into smaller subdivisions based on type of activity, demographics and economic drivers, the modeling structure can be underpinned by several levels of resolution, demanding a certain type of method assigned at different scales. In discrete zone conceptualization of the space, flows are assumed to be migrating back and forth between the centroids of the zones. The movement of phenomena within any of these zones or regions, or the spatial interactions between collections of regions are modeled. This requires and enables as well, an ability to swing from fine to coarse gradients. Depending on the output or phenomenon being analyzed, simulating urban flows must occur at a range of different scales.

2.5 Demographic Factors

IUMAT's approach to simulation in larger scales implicitly forces collecting and collating statistical information on population dynamics, characterizing the ways that demographic factors influence diverse urban processes. The U.S. Census Bureau keeps track of census count and publishes a public report every decade that summarizes demographic data at both state, county and town levels. These reports are helpful in understanding urban population and defining directions of growth and patterns of change in demographic texture to support projections. Both demographic (e.g. ethnicity, age, sex) and non-demographic (e.g. unemployment, public amenities) parameters can impact the trends of population growth and the decision making process by the people.

Complex structural models are used to analyze the effect of non-demographic variables on population growth. Simple trend extrapolation methods use straightforward mathematical techniques to find the best fit to the observed pattern of population growth (Smith and Sincich, 1992). The latter kind of projection based on historical trends does not account for the causes behind the pattern (Smith et al., 2001). In the middle of the spectrum are cohort-component methods that divide the population into an assortment of cohorts that are subject to births, deaths and migration. These methods are more data intensive compared to extrapolation methods (Alho, 1990). IUMAT employs cohort-component methods to make projections of population growth and composition over the time based on availability of data and level of details desired. These methods are best for this framework since they do not completely disregard assortments of the population that can relate to environmental consequences and at the same time do not necessitate dealing with details in an unwanted rigid fashion. As an example, the extent that an adult who is active in the job market travels or uses energy is not the same of an infant or a retired elderly member of the household. So in this case the population is divided into four different age/sex groups of 0-6, 6-18, 18-65 and 65 plus. For making projections for cohort population in k-years, we use the following equation:

$$P_i(t+k) = P_i(t) * S_i(t, t+k) + N_i + M_i - O_i$$

where $P_i(t+k)$ is the population of cohort *i* in k-years after t; $P_i(t)$ is the population of cohort *i* at t; $S_i(t, t+k)$ is the survival ratio between t and $t + k$; N_i is the number of new population in *i* group both from birth or aging from the lower age group; M_i is the net migrants number; and O_i is the population that goes to the upper age group in *k* years. These elements are calculated based on specific characteristics of the study area.

The main goal of IUMAT is to provide a basis for understanding the environmental impacts of collaborative decisions made by a population of human beings within municipal borders of an urban region. As long as comparing environmental impacts of different scenarios is of concern and the projection of population is not geared to strategic planning for facilities and public services provisions, cohort-component methods are acceptable and reliable, since they allow grouping of the population based on characteristics that impact the resources use intensity, without addition of unnecessary details. Demographic factors that could be practical in such a study are actual size, age composition and spatial distribution of a population. How the population is distributed into households and how those households can be grouped based on size and age composition can become important as well. Crude birth, mortality and migration rates are demographic components of change that should be applied to each defined subdivision of the population to enable projections for a desired time period.

2.6 Economic Factors

The environmental impact of a set of economic variables (e.g. income, employment, energy pricing, and taxing regulations) is a key part of the IUMAT framework. By using an arrangement of multipliers (factors) to estimate changes in environmental impacts, alterations in economic variables are modeled. Overall processes of economic transformation, patterns of growth or decline in regional economy, or if the economy is export or import oriented are beyond the scope of this framework. However, how certain economic statistics are related to behavioral aspects of acting agents will be analyzed and the general structure of the economy will be considered in identification of decision makers and active agents.

IUMAT defines governments, households and businesses as the three main economic decision makers in urban life. Transactions are governed by supply and demand forces operating in merchandise, financial and labor markets. To illustrate, the buying power of an average household is influenced by generic characteristics of the regional economy, but a parameter such as the average amount of savings per household might not necessarily have immediate environmental impacts, though it can make a difference to behavioral attributes and lead to a gradual changes in overall status of local economy in long term. Moreover, the aggregated income of families directly impacts household energy consumption.

The consumption of resources by households can be represented as functions of household level of wealth, gross income, or perceived economic security. IUMAT simulates economic indicators related to energy consumption and environmental conservation. This enables mapping correlations between specific economic indicators and environmental impacts. Variables such as population size, average age, educational achievements, average household/family size, average family compositions, median household/family income, earnings per job, per capita income by location, number of owner/renter occupied units, employment factors, and multitude of other possible indicators define default average values in scattered sets of data. This enables comparative analysis of the study region against other standards at different scales and facilitates immediate evaluation of baseline economic features of the area. A data set for employment by main industries will identify how different industrial activities influence regional economic prosperity.

The economic theory applied to a region depends on scale of the study and size of the economy being analyzed as well as availability of data at various geographic levels. Determining the economic borders of the study needs to be carried out coherently to enable tracking the flows of interaction between the local economy and larger economies of which the study region is a part. Economic base theory is widely implemented in urban economic studies and assumes that households spend money either to import services and goods exogenously or endogenously from local businesses (Rutland and O'Hagan, 2007). Input-output analysis is another economic accounting analysis method to investigate inter-industry transactions (Leontief, 1974). This kind of analysis focuses on the intermediate flows of goods and services within the industrial and producer division of the economy.

Analyses based on households or industrial transaction oversimplify and overcomplicate the IUMAT framework. Defining the demand only with regards to final consumer side of the economy in the economic base theory is inaccurate and simplistic. The addition of value to the final products as they flow down the economic chain to consumers creates unnecessary complexity. A new method needs to be defined. The unit of economic analysis in the IUMAT framework is the building, which forms the unit structure of urban economy. Regardless of the building's placement in the production-consumption chain, its part in transmitting and receiving varied flows can be tracked as separate economic transactions in contact with other separate units.

2.7 Land Cover

In the IUMAT framework, land is defined in spatial coordinates that characterize land cover and use. Prevailing land cover characteristics influence, inform, or control possible prospects of use. And, certain types of land use necessitate alterations to the existing land cover. Changes to land use and cover are also governed and limited by rules and regulations enacted by public or private administrative authorities.

Notwithstanding government rules and regulations, there are multiple elements that shape the way a parcel of land is used. Different economic and physical drivers such as the price of land, accessibility, capacity to support different types of use, as well as distribution of activities in the surrounding pieces influence land use (Verburg et al., 2004). Land cannot exist isolated and land development could force changes to the surrounding area. For an in-depth land use analysis all parcels of land have to be classified into different categories of use and land cover as a means to characterize the human-land relationship.

Changes in land use are not free of environmental consequences (Lambin and Meyfroidt, 2010). Sustainable land use planning is predicated on minimizing transformation of green-sites into brown-sites with simultaneous sufficient provision of land for urban activities (Schädler et al., 2012). Replacing permeable land with impervious surfaces increases the risk of flooding (Pattison and Lane, 2012). Intense use of air conditioning units and dark paving materials trigger the heat island effect in urban areas (Tremeac et al., 2012). New developments require roads to support traffic to and from developed sites. Contamination of soil or groundwater may occur if toxic materials permeate. Development of land may also disturb the ecosystem and pose threats to biodiversity of the region (Schiesari et al., 2013). Although quantification of all these various impacts is beyond the scope of the IUMAT framework. Net carbon emissions from development due to differences in carbon sequestration capacity of alternative land covers, and the urban heat island effect are quantified.

Cities are made up of varied types of land use each possessing unique quantifiable demographic and economic characteristics that are best represented and understood using Geographical Information Systems (GIS) (Geyer et al., 2010). GIS land use mapping uses discrete zones (versus continuous space representation) that treat borders of properties as geographic boundaries between zones. Discrete conceptualization of the space enables mathematical formulation and use of computational techniques. Land use mapping is the starting point in embedding functionalities of GIS approaches into urban simulation where discrete zones can be referenced and identified using algebraic subscripted and superscripted factors such as Zone No. $\binom{Cover\ type\ indicator}{Use\ type\ indicator}$. Using GIS features for planar conceptualization of space allocation of activities in buildings and other spatial units enables appending non-spatial data to layer attribute tables. The accurate mapping of land use location is necessary for the integration of transportation and resource consumption patterns. The IUMAT framework employs two distinctive GIS approaches, distinguishing between mapping and modeling techniques.

In 1965, a classifying numeric coding scheme that was based on the Standard Industrial Classification system (SIC), the Standard Land Use Coding Manual (SLUCM), was introduced by the Bureau of Public Roads (Federal Highway Administration) and the Urban Renewal Administration (Department of Housing) (Standard land use coding manual, 1965). In 1994 American Planning Association (APA) provided a report for the Federal Highway Administration (FHWA) to update the 1965 SLUCM and create a more comprehensive and up to date coding system with better adaptability to GIS networks (Lawson et al., 2012). APA's Research Department introduced Land Based Classification Standards (LBCS) via five main dimensions: activity, function, structure type, site development character, and ownership based on different case studies at different scales (American Planning Association, 2014). IUMAT uses the APA's 2001 LBCS tables and the associated color-coding system as a standardized land use coding system for mapping purposes.

For modeling objectives, a different system is required. Changes in land cover may occur naturally due to climate conditions as well as human induced alterations. The IUMAT framework employs Anderson et al. (1976) land coding system for monitoring conversion of natural land to built environment. Since transformations of green-fields into brown-fields usually originate from new construction or change of use projects, this system classifies land into nine basic categories as urban/built-up, agricultural, rangeland, forest land, water, wetland, barren land, tundra, perennial snow/ice. The impact of changes in land cover is quantified in the context of buildings as core elements. Land cover is the cornerstone of the land use analysis and is based on transformation of land cover between nine principal categories introduced in the Anderson land use classification system (See Figure 2:1).

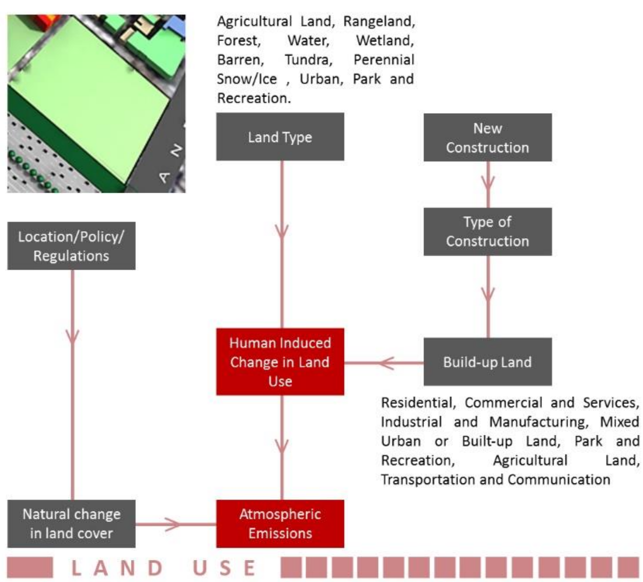


Figure 2.1: Land Use analysis algorithms for IUMAT

2.8 Transportation

Transportation systems are designed to support mobility associated with land use allocation in a community. Urban transportation planning is aimed at creating the most viable alternative systems of transportation based on the type and volume of activity and compactness of settlement. The transportation simulation implemented by IUMAT determines the traffic-related environmental consequences of change in land use, and characterizes mobility within the urban region. This is the fundamental distinction between the IUMAT framework and other methods of transportation modeling. In transportation modeling scenarios, individuals make choices for their urban travels based on many factors such as cost, comfort, availability of public transport, time, and privacy (Klöckner, 2004). In contrast, the IUMAT framework focuses on the environmental consequences resulting from the demand for various traffic modes.

The IUMAT study area is divided into a network of separate traffic analysis zones (TAZs). The TAZs are buildings grouped as neighborhoods with relatively uniform distribution of activity throughout the zone. Every TAZ is assigned a centroid that is at an optimal distance from buildings. The centroid connects the street network nodes. The path taken from the centroid of a zone (origin) to one's destination is called a trip. The number of the trips originating from or ending in a TAZ changes according to land use types in a zone and the amount of attractions a zone has to offer, along with demographic and economic factors that are directly related to the trip generation process. Traffic demand models are specified to include the demand for travel as well as specific features of the traffic analysis zones. After comparing the traffic flows calculated by the travel demand model against the actual collected traffic flow data, the calibrated model can be used to forecast traffic flows generated by different cases of growth and alternative types of human activity. The most common travel demand modeling process, commonly known as Four Step Travel Demand prediction incorporates four separate key parts (McNally, 2008). Trip generation predicts trip frequency from and to a traffic analysis zone as an origin or destination. Trip distribution in which the generated trips are distributed between the TAZs, mode choice that predicts the proportion of trips by alternative modes of travel, and finally route choice whence the trips are assigned to routes of transportation network that connect the TAZs (See Figure 2.2).

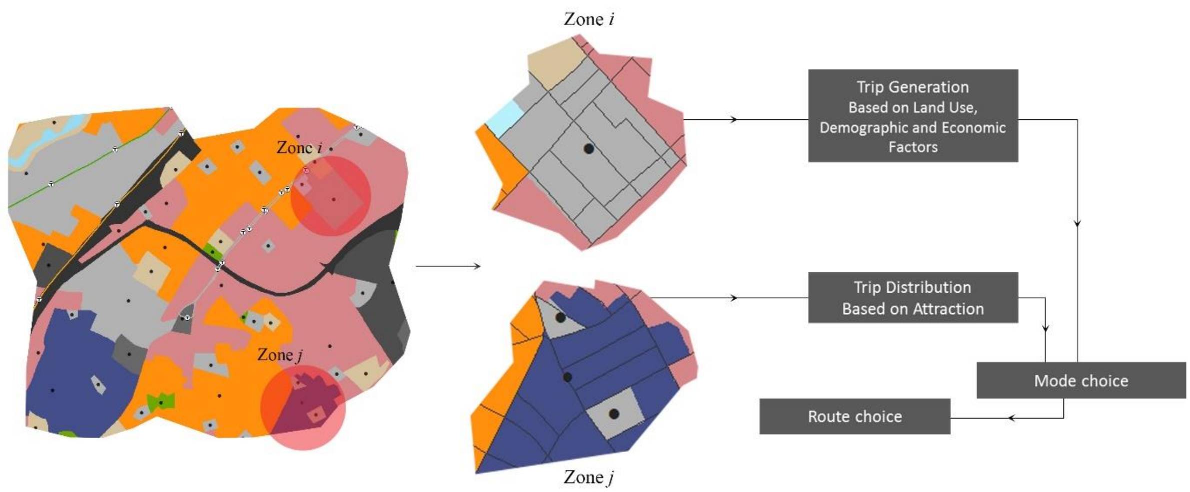


Figure 2.2: Four step travel demand prediction model used by IUMAT

Traffic analysis zones are connected to the street network nodes from the centroid of the zones. In this framework based on the land use type (or building type), the trip generation process will be carried out in trip/building and trip/acre format for indoor and outdoor types of activity respectively. This indicates that IUMAT's travel demand model generates the trips at a lower level (buildings) before assigning them to the TAZ centroids compared to conventional transportation modeling software. Within every building, parameters such as number of workers and students per household, level of education and income, number of vehicles owned by the household, size and age distribution of the family, and availability of attractions at the nearby zones are all factors that impact the number of trips being produced by a residential building. At the scale of the zone, parameters such as density of development and distribution of land use type are effective as they specify overall characteristics of the zones. Trip distribution is carried out using the well-known gravity model based on number of produced and attracted travels and impeding factors between the zones such as time and cost (Erlander, 1990):

$$T_{ij} = \frac{A_j\, F_{ij}\, K_{ij}}{\sum_{j=1}^{n} A_j\, F_{ij}\, K_{ij}} * P_i$$

where Tij is the number of trips generated at zone i and destined at zone j; Pi is total number of trips generated at zone i; Aj is the total trip attraction at zone j; Fij is the friction factor relating to travel impedance between i and j; and Kij is a socio-economic adjustment factor.

The mode choice model estimates the percentage of trips assigned to different transportation modes based upon trip characteristics, quality of public transportation systems, vehicle ownership, environmental literacy and behavior of travelers. Route choice modeling focuses on using a minimum time route algorithm. In this method trips that cross the boundary of the study area are ignored. These four steps are not necessarily followed in a sequential chain. For instance, availability of transportation modes at/to a zone will impact trip production/attraction of the zone. Also the impedance associated with different transportation modes (such as expected time for public transportation vehicles) might affect decisions made by travelers.

The travel demand produced by buildings is assigned to a TAZ centroid, and the origin-destination matrices show the number of trips between different zones and within each zone, involving different modes of travel. These matrices are introduced to the route choice model to calculate miles travelled in different traffic modes. Quality of the public transportation fleet, efficiency of personal cars, and types of fuel put into vehicles are factored by calculating carbon emission based on results from the route choice model. IUMAT has the capacity to project factors such as traffic volume, average peak hour traffic (PHV) and average daily traffic (ADT) for all of the traffic links.

This approach differentiates between person trips (public transportation) and vehicle trips (automobile), but does not require characterizing the trips as home based work, home base non-work or any other type. Trip chaining is not IUMAT's intent. However, it has advantages over conventional transportation modeling structures that may assume transportation demand is only generated at residential TAZs. IUMAT accounts for commercial and industrial transportation as well as public transportation. Given that the number of public transportation trips is not directly influenced by decisions made by individual travelers (bus system runs on a given schedule regardless of how many people choose the bus mode on a certain day), public transportation emissions are calculated separately and added up to the aggregate transportation emissions figure. The demand for public transportation produced by residents of individual buildings is estimated by modeling the public transportation schedules of different modes. This methodology enables analyzing traffic demand based on distribution of human activity (land use) and emphasizes environmental impact analysis of the transportation related issues tailored towards analyzing policies towards mitigation of negative environmental impacts (see Figure 2.3).

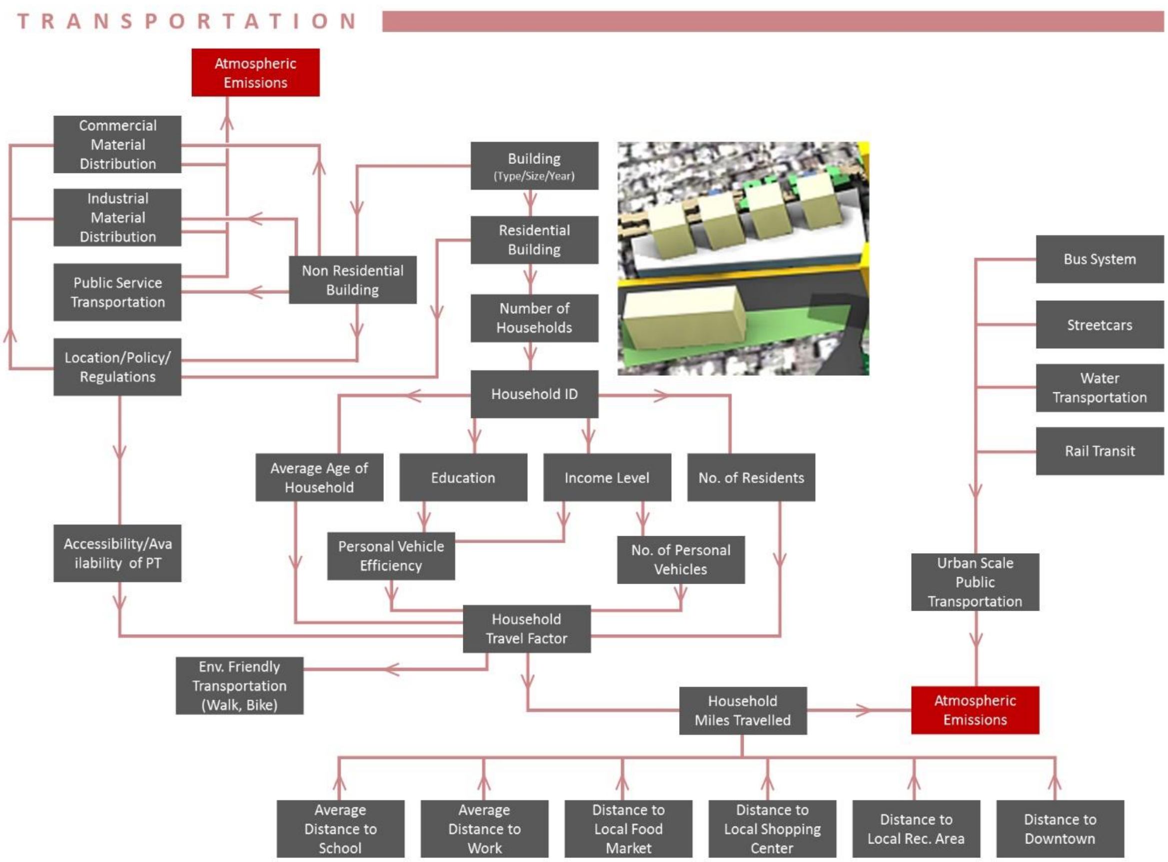


Figure 2.3: Transportation algorithms for IUMAT

2.9 Energy, Water and Materials

Creating environmentally sound policies requires the ability to analyze and project impacts and implications of different growth and development scenarios. Energy, water and material (EWM) flows must be optimized to mitigate resource consumption. IUMAT's model for EWM is a bottom-up model for generating daily spatial distribution demand profiles for a large number of buildings from different urban sectors. Detailed information on buildings and neighborhood characteristics extend the accuracy of the model to higher levels. The flexibility of the model enables switching between statistical and engineering methodologies, even in the absence of fine scale data. By employing regression analysis methods, electricity and fuel intensities are determined for building types based on size, location, and year of construction.

The EWM model works in connection with the GIS mapping model that stores land use (building type and land cover) data in attribute tables. This component is critical since the building type and land cover are the physical factors with most substantial impacts on resource use. Moreover, mapping provides an effective visual communication of the physical structure of the urban area. Connector tools that associate the databases with various data layers tag the buildings' geometry by type of use including social and economic characteristics required for predicting EWM profiles.

The layers contain analytical components to convey land use and cover. Generic EWM templates based on loads, gross area, window-to-wall ratio, year of construction, activity types etc. are stored in the background to be accessed when collected data is insufficient.

The templates reflect the building codes based on location, type of use and year of construction. Depending on the technology used for energy generation, different amounts of water may be consumed. Supplying the required water is itself associated with energy use. The IUMAT EWM model characterizes the energy, water and material use dependencies between five subcategories (land cover, transportation, energy, water, materials) using calculative algorithms. The constructed network of algorithms is presented in Figures 2.4 and 2.5.

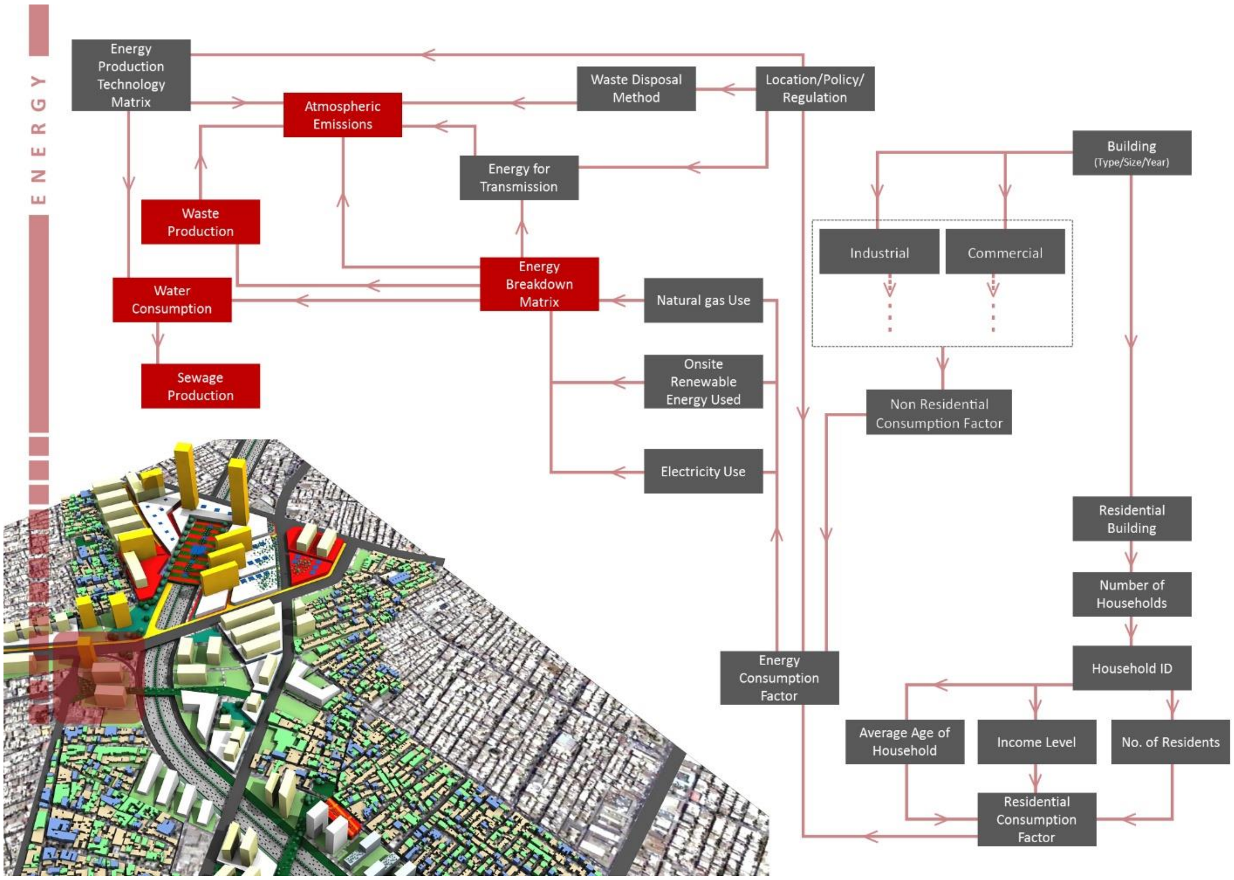


Figure 2.4: Energy use algorithms for IUMAT

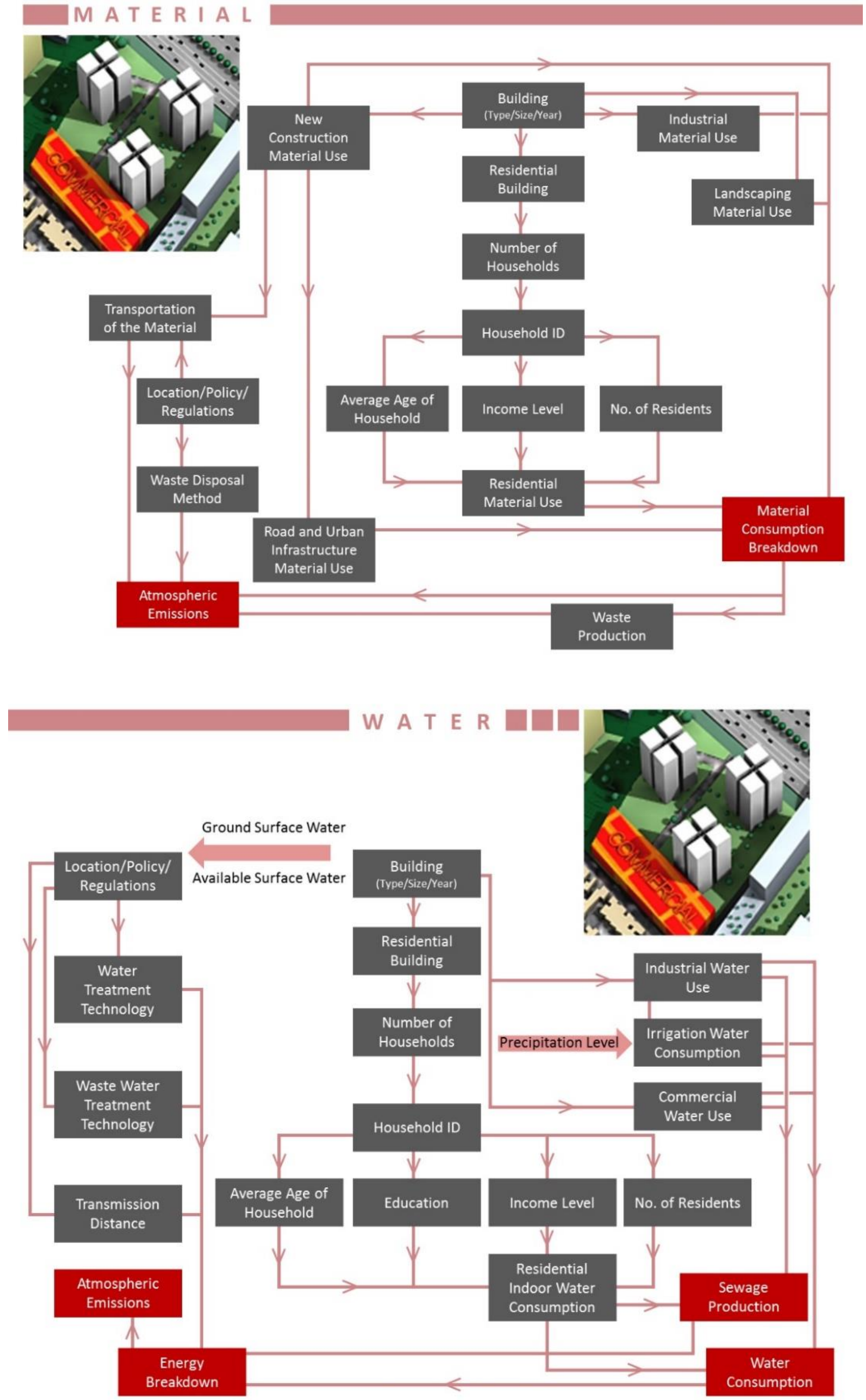


Figure 2.5: Water and material use algorithm

For a list of organizations and manufacturing unit types the North American Industry Classification System (North American industry classification system, 2014) which has replaced the Standard Industrial Classification (SIC) in 1997 (Standard industrial classification, 2014) is used by IUMAT. To collect primary template energy data, end use consumption surveys provided by the U.S. Energy Information Administration (EIA) that are Residential Energy Consumption Survey (RECS), Commercial Building Energy Consumption (CBECS), Manufacturing Energy Consumption (MECS), and Transportation (RTECS) for the establishments classified within NAICS subsector codes provide the basis for a general understanding of patterns of energy use in different sectors (EIA consumption and efficiency, 2014).

The deterministic component of the models is critical in showing the correlations between independent variable and the environmental impact which is of interest. Initial examination of the data and the interpretation of the expected patterns provide the basic insight for choosing the models. In order to deduce the parameters of deterministic models, fitting techniques need to be applied. In addition, a complete understanding of the physical nature of patterns is essential. For example, having a constant number of residents, energy and water usage of the household should increase with the living space area. But this increase is not expected to be of the same nature: the impact of increasing square footage on water use is less significant compared to its impact on energy use. Dividing a household of four into two separate households of two is not expected to affect the amount of potable water use, to the same extent that it does for the energy demand.

The functional response for water usage versus living area is more likely to be of a $\mathrm{f}\,(\mathrm{x}) = \frac{ax^2}{b^2 + x^2}$ type function (since a maximum limit is expected for a constant number of residents), compared to energy use versus living area which is likely to follow a power functional response of response of $\mathrm{g}\ (\mathrm{x}) = cx^d$ (0 < d < 1) nature. However, the existence of noise around the expected pattern (deterministic model) is theoretically unavoidable. The noise appears in the system due to both measurement (variability in measurements) and process (unmeasurable randomness in the system) errors, and leads to larger confidence intervals and lower statistical power for inferring the desired environmental patterns. The errors need to be explained by probability distributions that stand for variations around the expected (fitted) value. The probability distribution can be regarded as a mechanism for data generation in simulation cases that generates data points in a random fashion that are expected to occur in real case examples. Since the desired outcome of simulation processes by IUMAT is basically numeric values (numbers for resource use intensity for example) which is a continuous range, normal distribution and other probability distributions (if necessary) for continuous data will be used for describing the stochastic component of the models.

2.10 Aggregation

IUMAT holistic framework (Figure 2.6) incorporates four primary components:

a. Input/output interfaces that directly communicate with the user through setting, translating, coding, and exporting data.
b. Spatial storage unit that holds the spatial compiled simulation results. This unit keeps record of socio-economic attributes as well.
c. Modules that are the main simulation engines for capturing the urban metabolism features.
d. Coordinators that are responsible for data distribution between the modules.

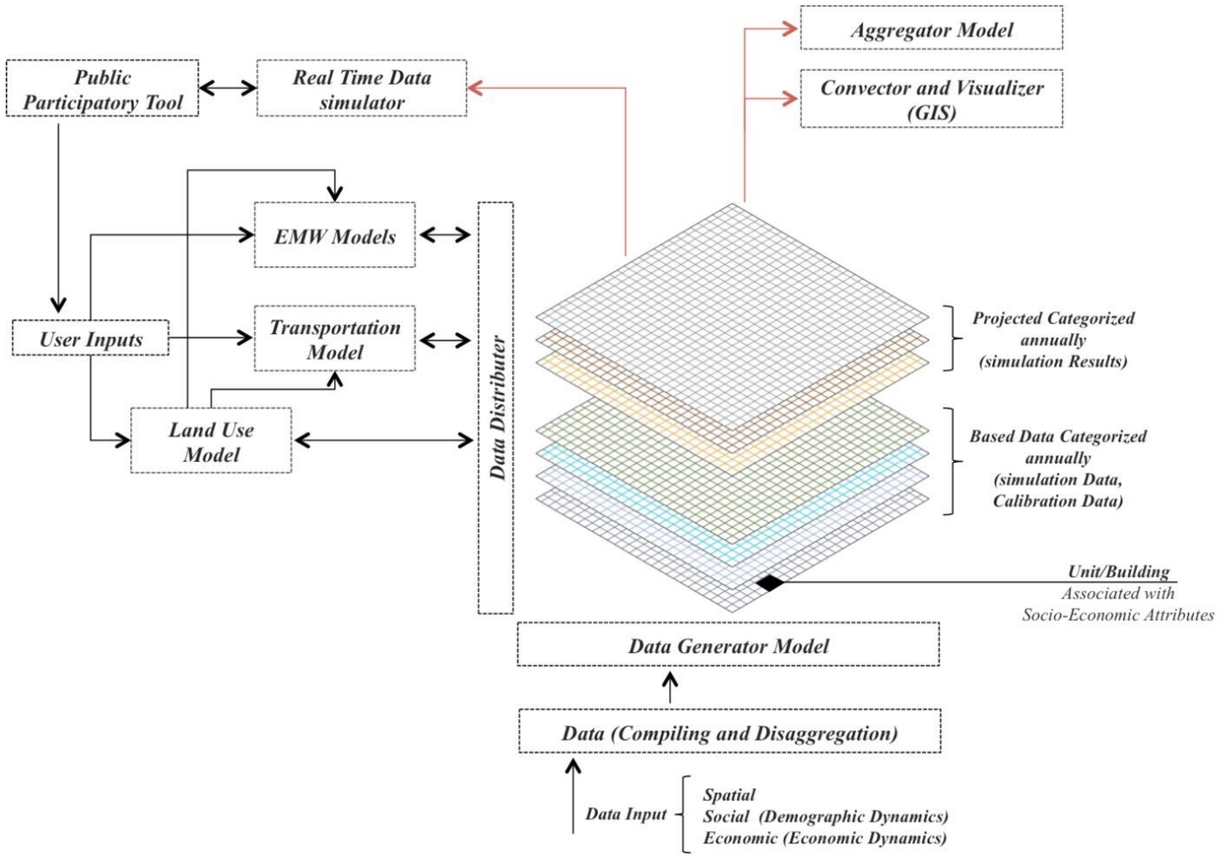


Figure 2.6: IUMAT holistic structure

These components each consists of different sub-units such as data generator module, spatial data store, IUMAT wizard connector, metabolism modules, and data exporter. Raw data and user inputs are introduced at the input entry, while topography, land use and socio-economic elements are spatially compiled and disaggregated. The data generator takes advantage of compiled data to generate large samples. The Energy, Material and Water Module (EMW Module), Transportation Module and Land Use Module work within the IUMAT Wizard connector. This connector is responsible for querying data from/to the data storage unit. This unit also controls the data distribution and facilitates communication between metabolism modules. With respect to local regulations and policies, users are able to actively manage modeling coefficients and parameters within the modules. The Wizard connector forwards projected data and real-time data to the Calibration Module that provides statistical comparison results and marginal errors for users' review. Based on statistical results, this Module also provides suggestions for calibration of the simulation modules. The Result Aggregator Module compiles and aggregates simulation results and creates a detailed report. Finally, user is able to create different comparative maps or spatial data exports of simulation results by adjusting preferences in the Exporter and Visualizer Tool.

2.11 Conclusion

Cities are complex systems that require large-scale simulation tools to quantify, analyze, and predict environmental impacts. IUMAT aims to simulate the inter-dependencies between the variables and subsystems of an urban region to create an integrated framework for computing urban environmental performance.

IUMAT uses spatial and temporal data for comprehensive microscale analysis. There are high levels of uncertainty in urban temporal and spatial dynamics, plus cities are open systems that are continually interacting with the environment. This requires conceptualizing the urban simulation framework in a way that maximizes the prospects for practical collection of data (statistical methods) and enables executing randomization procedures based on probability functions of different variables (engineering methods). IUMAT models the city as a complex system using an iterative network of distribution models that generate and assign locational variables in patterns derived from maximized probability distribution functions. Inductive statistical methods and data fitting techniques are employed to examine how different parameters (atomic elements of the model) relate urban variables to observed patterns of data.

Practical limitations of the framework are the availability of data and capability of mathematical analysis methods in handling large numbers of parameters.

The IUMAT framework supports collection of a database that reflects the syntax of the urban study area. It motivates understanding buildings as individual agents that are embedded with relationships and rules to mimic real scenarios of change in the urban context. To achieve both mapping and modeling goals, statistical methods are employed to create functional data patterns wherever the existing information is unavailable. The presented framework demonstrates a method to investigate the influence of dynamics and demographic/economic factors in an intertwined network of land cover, transportation, and energy/water/materials use analysis. IUMAT is distinctive from existing land use/energy/transportation simulation tools because it focuses on the environmental consequences of development rather than correlated outcomes.

IUMAT models the impacts of social/economic/physical factors on the environmental footprint of a group of buildings at varying scales. It is a calculative/evaluative tool not restricted to rural/urban dichotomies. Its outputs help to inform the overall sustainability of different classes of urban settlement in terms of energy/water/materials use, waste/sewage production, and atmospheric emissions.

CHAPTER 3

URBAN RESIDENTIAL ENERGY CONSUMPTION MODELING IN THE INTEGRATED URBAN METABOLISM ANALYSIS TOOL (IUMAT)

The following chapter is submitted to an academic journal for review. Mohamad Farzinmoghadam and Dr. Simi Hoque (Corresponding Author) are other coauthors of this chapter.

3.1 Abstract

The Integrated Urban Metabolism Analysis Tool (IUMAT) is a system-based computational platform for quantifying the environmental impacts of urban development. IUMAT's EWM module is a bottom-up approach to generate energy, water, and material resources demand profiles based on building and neighborhood characteristics. This paper presents the EWM approach using national and regional datasets to identify the relationships between environmental impacts and resource use determinants within a simulation platform for urban metabolism analysis. We focus on residential energy consumption, which will serve as a template for how the EWM module will be used to simulate commercial and industrial demand profiles. Quantile regression methods are applied to Residential Energy Consumption Survey (RECS) 2009 data to describe the impacts of physical and socio-economic parameters on end use residential energy profiles. A method for quantifying CO_2 emissions and water consumption associated with energy production is also described.

3.2 Introduction

Urban areas account for 67-76% of the energy use and 71-76% of the carbon dioxide emissions at a global scale as reported by the Intergovernmental Panel on Climate Change (IPCC) (Seto et al., 2014). Cities currently accommodate 54% of the world's population and are projected to add 2.5 billion new inhabitants by 2050 (UNPD, 2014). This predicted growth of urban areas will further stress energy security and environmental conditions, as sustainable development and operation of urban communities remain a grand challenge. Energy conservation mandates and climate action plans are intended to offset greenhouse gas emissions and reduce energy use and associated air pollution and waste production, as well as improving the standards of living for the city inhabitants. However, there exists a knowledge gap between a given set of sustainability policies and the outcomes expected. This is because the goals of city masterplans are based on outputs from discrete and disaggregate analytical models or existing Best Management Practices (BMPs) that are used to characterize specific urban sectors and are neither combinatory nor complementary (Cullen, 2013). Disaggregated one-dimensional models do not adequately address the complex interrelationships between urban sectors. Equivalently, sector-based models are insufficient for high level decision making as they may result in policies that improve the outcomes for one sector and negatively impact others with unintended consequences. An integrated and systematic approach for assessing the overlapping and sometimes conflicting relationships between urban sectors is critical to advance sustainable development and planning. This work builds on previous research by the authors to create an urban metabolism analysis tool for evaluating the overall sustainability in cities. In this paper, we focus on the mathematical methods and outputs for an urban residential energy use model, as a part of the broader Integrated Urban Metabolism Analysis Tool (IUMAT).

3.2.1 Urban Residential Energy Modeling

Identifying the parameters that determine consumption rates of urban resources through energy-water-materials use, transportation, and land use analysis is essential for effective policy decision making. In 2012, the residential sector was responsible for 21% of the total U.S. primary energy use and 20% of the national CO_2 emissions (EIA, 2015). According to the Residential Energy

Consumption Survey (RECS), U.S. homes used 2.99 Trillion kWh of energy in 2012, indicating an 8.9% growth since 1980. While federal and state governments attempt to reduce and regulate energy consumption rates, municipalities and county planners are focused on local climate improvements and sustainability initiatives (Parshall et al., 2010). Urban energy systems are socio-technical systems comprised of combined processes in which energy is acquired and used by a given economy or society (Keirstead et al, 2012; Jaccard 2006). In larger metropolitan areas, due to the high density and diversity of demand, a wide range of technological and policy options that could mitigate per capita energy use and carbon emissions are available. However, decentralized platforms for energy policy making, the lack of reliable datasets and models, and complications around shaping local policy in alliance with federal and state regulations are some of the major challenges yet to be overcome by the planning authorities and practitioners. Large scale energy modeling has the capacity to inform building regulations and energy conservation policies by quantifying the performance of the building stock and its outputs can be used to update building codes, development standards, and refurbishment incentives. Modeling results can provide scientific support that decision makers need to create performance targets, compare baselines, set realistic reduction goals, and monitor the outcomes in the long run.

Energy modeling at the single building level does not account for the impact of uncertainty in the modeling process. Most of the current tools require deterministic values at data entry. In addition to deterministic rejection of uncertainties, the challenging nature of simulating human-building interactions, average dwellings/dweller identification, and the modeling tools' inability to include future datasets and emerging information are other limitations of current building energy modeling methods (Natarajan et al., 2011; Mostafavi et al., 2015a). Scaling from a single building energy model to neighborhood and urban models requires a shift from fixed data inputs to more complex probabilistic datasets. Urban energy modeling processes need to include physical, behavioral and regional complexities. Energy consumption determinants such as climate variables, housing mix, and economic factors change from one location to another and analytical methods such as the one presented here can be of significant assistance in establishing sustainability targets as well as optimizing energy reduction policies.

The interactions between energy systems and social economies are represented by two modeling paradigms (Böhringer and Rutherford, 2009). Top-down models take a macro level perspective to represent the economy in a wide scale and lack the required details for investigating technologies from an engineering standpoint (Tuladhar et al., 2009) featuring market fluctuations, financial flows, and economic power of agents at different levels (van Vuuren et al., 2009). Bottom-up models in contrast, are partial equilibrium portrayals of energy systems, underscoring discrete technologies to track replacement of energy carriers, enhanced efficiencies and process changes (Hourcade et al., 2006; Böhringer and Rutherford, 2008). Recently, alternative approaches are being developed as hybrids to overcome particular disadvantages of single approach models, by integrating elements of one approach into another, or introducing outputs of bottom-up models as external inputs to top-down frameworks (Bhattacharyya and Timilsina, 2009; Barker et al., 2007; Fleiter et al., 2011), and soft-linking (Dai et al., 2016) the two types of models is being considered as a pragmatic solution for narrowing the gap between them.

The IUMAT residential energy module relies on large national survey-based datasets to predict energy form mix, type of appliances and end-use energy figures based upon climate variables, physical attributes of buildings, and socio-economic characteristics of occupants. The inclusion of socio-economic factors is important for connecting the energy model to other modules (water, material, transportation, and land use) and may represent a hybridizing modification between bottom-up and top-down approaches. Demographic and economic characteristics could have contrasting impacts on different categories of consumption, and therefore emphasize the importance of connecting the modules. For example, although higher income can increase the household's budget allocated to air conditioning, it allows families to choose their desired downtown residential location with less transportation demand, or the other way, depending on the regional culture, towards wealthier neighborhoods in the peripheries that require more traveling.

3.2.2 Human-Building Interactions in Urban Residential Energy Modeling

Building occupant behavior plays an important role in household energy consumption (Masoso and Groble, 2010). Strong correlations exist between household characteristics and ownership of appliances, equipment energy rating and level of domestic appliances' use (Lutzenhiser and Bender, 2008; Weber and Perrels 2000). In most energy modeling tools, however, human-building interactions (i.e. occupant behavior) are rarely simulated, and are usually represented solely through occupancy schedules that assume average behavior for all of the building occupants. These behavioral patterns are based on surveys that in many cases have not been updated for decades and have questionable relevance today (Gaetani et al., 2016; Shipworth, 2013). As the number of modeled dwelling units increases, the influence of behavioral variances in the energy model intensifies. And, as building energy codes improve, the impact of behavior becomes more significant (Newton and Meyer, 2010). Quantifying the influence of design-driven consumption and behavior-driven consumption is therefore critical. Research to improve the dynamic and stochastic characterization of occupant behavior in energy models is emerging. Yohanis et al. (2008) used half-hour load metering to measure household electric use against occupancy schedule and occupants' employment status. Seryak and Kissock (2003) report that even after accounting for number of occupants and schedule, the variation in energy use among similar residential units can be significant. Muratori et al. (2013) used a heterogeneous

Markov chain to model the activity patterns of individuals for energy demand prediction. Richardson et al. (2010) suggest a modeling approach to combine occupancy patterns with daily activity surveys to simulate domestic appliance use. Widen and Wackelgard (2010) used empirical data to create models to generate synthetic activity sequences and their associated energy demand. Zaraket et al. (2015) recommend an occupant-based energy modeling method to be integrated into the residential building design process.

Besides the challenge of accurately reflecting the behavior of the occupants over a large area, obtaining geometrical detailed data at district scales is not uncomplicated. Measuring all the physical attributes of the built environment is impractical and inputs to urban models at best are good estimates (Ryan and Sanquist, 2012). Engineering models have the weakness of making so many assumptions regarding the impact of behavioral elements on energy use (Kavgic et al., 2010). Such precise calculation of energy use by physics-based models often obscures the extent to which the results of these models are dependent on the blackbox assumptions. However, extended-scale neighborhood housing models and analytical inference methods such as the one presented, provide reliable estimations and reduce the need to measure the performance of large number of buildings which is costly as well as time consuming.

Defining “behavior” and its physical attributes contributes greatly to the uncertainties in household energy prediction. Behavior in many cases is taken to be interchangeable with ‘occupancy’, and yet, most models only handle electricity use. Improved occupant-based modeling of residential energy use should result from analyzing data on the households’ priorities, choices and patterns of use, and accordingly, improved reflection of socio-economic and demographic factors that impact end use profiles. Socio-economic factors, if accounted for properly, can be reliable predictors of behavior. Cheng and Steemers (2011) illustrated that 85% of the residential energy consumption variance can be allocated to type of use and socio-economic status of the household. They introduced a method that adopts an occupancy pattern simulation based on the dwelling's employment status and acts within a domestic energy and carbon model. Gadenne et al. (2011) propose age, gender, occupation, income and highest level of education as factors that drive environmental behavior. Newton and Meyer (2010) emphasize income level and environmental literacy, suggesting that by increasing knowledge on the life cycle impacts of the built environment materials and manufacturing chains, behavioral changes can be achieved. From the literature, ranking each variable's impact on energy use in descending order is as follows: type of use, income level, appliances, household size, location, household composition, head of household age, floor area, heating type, dwelling age, employment status, insulation quality, disposable income, social group, number of bedrooms and education level (McLoughlin et al., 2012).

Large datasets from large population surveys can reveal the relationships between socio-economic parameters and heating and cooling equipment, lighting installations and number/type of appliances such as cookers, microwave ovens, freezers, washing machines, washer-driers, dishwashers and computers. The IUMAT framework applies socio-economic indicators with environmentally significant consequences to quantify the weight of human-building interactions in energy use.

3.2.3 Methods for Urban Residential Energy Modeling

Swan and Ugursal (2009) present a comprehensive review of modeling techniques for residential energy consumption. They classify bottom-up models into two categories of statistical and engineering models. IUMAT aims to develop a hybrid of the two techniques that enables the use of statistics of empirical data, to create reliable average figures and archetypes that can be used in physics-based models. Its modeling framework depends on detailed datasets to estimate the influence of physical and behavioral parameters on annual energy consumption profiles.

Bottom-up methods rely on extensive sets of empirical data that are built on disaggregated components. Over the last two decades, bottom-up models have been developed to close the gap between quantitative evaluation and policy making in the residential sector. Farahbakhsh et al. (1998) introduced CREEM (Canadian Residential Energy End-use Model) to study the carbon reduction impact of renovations or fuel switching policies for single-attached and single detached dwellings. Snäkin (2000) proposed a numerical model for annual heating demand and CO_2 emissions in North Karelia, Finland based on building type, heating system/fuel, and construction year. The Building Research Establishment's Domestic Energy Model (BREDEM) (Dickson et al., 1996) and the Building Research Establishment's Housing Model for Energy Studies (BREHOMES) (Shorrock and Dunster, 1997) were developed in the UK, using historical data, empirical correlations and a series of energy balance equations to project monthly consumption by single units for space heating and cooling, lighting, cooking, water heating and appliances (Anderson et al., 2002; Shorrock et al., 2005). Huang and Brodrick (2000) developed a DOE-2 model of prototypical buildings (112 single-family and 66 multi-family prototypes) to analyze energy loads assigned to particular building components. Hens et al. (2001) constructed a set of 960 reference dwellings based on year of construction, type, total floor area, primary fuel, and heating system to predict heating energy and carbon emissions for Belgium's residential stock under alternative efficiency scenarios. There are other approaches that use BREDEM as their energy analysis engine. Natarajan and Levermore (2007) developed an object-oriented housing stock and carbon model, DECarb, and concluded that higher disaggregation in the modeling approach increases the credibility of the results. Firth et al. (2010) created the CDEM (Community Domestic Energy Model) with 47 house archetypes. Johnston et al. (2005) furthered the work of

Shorrock et al. (2001) to find the most feasible alternatives for reducing UK carbon emissions by 2050.

Modelling the physical complexities of building energy consumption requires simplifying the building stock. Archetypes models are based on defining templates for building type (residential, industrial, etc.), morphology and form (apartment, detached, etc.), mechanical systems, age, envelope construction materials and other parameters. Uncertainty in identifying these input parameters is significant. Measurements of U-factors, HVAC efficiencies, and ventilation and infiltration rates are not possible across the entire building stock. Building stock in most bottom-up modeling methods is categorized into average performance groups and scaled up to represent larger districts. The level of disaggregation determines the accuracy of the results since averaging methods can significantly skew the individual consumption profiles and increase unpredictability. The crucial challenge in this method is defining the number of categories that is neither too coarse nor too detailed, and success depends on the availability of data and level of detail in the model libraries. Information provided by energy use survey datasets controls the number of averaging groups relative to the variables that the inquiry covers. More disaggregation is possible by conducting geographically widespread building surveys drawn from an unbiased sample of the larger population.

Regression is a common statistical method that has widely been employed to describe the relationship between energy model coefficients and input parameters. Bianco et al. (2009) employed multiple regression to project Italy's household and non-domestic annual electricity consumption using population time series and GDP. Sanquist et al. (2012) used multiple regression of lifestyle factors such as ownership of appliances, thermal comfort, family composition and routines as predictors of electricity consumption. Asadi et al. (2014) applied Monte Carlo algorithms to generate different types/levels of building variables as inputs to the

DOE-2 simulation software, and used multi-linear regression to explain the relationship between annual energy consumption and seventeen generated explanatory variables. In comparison, the IUMAT residential energy module combines regression statistical techniques and engineering models using Quantile Regression and emissions calculation equations, described in the next section.

3.3 Methodology

3.3.1 Quantile Regression

Quantile Regression (QR) was first introduced by Koenker and Bassett (1978) as a robust alternative to the classical Least Squares Estimator due to the deficiency of Least Squares in linear models with non-Gaussian errors. It extends the conventional least squares estimation to conditional quantile functions (Davino et al., 2013).

In IUMAT's urban residential energy module, QR is used to track how different resource consumption groups are impacted by changes in physical and socio-economic factors. Upper and lower tails of energy use distribution may arise from different levels of sensitivity to climate or income variables. Applying Ordinary Least Square (OLS) regression will not accurately predict the marginal policy impacts on different tiers of energy consumers. QR methods are appropriate because of the heterogeneous variations between energy use indicators, specifically, when specific populations are a subset of the distribution. Furthermore, with a skewed distribution of attributes of interest, QR methods provide more insight into the distribution compared to simple measures of central location and dispersion (Hao and Naiman, 2007). QR demonstrates effects of individual independent variables on quantiles of the variable of interest, and since it runs the analysis through the entire sample not only the conditional mean, it rules out subjective inference due to sampling bias. QR describes the functional relations between variables throughout a distribution. If $F_Y(y|X_i)$ is the probability distribution of Y_i given X_i, conditional quantile function (τth quantile of Y) can be defined as (Chen, 2005):

$$Q_\tau(Y_i|X_i) = F_Y^{-1}(\tau|X_i)$$

By solving

$$\hat{\beta}(\tau) = argmin\ E\ [\rho_\tau(Y_i - \acute{X}_i\beta)]$$

$$\rho_\tau(z) = \begin{cases} -z(1-\tau), & z < 0 \\ z\tau, & z \geq 0 \end{cases}$$

where $\hat{\beta}(\tau)$ is the τth regression quantile, the linear quantile function is produced as

$$Q_\tau(\tau|X_i = x) = \acute{x}\beta(\tau)$$

with β and X as the vector of estimator coefficients and the set of covariates respectively (Angrist and Pischke, 2008). This is an extension of minimizing the sum squared residuals for the sample, to the linear conditional mean function $E(Y_I|X_i = x) = \acute{x}\beta$. In a QR run, a result of $\beta_{0.05} < 0$ indicates that the 5th percentile of the response variable is negatively influenced by the increase in the predictor variable and $\beta_{0.95} > 0$ implies that the correlation is positive for the 95th percentile, compared to an OLS run which may yield $\beta \approx 0$, indicating no correlation at all. In instances of high variability in the data and large number of explanatory variables, results of OLS regression are less reliable compared to QR, as the outliers on left or right can significantly influence the average estimates (Yu et al., 2003).

QR is invariant to monotonic transformations (such as log), which therefore makes it easier to interpret the independent variable's effect on the original response variable in cases that nonlinear monotone transformations are applied to the dependent variable. If P is a monotone transform of y, the quantiles of P(y) are P(Qq(y)) and for translating the results back to y the inverse transformation can be used. This is not the case for the conditional mean function E since $E(P(y)) \neq P(E(y))$ (Hao and Naiman, 2007). Also, analogous to standard linear regression techniques that estimate the relationship between energy use and a set of variables based on the conditional mean function, QR provides the capacity to assess these relationships for different quantiles of data with heterogeneous conditional distributions, using the conditional median function which is more robust to outliers and non-normality of errors (Koenker and Hallock, 2001) as it makes no assumptions about the distribution of error within the model.

One example of QR's applicability to energy conservation policy is the use of tiered utility price structures. Tracking the extent to which upper and lower tails of energy consumption distribution respond to changes in energy pricing demonstrates how prices should change in order to meet expected reduction goals. To effectively employ QR, the variables to be included should be carefully chosen. IUMAT relies on actual data to identify indicators of regional, social, and economic conditions that are related to energy consumption and environmental conservation, and uses the correlation matrices as well as the literature to select predictors.

The use of QR on energy surveys for identifying patterns of change was first suggested by Kaza (2010). He used a series of QR models for dwellings clustered by the magnitude of their energy use on a national scale. But because he ignored municipal or state divisions, regional effects that could complicates the interpretation of different variables' impact on energy consumption were ignored in his study. Tso and Guan (2014) introduced a multilevel regression model to examine regional and socio-demographic effects on total residential energy consumption, without categorizing heating, cooling or other parameters of consumption. The method demonstrated in this paper builds upon Kaza's work, advancing the QR beyond an inference-only tool to create an energy forecasting platform that includes regional cultural/contextual indicators in the analysis to predict space heating, cooling, lighting and appliances, water heating and refrigeration residential energy use . We attempt to minimize the impact of climatic and geographical perturbations on the inference by running the analysis through individual Census divisions. We also address the influence of physical and socio-economic variables on heating, cooling and other categories of energy consumption separately. The analysis is carried out using the "quantreg" package (Koenker, 2013) in R software (Venables and Smith, 2009) that tabulates the estimated coefficients with p-values, standard errors and t-statistics for parametric components of the model.

3.3.2 Data

The Residential Energy Consumption Survey (RECS) conducted by the U.S. Energy Information Administration (EIA) is a nationally representative sample that has collected household demographics, usage patterns, and energy characteristics of housing units since 1978. The 2009 survey (the thirteenth RECS) incorporates energy data from 12,083 households representing 113.6 million primary residence housing units. The publicly available microdata is tabulated for ten Census divisions and higher resolution location attributes are clipped out of the report. However, climate variables such as heating and cooling degree days are provided and can be used to locate the dwelling units. End use residential energy consumption is sorted in three categories of heating, cooling and other (lighting/electronic/appliances, water heating and refrigerators) energy use. The fundamental characteristics of RECS 2009 are summarized in Tables 3.1 and 3.2.

Table 3.1: Basic distribution of some of the analysis variables in RECS (2009)

Variable	1st quartile	Median	3rd quartile	Mean	Standard dev.
Heating Energy (KWh)	943	7,998	16,308	10,804	10,428
Cooling Energy (KWh)	0	751	2,290	1,685	2,479
Other Energy (KWh)	2,379	6,745	10,196	7,876	5,822
Total Energy (KWh)	9,297	23,643	34,351	26,375	15,963
Heating Degree Days	1,151	4,502	5,854	4,135	2,260
Cooling Degree Days	439	1,179	1,842	1,444	1,022
Total Cooling Area (m2)	0	95	170	117	114
Total Heating Area (m2)	51	130	200	156	112
Total Area	69	173	261	202	135
Number of Household	1	2	4	2.67	1.51
Average Cost per MWh	50	79	103	85	32

Table 3.2: Descriptive statistic of independent RECS variables (2009)

Variable	Count	%
Housing type		
Mobile Home	541	4
Single-Family Detached	7,803	65
Single-Family attached	890	7
Apartment in Building (2-4 Units)	926	8
Apartment in Building (5+ Units)	1,923	16
Neighborhood		
Rural	2,427	20
Urban	9,656	80
Ownership		
Owned by someone in the household	8,140	67
Rented	3,801	32
Occupied without payment of rent	142	1
Year Built		
Before 1950	2,063	17
Year Built 1950-1969	2,869	23
Year Built 1970-1989	3,825	32
Year Built 1999-2000	2,598	22
Year Built 2000+	728	6
Income		
Income Level < $25K	3,000	25
$25K < Income Level < $50K	3,533	29
$50K < Income Level < $75K	2,149	18
$75K < Income Level < $100K	1,359	11
$100K < Income Level	2,042	17
Education		
Education: K-12	1,233	10
Education: High School-Some College	5,894	49
Associate's or Bachelor's Degree	3,621	30
Master's Degree and above	1,335	11
Age of Householder		
Age of Householder < 25	604	5
25 < Age of Householder < 40	3,114	26
40 < Age of Householder < 60	4,911	41
60 < Age of Householder < 80	2,787	23
80 < Age of Householder	584	5
Total observations	12,083	

IUMAT generates large square matrices that incorporate the bivariate correlation coefficients between every two variables provided in the data (Pearson, Cramer, Spearman, or point bi-serial depending on the type of variables) in order to select the variables to be included in the analysis. For example in the case of RECS 2009, the inverse correlation between HDD and CDD is robust (ρ= -0.80) as expected. The correlation matrix shows no strong correlation between type of housing and urbanization state (ϕ_c = 0.18) or ownership status and urbanization (ϕ_c = 0.17), and rather moderate relationships exist between income and education (ρ= 0.45), and between household size and age of householder (ρ= -0.35). The detailed graphs and tables regarding the QR results are attached in the appendices. Instead of intercept, the "centercept" concept is used in this analysis for the sake of easier interpretation of the regression results. Centercept is the value of the dependent variable when the independent variable is at its middle value (Wainer, 2000). The regression is run for the deviation score as the explanatory variable. The centercept based on the 2009 RECS data is the estimated conditional quantile function for the distribution of annual energy consumption by an *average household* with an income less than \$25K, that pays \$85.1 per MWh of energy, and lives in a single family detached unit of 202 m^2 built before 1950, in a rural area located in a climate zone with 1415 CDD and 4141 HDD. Based on the OLS estimates, national average figures for the average household space heating, cooling and other uses are 12.6, 2.0 and 12.8 MWh respectively. Note that energy consumption of the average household should not be confused with average household energy consumption (average household can also be referred to as typical household). In the lower and upper tails of the consumption distribution (τ =0.1 and 0.9), air conditioning energy use of an average household is 0.4 and 3.3 MWh, respectively 5 times less and 1.65 times greater than the 2 MWh average. The QR results are compared against baselines that are less than \$25K for income, single family detached for housing type, rural for neighborhood density, renting for ownership status, under 25 for householder age, built before 1950 for building age, and householder holding a masters or PhD degree for education. In Figure 3-1, the "multi-family 5+" row shows the change in energy use from single family detached to multi-family unit in a 5+ units complex, keeping every other parameter constant, or the “$100k<Income Level” in Figure 3-4 is compared against households with income below $25K.

The results indicate that household size does not impact gross heating and cooling energy as strongly as it affects other energy (lighting/electronic/appliances, water heating and refrigerators). On the national scale, a one person increase in the household size results in a 1.8 MWh growth in other energy on average (1.2 and 2.3 MWh for tau = 0.1 and 0.9) and consequently increases the total energy to almost the same extent (1.3 and 2.1 MWh for tau = 0.1 and 0.9). The influence of age of householder (AH) is highly dependent on the age groups. Compared to AH<25 which is the baseline, cooling loads are marginally (almost 0.1 MWh) increased for 25<AH<60 and decreased for AH>80. However, space heating energy use is increased by 0.1, 0.8, 1.6 and 3.0 MWh respectively for 25<AH<40, 40<AH<60, 60<AH<80 and AH>80, which is likely due to higher thermal comfort expectations with advanced age. Other energy use rises by around 0.8 MWh for 40<AH<80 and drops by 0.3 MWh for AH>80, because senior households are typically smaller size families that may use fewer electric and electronic devices (OLS estimates, for QR results see the Appendices). The impact of ownership on heating and air conditioning is not statistically significant; however, owners are likely to use slightly more (0.37 MWh) energy on lighting, appliances and water heating compared to renters. The relationship between education and energy use is fairly inconsistent across the groups and often insignificant. Nonetheless, in some cases the correlation is strong and those with high-school or some-college education are likely to use more other energy (+0.6 MWh) annually compared to households with a masters or PhD degree.

Age of the house (year built) primarily affects space heating rather than cooling and other energy use. It is remarkable that while the 50 years change in the age of the building can lead to 9.5 MWh annual difference in heating energy in the upper tail, it can be as small as 0.83 MWh in the lower tail (see the row “year built 2000+”). This emphasizes that weatherization measures and environmental literacy have the potential to substantially counter the influence of age of the house. Energy price is not significantly correlated with air conditioning and its impact on space heating is nearly two times greater than other energy. Overall, a 10 USD per MWh rise in price has the same impact of 15-50 m^2 (≈161-538 ft^2) reduction in the house area from the upper to lower tail on the total energy use.

Conventional wisdom suggests that by moving from detached single family housing to more clustered housing blocks, gross energy consumption will be reduced (Druckman and T. Jackson, 2008). Based on the regression results, this reduction is greatest in large apartment complexes, single family attached, multifamily 2-4 units in descending order. In other words, the outcome suggests that single family attached housing is more energy efficient than small multifamily compounds. The reduction in space cooling energy is minimal and negligible for most of the tiers and surprisingly most of this reduction is attributed to other energy and not to heating energy. Heating energy use actually increases in the 50th+ percentiles by moving a household from a single family detached to a 2-4 units apartment complex. The rise in other energy can be attributed to the fact that there are not large enough number of households to reduce the energy use per household figure in smaller compounds of 2-4 units, where more energy intensive equipment are required for hot water or common area exterior lighting compared to single family attached.

The marginal impacts of some covariates of interest on quantiles of three categories of other energy is shown in Figure 3.1. Lighting/appliances, water heating and refrigerators make nearly 7.9, 3.8 and 1.2 MWh of annual energy use. None of the three categories, show a strong correlation with the climate variables. However, an extra family member adds 560 MWh to water heating energy on average. The impact of the one person increase in the household size is twice as high on lighting and appliances. Likewise, square footage has a higher influence on electronic devices energy use compared to water heating. Interestingly, higher energy prices is nearly four times more effective in lowering hot water energy use as to lighting and appliances. Another interesting finding is that by moving from rural to urban settings, energy for lighting, electronics and miscellaneous uses decreases (by 0.8 MWh) which is almost entirely (0.6 MWh) offset by higher hot water demand in urban housing.

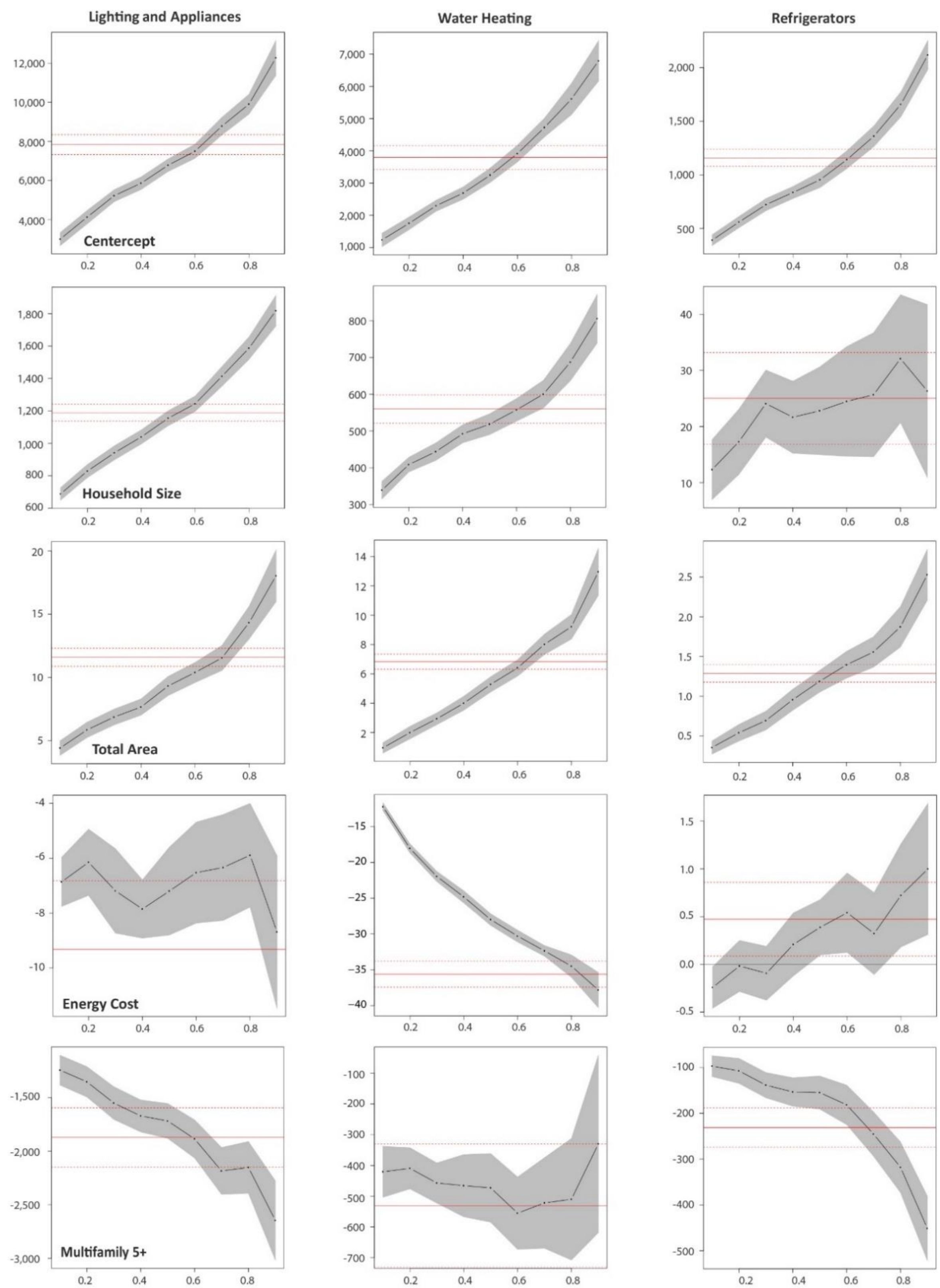


Figure 3.1: Marginal impacts of some variables on different quantiles of residential lighting, water use and refrigeration energy use distribution

3.3.3 QR for forecasting

The equations obtained from the 2009 RECS data QR analysis have been applied to RECS 2005 dataset in order to examine the applicability of QR to large scale energy forecasting. The 2009 dataset is larger and was collected using more advanced surveying methods. This justifies using 2005 data for validation purposes (2005 dataset includes 4,383 observations compared to 12,083 in 2009). The model already takes into account the climatic differences between 2009 and 2005 by including HDD and CDD, and adjusts the value of the dollar based on inflation rates for the impact of energy cost. A standard approach for testing the predictive power of the model is to use mean absolute deviation of sample and model (MAD) as a summary measure of out-of-sample forecast error:

$$MAD = \frac{\sum |Y_i - \hat{Y}_i(\tau)|}{n} = \frac{\sum |\hat{\varepsilon}_i(\tau)|}{n}$$

where $\hat{Y}_i(\tau)$ is modeled value at the selected quantile and $\hat{\varepsilon}_i(\tau)$ is the model errors at the quantile τ. As shown in Table 3.3, the data for almost all of categories of consumption are highly skewed to the right. Both measures of skewness and kurtosis (sharpness of the peak of the distribution curve) are very high, indicating significant deviation from normality.

Table 3.3: Distribution of the energy consumption breakdown in the RECS 2005 data

	Mean	**SD**	**Skewness**	**Kurtosis**	**Median**
Space Heating	13,301	12,881	1.99	8.95	10,220
Cooling	2,121	2,568	2.32	10.23	1,267
Lighting and Appliances	8,050	5,255	2.24	14.32	7,146
Water Heating	5,742	4,507	2.21	8.53	4,653
Refrigeration	1,850	1,427	2.37	12.87	1,436

QR has been used frequently across different fields for identifying patterns of change in data. However, the literature on the use of QR for modeling purposes is limited and in the few examples in which QR is used for forecasting (e.g. Furno, 2014), the specific quantile estimated coefficient have been applied to an entire population, regardless of conditional quantile distributions. Figure 3.2 shows density plots obtained from equations based on 2009 QR coefficient estimates. For space heating and cooling categories, the model fails to include the tails of the distribution due to high non-normality of the 2005 data. The models show better performance in capturing the other energy category; however, they all poorly represent the subcategories of other energy as the skewness increases.

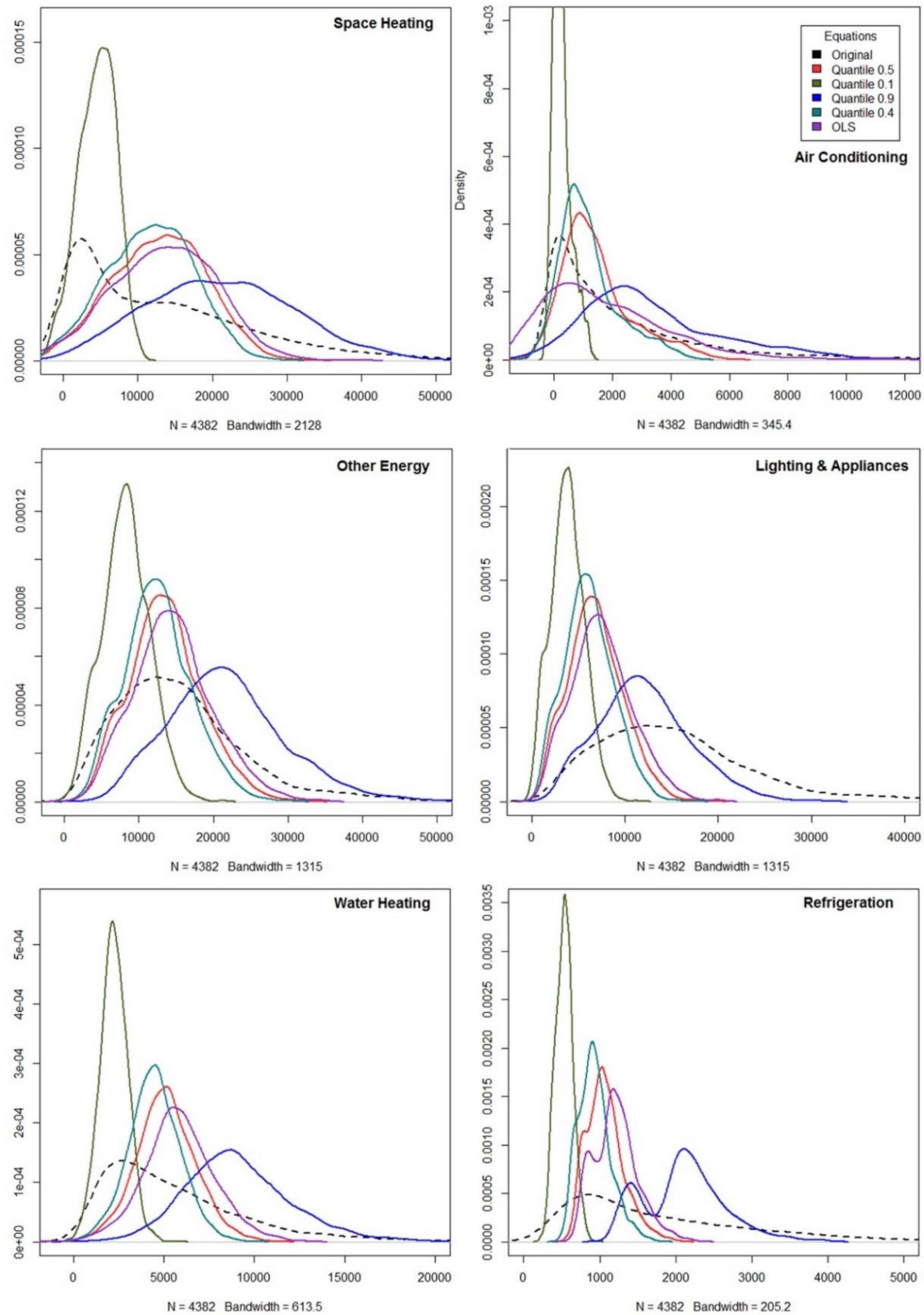


Figure 3.2: Density plots for actual vs. modeled 2005 distribution using quantile estimated coefficients for 2009 data

Table 3.4 shows the mean absolute errors of prediction for both OLS and conditional quantile regression. At this stage, the forecast of the 2005 RECS data is based on the 2009 data quantile regression estimated coefficients, regardless of the 2005 data distribution. All of the equations yield MAD_{OLS} and MAD_{τ} within one standard deviation of the corresponding category of consumption data. Yet, in nearly all of the cases, OLS and the median regression (τ=0.5) are comparable with very minor discrepancies, although they do not necessarily provide the most precise forecasts compared to other equations obtained from regression for other quantiles.

Table 3.4: Mean absolute errors of modeling when applying estimated conditional QR coefficients to the 2005 data regardless of the distribution

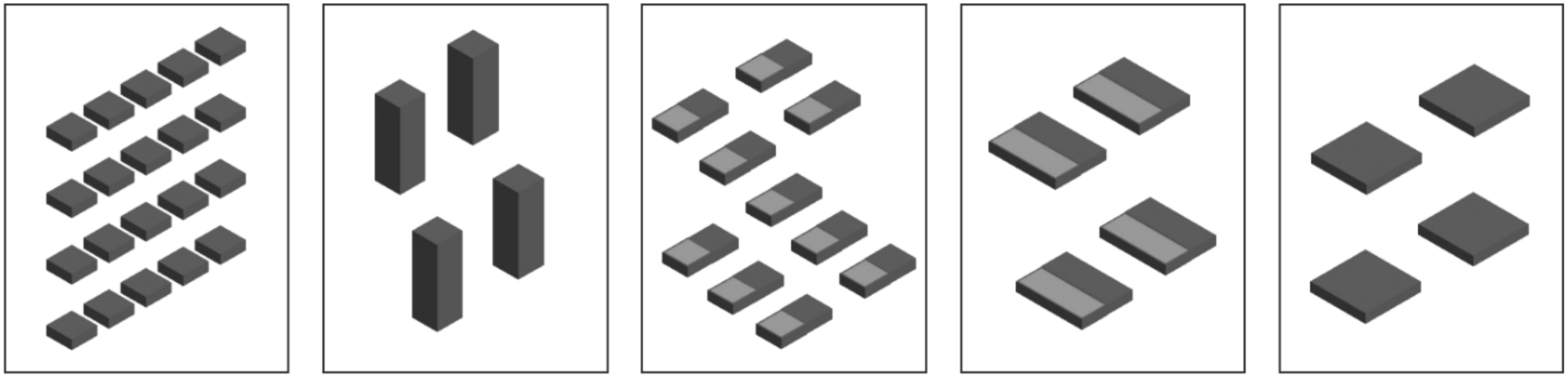
	OLS	**τ = 0.1**	**τ = 0.2**	**τ = 0.3**	**τ = 0.4**	**τ = 0.5**	**τ = 0.6**	**τ = 0.7**	**τ = 0.8**	**τ = 0.9**
Space Heating	6,448.7	9,364.6	7,376.7	6,639.6	6,418.5	6,453.5	6,660.0	7,123.4	8,001.0	10,147.3
Cooling	1,182.7	1,912.0	1,648.3	1,476.4	1,327.2	1,240.8	1,194.7	1,233.8	1,362.2	1,748.0
Lighting and Appliances	2,852.7	4,355.7	3,684.6	3,269.9	2,999.2	2,842.5	2,836.6	3,006.5	3,506.5	4,913.3
Water Heating	2,734.0	3,647.0	3,079.7	2,807.8	2,675.0	2,645.8	2,721.2	2,905.5	3,337.7	4,405.7
Refrigeration	942.9	1,336.5	1,221.2	1,125.6	1,055.4	991.8	937.8	902.2	903.2	997.9

Using OLS or median regression for modeling purposes could limit the forecasting capacity of the models since usually the difference between 10th and 90th quantiles of energy use are major and not represented by the conditional mean/median. Not surprisingly, the conditional quantile estimates for 2009, yield best forecasts when applied to corresponding quantiles of 2005 data. Table 3.5 shows the MAD_{OLS} and MAD_{τ} for 10th, 50th and 90th quantiles of five categories of energy consumption in 2005 RECS data, when predicted by corresponding quantile regression estimate coefficients of 2009 data. The smallest values are marked with (*), indicating best predictions for matching quantiles in almost all of the cases (the results for the 5-15th percentile for cooling are shown as not available, since the buildings that fall in that range do not use any cooling). An important factor is that partitioning the quantity that is to be modeled is not theoretically possible before actual modeling. However, for applications such as residential energy in which modelers can intuit a range of results based on historical data and previous benchmarking efforts, applying the suggested quantile-for-quantile forecasting technique can increase the precision of the modeling process. This method provides a range of results, instead of unrealistic definite values for energy consumption, and offers more flexibility to satisfy diverse needs of energy modeling customers. For instance, for a capital investment infrastructure development project, a utility operation and planning company might be mainly concerned with securing the supply for a greater number of consumers in the middle, or alternatively with ensuring the demands of consumers in the upper tail and this framework allows forecasting the needs of various subgroups.

Table 3.5: MAD in predicting the 2005 energy consumption with a different equation per different quantiles

		OLS	τ=**0.1**	τ=**0.5**	τ=**0.9**
Space Heating					
	(5-15th percentile)	4,732.2	1374.9*	4,293.1	8,892.4
	(45-55th percentile)	4,440.9	5,339.8	3644.5*	10,370.4
	(85-95th percentile)	10,573.9	23,596.0	12,159.6	5601.2*
Air Conditioning					
	(5-15th percentile)	Na	na	na	na
	(45-55th percentile)	861.9	853.2	574.0*	1,846.5
	(85-95th percentile)	1,984.5	4,517.6	2,471.4	1653.0*
Lighting and Appliances					
	(5-15th percentile)	2,011.6	1016.8*	1,705.4	4,705.2
	(45-55th percentile)	1,948.6	3,214.7	1743.9*	5,225.7
	(85-95th percentile)	4,709.4	9,307.7	5,449.0	3432.8*
Water Heating					
	(5-15th percentile)	2,833.2	507.3*	2,293.4	5,460.5
	(45-55th percentile)	1,574.0	2,346.2	1079.3*	4,557.5
	(85-95th percentile)	4,083.9	8,497.9	4,997.6	2269.3*
Refrigeration					
	(5-15th percentile)	499.4	122.2*	388.6	1,257.5
	(45-55th percentile)	306.4	917.7	406.7*	656.7
	(85-95th percentile)	2,309.8	3,094.9	2,472.3	1284.6*

Figure 3.3 shows the energy consumption breakdown of 5 hypothetical neighborhood cases with a population of 40 as predicted by IUMAT residential energy model (for simplicity only τ=0.1, 0.5 and 0.9 results are shown). The model uses different equations to forecast the amount of energy use. For comparative purposes, the results of the median regression (τ=0.5) can be used to reliably choose the most energy efficient setting of all. Nonetheless, for more accurate prediction of the actual energy use, the specific equation to be chosen needs modeler expertise and input to identify where in the distribution of each category of energy consumption their particular project stands. This can be obtained by looking at the data for similar projects operating in analogous climate conditions, and is challenging in new projects. In cases of renovations, these data is usually already available to design teams. As can be seen in Figure 3, in all cases the difference between different quantiles is significant, which underlies the importance of a more detailed approach compared to OLS as well as the risks involved in failing to get the right estimates for strategic energy planning.



Case 1:	Case 2:	Case 3:	Case 4:	Case 5:
Household Size: 2	Household Size: 2	Household Size: 2	Household Size: 5	Household Size: 10
Year Built: 1945	Year Built: 1945	Year Built: 1950	Year Built: 1950	Year Built: 2005
Householder Age: 85	Householder Age: 24	Householder Age: 85	Householder Age: 70	Householder Age: 45
HDD: 5000	HDD: 6000	HDD: 4500	HDD: 3000	HDD: 4100
CDD: 1400	CDD: 1000	CDD: 1600	CDD: 2000	CDD: 1300
Own, Rural	Own, Rural	Own, Rural	Rent, Rural	Rent, Rural
Income < $25K	Income < $25K	Income < $25K	Income > $100K	Income < $100K
Energy Cost: $85/MWh	Energy Cost: $75/MWh	Energy Cost: $75/MWh	Energy Cost: $75/MWh	Energy Cost: $65/MWh
Area: 200 SQM	Area: 300 SQM	Area: 300 SQM	Area: 400 SQM	Area: 300 SQM

Energy Use (MWh)	Energy Use (MWh)	Energy Use (MWh)	Energy Use (MWh)	Energy Use (MWh)
tau=0.1 | tau=0.5 | tau=0.9	tau=0.1 | tau=0.5 | tau=0.9	tau=0.1 | tau=0.5 | tau=0.9	tau=0.1 | tau=0.5 | tau=0.9	tau=0.1 | tau=0.5 | tau=0.9
Space Heating	**Space Heating**	**Space Heating**	**Space Heating**	**Space Heating**
123.53 | 367.14 | 644.03	127.57 | 385.91 | 668.69	134.87 | 385.86 | 665.07	45.35 | 137.44 | 249.34	18.33 | 54.81 | 85.47
Cooling	**Cooling**	**Cooling**	**Cooling**	**Cooling**
12.81 | 35.22 | 79.73	17.35 | 38.85 | 90.48	20.09 | 49.84 | 109.76	11.01 | 29.12 | 60.57	3.37 | 9.86 | 21.36
Lighting and Appliances	**Lighting and Appliances**	**Lighting and Appliances**	**Lighting and Appliances**	**Lighting and Appliances**
49.51 | 97.12 | 186.95	31.82 | 89.55 | 190.38	44.89 | 92.09 | 192.24	40.37 | 75.24 | 141.42	38.10 | 64.20 | 105.51
Water Heating	**Water Heating**	**Water Heating**	**Water Heating**	**Water Heating**
29.99 | 89.60 | 173.02	24.65 | 93.98 | 184.39	28.69 | 99.65 | 203.52	21.21 | 55.82 | 106.78	20.24 | 39.16 | 63.75
Refrigeration	**Refrigeration**	**Refrigeration**	**Refrigeration**	**Refrigeration**
8.50 | 19.21 | 43.51	6.70 | 17.93 | 40.35	7.62 | 18.68 | 40.14	3.62 | 9.31 | 19.07	2.83 | 5.82 | 10.73

Figure 3.3: Energy modeling results for 5 hypothetical scenarios for neighborhoods of forty people

The large gap between first and ninth quantiles in not only because there are a large number of variables involved in the analysis, but also the regression is run for a vast geographical spread. In the data patterns, the inter-quantile differences can be explained by different sets of variables for different categories of consumption. Heating and cooling energy use inter-quantile changes are due to regional and climate variables, as opposed to other energy categories that can be attributed to household demographics and urbanization regressors. Tails of the consumption categories do not necessarily overlap. For example, the buildings that are in the upper tail of the space heating distribution, are more likely to be on the opposite side of the air-conditioning distribution. In addition to the suggested quantile to quantile technique, the impact of regional and climate regressors can be controlled by narrowing the scope of inference to finer geographical resolutions if sample size permits.

To reduce the inter-quantile change and increase the forecast precision, the analysis is repeated for the ten U.S. Census Divisions (New England, Middle Atlantic, East North Central, West North Central, South Atlantic, East South Central, West South Central, Mountain North, Mountain South, and Pacific). These divisions have unique geography, cultural values, building practices, and climate factors that have the potential to influence the outputs of an energy model. Although this influence is at the neighborhood, city, regional, and national scales, running a detailed analysis beyond the Census division level is not viable with this dataset. Results from the West North Central (IA, KS, MN, MO, ND, NE and SD), West South Central (AR, LA, OK and TX) and Pacific (AK, CA, HI, OR and WA) divisions with major differences in climate and cultural factors are provided to demonstrate the substantial discrepancies between divisional regression coefficients and underscore the importance of higher resolution analyses.

Figure 3.4 highlights the utility of analyzing smaller geographical districts. The influence of total area on cooling demand for the Pacific (PC) and West South Central (WSC) divisions is almost 1.5 and 3 times greater across the distribution compared to West North Central (WNC) division. In the PC division, income does not affect air conditioning (AC) energy use for the first 5 tiers, indicating AC being more a requirement than a life-style choice. The rise in income from income level (IL) less than \$25K to IL>\$100K has a three times greater of an impact on air conditioning in WSC compared to WNC. The effect of energy price on space heating is not statistically significant in PC. However, a \$10 per MWh increase in price leads to 0.1-0.7 MWh reduction in heating loads for WSC, compared to 1.7-2.3 MWh reduction for WNC. Interestingly, AC use is not affected much by the price, either at national or division levels. The impact of total area on space cooling energy in WNC is two times than WSC and PC. Influence of income on space heating is much greater in PC and WSC compared to WNC, demonstrating space heating is likely driven by lifestyle in those divisions. Age of the building, is more of a factor in WNC rather than WSC and PC. A building built after 2000 in contrast to the same building built before 1950, uses 0.2-4.5, 0.1-6.9 and 2.1-10.4 MWh less for PC, WSC and WNC respectively for space heating. This can be attributed to the higher HDD and more severe winters in the WNC division. The influence of neighborhood density (urban/rural) is not statistically significant on any of the heating, cooling or other energy for the three aforementioned regions. But the impact of neighborhood urbanization index is unexpected at the national level. Moving from rural to urban settlements negatively impacts cooling and increases heating demand, counter to urban heat island predictions (more details in Appendix B). The lack of detailed locational neighborhood density and microclimate site data makes these results difficult to explain, especially since the RECS data now classifies neighborhood density as urban/rural in 2009 compared to rural/city/suburbs/town in 2005. However, the data shows that buildings in urban neighborhoods are likely to use 0.1-0.5 MWh less other energy compared to rural houses which is a minor difference. The influence of the variables of interest on other energy is more or less similar across the three divisions and resembles the national patterns.

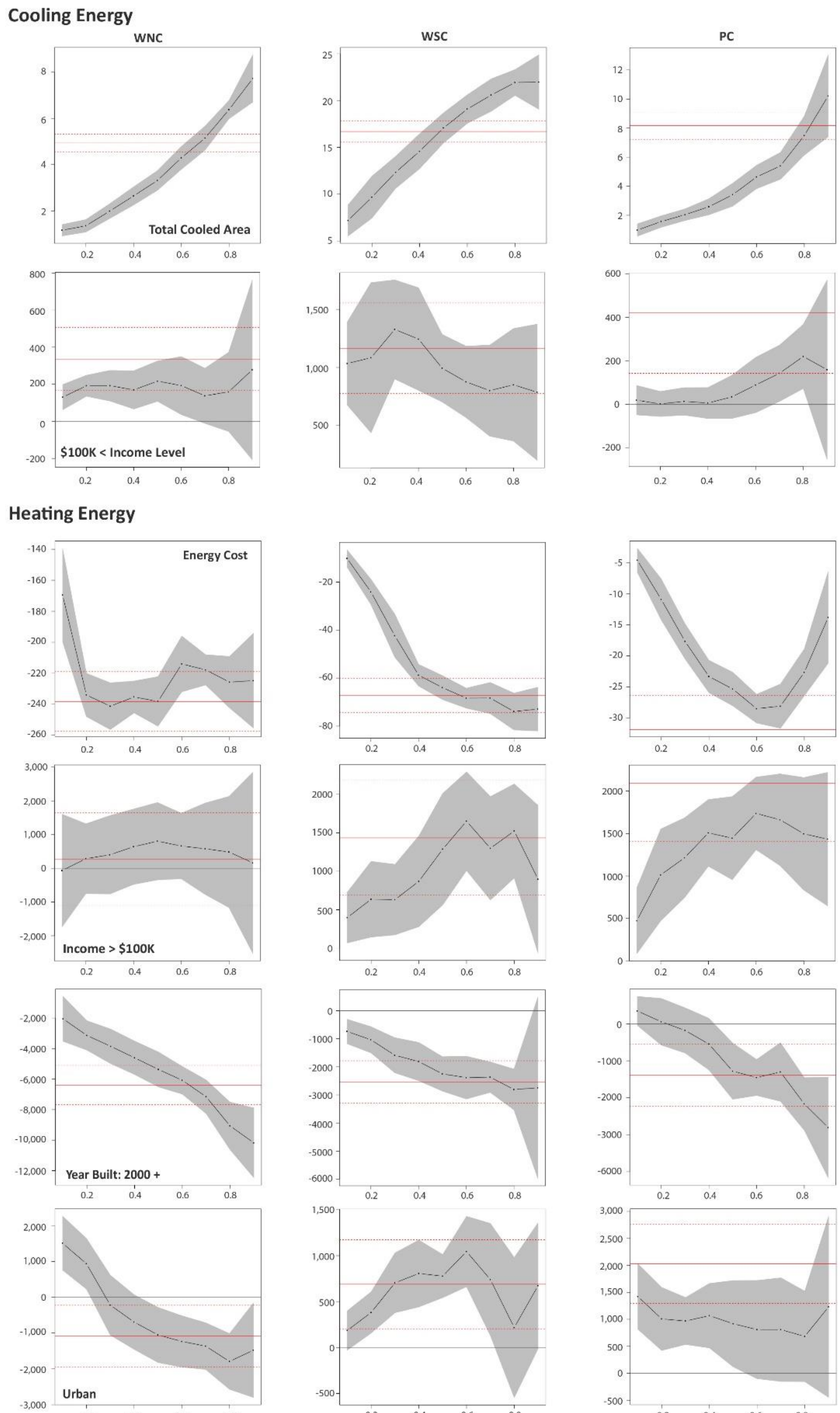


Figure 3.4: Conditional quantile estimates of household energy use for WNC, WSC and PC Census Divisions

3.4 Impacts of Consumption

What are the environmental impacts of the estimated residential energy consumption whether it is supplied for plug loads (electricity) or for heating and/or cooling (fuel)? For electric use, energy production datasets at the county level are required to analyze lifecycle stream stages including extraction of resources, transportation, production, generation and transmission. IUMAT's urban residential energy model does not take all these stages into account (see Mostafavi et al., 2014b for overall IUMAT framework). Since the EWM module uses buildings/parcel as the smallest unit of the analysis, it focuses on the supply side, on energy generation in the plant and during the transmission process. Emissions beyond the plant such as the mine in the extraction phase, are calculated by IUMAT separately since the mine is an independent unit and assigning the mine emissions to the plant would lead to double calculating the primary process emissions. The well-to-meter approach to energy consumption calculates the supply energy as:

$$
\begin{aligned}
&Energy\ Use\ (supply) \\
&\quad = \sum_{i=1}^{n}\sum_{j=1}^{m}\sum_{k=1}^{p}(process\ fuel\ use\ for\ energy\ obtained)\ (MWh)_{j,k} \\
&\quad * (primary\ energy\ use\ for\ 1\ MWh\ of\ process\ fuel)(\frac{MWh}{MWh})_{i.j}
\end{aligned}
$$

where i is the primary energy, j is the process fuel, and k is the stage of energy generation. Primary fossil energy use from well to meter includes both direct energy for extraction and indirect upstream energy use for transportation and process fuel. However, the urban residential energy model deals with direct emissions only. There is also secondary energy consumption during the cycle for plant construction, manufacturing of the machinery, and labor that are calculated by the EWM module separately. In the urban residential energy model, emissions from electricity use are reported in terms of direct emissions tracked to the power plant (p=2 for the two stages of power generation and transmission-distribution) and for domestic use of any fuels other than electricity, direct on-site emissions are calculated. This is a pseudo-disaggregated well-to-meter approach to environmental impacts calculation.

The applicable unit of resolution for the analysis is 1 MWh of supplied energy. For this level, the supply energy is classified into two groups of fossil fuel based and renewably sourced groups. In the fossil-fuel category, for a comprehensive and effective assessment, more than twenty different primary and secondary fossil fuel types are included. Process fuel for energy demand (PFED) which is the amount of process fuel combusted at the plant based upon the efficiencies of the generation technology and the distribution system is calculated as:

$$(PFED) = \frac{residential\ energy\ use}{energy\ conversion\ efficiency * efficiency\ of\ transmission}$$

The $MWh_{supply}/MWh_{demand}$ estimate that takes into account plant characteristics and the transmission and distribution stage is used to measure the CO_2 emission/$MWh_{supplied}$ figure. With respect to the fuel consumption for energy production, CO_2 emissions (CE) can be calculated using fuel type and oxidation rates:

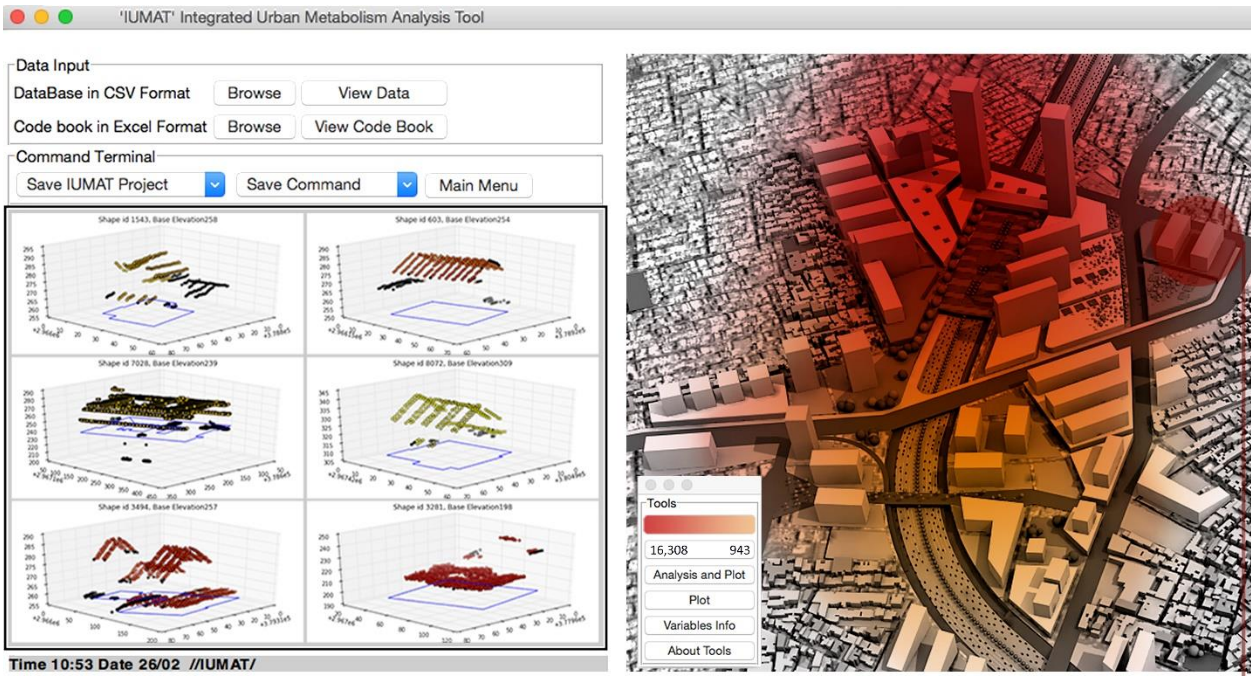
$$CE\left(\frac{g}{MWh}\right) = \sum_{j=1}^{m}\sum_{k=1}^{p}(PFED)\left(\frac{MWh}{MWh}\right)_{j,k} * (fuel\ type's\ carbon\ content)_j\left(\frac{g}{MWh}\right) * (fuel's\ oxidation\ rate)_j * 44/12$$

where 44/12 is the mass conversion factor from carbon to carbon dioxide. Depending on the fuel type and combustion completeness factor, other greenhouse gases such as CH_4, N_2O and beyond that volatile organics are emitted into the troposphere. CO_2 equivalent emissions (CEE) is calculated conforming to the global warming potential of the GHGs: CO_2

$$CEE\left(\frac{g}{MWh}\right) = \sum_{j=1}^{m}\sum_{k=1}^{p}(process\ fuel\ for\ energy\ demand)\left(\frac{MWh}{MWh}\right)_{k,j} * (CO_2 + 23CH_4 + 296N_2O + \cdots)_j(\frac{g}{MWh})$$

For any fuels other than electricity, direct on-site emissions are calculated. There are substantial variations in the on-site direct emissions even between the same fuel technologies due to the large number of variables such as carbon content and climate conditions. Direct emissions figures are highly site-specific based on input fuel conditions and technological and operational disparities. Extreme variation in emissions are also expected at the downstream and upstream stages of fuel cycle and technology (Weisser, 2007). EPA emission factors for greenhouse gas inventories are used for calculating direct GHG emission from on-site combustion of fossil fuels or renewable generation for meeting thermal or electrical demands. In cases of district heating, emissions by heating energy use are counted by factoring the EPA constants into the efficiency of combustion and heat generation method. This is done by implementing average district efficiencies of coal, gas and oil fired plants. Among non-fossil fuel heat and power generation methods wind, hydropower, geothermal, nuclear, solar are accounted for with regional emission factors.

EIA maintains a database (EIA-923 database) of monthly and annual power generation, fuel consumption and various environmental data for every power plant in the United States with 1 MW capacity or greater (EIA[a], 2016). Another database that stores information for every single active generator at United States' power plants (EIA-860 database) includes location, generation capacity, status of operation and primary fuel source (EIA[b], 2016). In Figure 3.5, we have connected the two datasets to determine the plant that is most likely to serve a specific zip code based on proximity analysis, and identify the type of fuel burned in the plant (forty different primary and secondary fuel types are used in the plants, according to the EIA). Efficiency at every plant is determined as net generation, fuel combustion and electric use figures are available for every coal, petroleum, natural gas, nuclear, hydro, wind, solar geothermal and wood plants with location resolution at the county level.



Plant Id	Zip Code	Plant Name	Operator Name	Reported Fuel Type Code	Total Fuel Consumption Quantity	Electric Fuel Consumption Quantity	Total Fuel Consumption MMBtu	Elec Fuel Consumption MMBtu	Net Generation (Megawatthours)	YEAR
3	36512	Barry	Alabama Power Co	BIT	2,153,948	2,153,948	46,083,543	46,083,543	4,559,961	2015
344	93643	Mammoth Pool	Southern California Edison Co	WAT	0	0	1,309,868	1,309,868	137,647	2015
345	93035	Mandalay	NRG California South LP	NG	95,606	95,606	99,398	99,398	4,284	2015
345	93035	Mandalay	NRG California South LP	NG	2,610,788	2,610,788	2,724,793	2,724,793	247,656	2015
350	93033	Ormond Beach	NRG California South LP	NG	4,400,482	4,400,482	4,572,861	4,572,861	405,013	2015
447	92267	Parker Dam	U S Bureau of Reclamation	WAT	0	0	4,183,448	4,183,448	439,900	2015
733	31405	Kraft	Georgia Power Co	DFO	437	437	2,542	2,542	169	2015
765	96707	Kahe	Hawaiian Electric Co Inc	PG	0	0	0	0	0	2015
913	62090	Venice	Union Electric Co - (MO)	NG	217,855	217,855	222,626	222,626	20,130	2015

Figure 3.5: Plant selection based on proximity analysis and fuel data from EIA-923 and EIA-860 datasets.

Energy production is associated with water consumption, typically involving the use of large amounts of chilled water and steam. Water is also used for equipment cleaning in energy generation plants. For example, coal plants use a lot of water for the crude coal purification.

Nuclear plants as well as oil, coal and natural gas fired plants have significant rates of water consumption to provide cooling and process steam. NREL (National Renewable Energy Laboratory) factors (Macknick et al., 2011) can be used to estimate the water usage (WU) from energy production technologies:

$$WU = \sum_{j=1}^{n} (MWh\ of\ energy\ supplied)_j * (energy\ production\ water\ use\ factor)_j (\frac{Gallon}{MWh})$$

where j is the generating technology. Other forms of water use such as industrial or domestic water consumption are adjusted separately by other IUMAT models, mainly the water module. The amount of water use is key in determining the amount of sewage discharged. By using the outputs of QR analysis, energy demand and its breakdown is analyzed for heating, air conditioning, lighting, equipment, appliances, and water heating. EIA-860 database is used to identify the plant that serves the unit, and the EIA-923 data provides technology, fuel mix and the plant efficiencies that are used for calculating carbon emissions, water usage, and sewage production associated with residential energy use.

3.5 Discussion

This work presents the opportunities and challenges of applying nationwide datasets for urban modeling and energy policy making. The larger the sample sizes and the more regional details provided, local level inferences can be carried out with higher confidence. In the RECS datasets used for this work only a few number of states are specifically identified and all the other states are coded at census division level. However the climate data can be used as a quasi-spatial-locator for drawing conclusions at local levels. The work presented here does not offer more details (although the data allows the analysis to be carried out for sixteen individual states) since we focused on describing how dataset such as RECS can be used by IUMAT rather than explicitly calculating energy and emissions for a specific region. Our results show that narrowing down the scale of the analysis to census division level, considerably reduces the inter-quantile change and therefore increases the prediction power of the model for heating and cooling energy categories, since they are more affected by climate and regional variables. However, the zooming in does not provide more insight on lighting and appliances, water heating and refrigeration, since the categories of other energy use are more influenced by demographic household parameters other than climate and regional factors. The RECS data is a random cross-sectional sample, and does not enable assessment of marginal impacts over time or due to behavioral changes. Our other goal in this paper is to describe how QR can be applied to illustrate the differential effects of marginal changes on energy use and consequent emissions.

According to RECS, the average energy use by a household in 2009 was almost equivalent to 1980 figures (with only 2% rise), despite the 30% increase in average home size. This suggests that the 56%, 18% and 3% increase in air conditioning, lighting/electronic/appliances, and water heating is nearly entirely offset by energy efficiency measures and more stringent codes that have cut the space heating by 21%. Considering the 52% increase in the total residential floor area, the energy use intensity (EUI) of the residential sector has decreased by 43.1% per square foot over the same time frame. IUMAT provides the means to efficiently run the same kind of analysis for different datasets (such as previous RECS versions) and compare how energy use and the variables that influence its magnitude have changed over time. For example, the model shows that a 50 m^2 (≈ 538 ft^2) increase in the house area has the same impact of a 10-30 USD per MWh cut in the energy price on the total energy use for the lower to upper tail in 2009. However, for the 2005 data the 50 m^2 is equivalent to 5-12 USD change in price per MWh, indicating that consumer price sensitivity is decreasing and tougher energy market regulations are having less of an impact. As such, strategic conservation policies need to go beyond price management. Despite a 35% population growth, the energy use per household index has declined by 24.2% during 1980-2009 due to the 33% increase in the total number of households. The trend does not point to a significant change in the average U.S. household size and the shift to smaller families. If this trend holds through 2015-2060, the projected US population growth from 321 to 417 million (US Census, 2016), will result in almost 28% more households of the same family sizes of today. This must be taken into account when planning for the future. RECS data also show that the share of heating and cooling energy in the total residential site use energy has decreased from 57.7% to 47.7% in the 1993-2009 period, showing significant energy-saving potential in the other energy category (lighting/electronic/appliances and water heating), and that this category is minimally affected by energy price and building age. Instead, promoting urban communities and shifting away from single family detached housing type have the highest impact on reducing other energy. These results could be different for every region, and IUMAT EWM module will be able to identify effective policies for a specific region or town upon availability of data.

While analytical results from tools such as the one presented here cannot be the sole decision aid in sustainable master planning, it is still a valuable resource as part of a suite of analytical tools for city planners. For example, there has been strong support for increasing the density of cities over the last decade, and there are arguments that although compact urban construction reduces the residential energy demand, at the same time it reduces the potential for PV due to the reduction of usable area for PV installation (e.g. Yamagata and Seya, 2013). Of course, in dense urban settings all empty places can be optimally used, and there may be opportunities for neighborhood scale PV installations or vegetation to reduce the UHI effect. However, a planning board's concern is not only energy conservation and the final decision needs to consider the urban morphology and livability as well. IUMAT estimates the resources needed for urban development under alternative growth scenarios and enables planners to use spatial demand profiles to create aggregate neighborhood energy figures to better understand the magnitude of carbon emissions as well as the geographical relationship between supplying sites and peak demand generation zones.

The QR method for urban residential energy can analyze environmental impacts of alternative energy technologies and simulate the regional energy demand profiles from a bottom-up approach. It lays the groundwork for calculating transmission losses, as well as emissions, water, waste and sewage production associated with the energy source and generation technology. Unlike most large scale simulation tools, IUMAT reports model uncertainties through confidence intervals. However, the validation process remains a challenge. Validating the results is much easier in extra-large scales using very coarse level governmental energy information or at the building level by comparing the outcomes to specific buildings' performance data, but actual energy profiles are required at sub-urban geographical resolutions to determine the accuracy of the model. It is challenging to obtain energy consumption data for the residential sector because detailed sub-metering for household energy consumption is not cost effective, and privacy concerns restrict the comprehensive collection of energy consumption data for given households. As a next step, data from other randomly sampled case studies will be used to verify the inference power of the model. IPUMS (Integrated Public Use Microdata Series) dataset as an example shows the households' expenditure on natural gas, fuel oil and electricity. Regional price data enables converting energy dollars to KWs and comparing it against the model results.

The link between urban climatology and building performance in most current urban modeling tools is weak. For example, the overshadowing or shading effect among buildings in a city block influences both outdoor and indoor climate as well as building energy consumption. This interaction has yet to be satisfactorily modeled. Given the occupancy patterns in residential and office spaces, one viable energy saving strategy may be to minimize solar gain (and cooling load) by assigning the daytime shaded units to office spaces, where there is greater occupancy during the day. In effect, this strategy would force buildings that overshadow the office spaces to be zoned as residential spaces. However, this is contrary to how spaces are typically zoned in cities, where low-rise buildings are typically residential while high-rise buildings are typically commercial/office. The urban residential energy use model offers both operational energy use and management policy impacts, especially as more detailed energy use, geometry, and street characteristics are available.

The next step is to develop a similar approach to apply to the Commercial Buildings Energy Consumption Survey (CBECS) and Manufacturing Energy Consumption Survey (MECS) in order to build the urban industrial and commercial energy models. By combining these with the residential energy model described in this paper, IUMAT will more fully represent real neighborhoods that include various types of buildings in an urban area.

CHAPTER 4

CONCLUSION

4.1 Summary

IUMAT is fundamentally comprised of five connected primary models (energy, water, materials, land use and transportation) that consider different urban sectors (e.g. residential, commercial, industry, and open space) and quantify the aggregate consumption of resources, waste and sewage production, and GHG emissions under different scenario choices. It is a tool for overall sustainability evaluation in cities that enables urban planners to better understand the performance of each sector and discover better practice or improvement potentials for new projects and the existing stock. The framework allows manipulating geographic/time borders of the study and provides quantitative results for assessment of ongoing trends and processes of change in cities towards advancing urban control and planning systems. Results generated by IUMAT can be used by executive and legislative authorities at various levels to interpret the performance of building stock and understand the effectiveness of refurbishment and mitigation policies to adequately act and reduce the undesirable environmental consequences by taking most sustainable pathways.

4.2 Advantages of the Residential Energy Model

Cities are complex, open systems with many interdependencies between variables and sub-systems that produce many prediction and measurement uncertainties. Dealing with these uncertainties is not a point of strength for energy modeling at the building level as most of the commercial tools take a deterministic approach and only take fixed values at the data entry. Urban modeling requires a shift from fixed data input deterministic arrangements to more complex probabilistic simulation designs. The residential energy model provides possible ranges of consumption, instead of definitive absolute predictions.

Exploring the determinants of urban resources use that underpin energy/water/materials consumption, space use, urban transportation, and domestic appliances is critical to point out the direction of public policy. For every city, it is important to understand what percentage of consumption is design driven and how much of it is related to the residents' discretion or climate variables. All-inclusive bottom-up arrangements such as IUMAT residential energy contribute to this objective by segregating the explicit impact of unique variables on different categories of consumption. For instance IUMAT energy model results show that residential hot water use is not affected much by heating or cooling degree days or urban form, but highly influenced by occupant characteristics or energy prices. Or, the outdoor lighting demands are highly correlated with urban form and by shifting away from detached structures towards denser neighborhoods and connected buildings street lighting loads can be effectively controlled.

For a confident use of energy modeling in policy evaluation, the model should be ready to capture behavioral complexities as well as climatic aspects that surround urban flows of consumption. Research shows that up to 85% of the consumption variance can be allocated to type of use and behavior of the household members. Within the same patterns of activity, variability between energy-efficient housing is very significant compared to the average residential stock. Environmental literacy of the occupants and their increased awareness on the life cycle impacts of the built environment materials and manufacturing chains have the potentials to achieve behavioral change. The residential energy model results emphasize the importance of behavior by showing that energy saving behaviors can greatly counter the impact of an aged housing stock. Imperfect simulation of user behavior is usually recognized as another significant source of error in energy modeling. Human-building interactions in building scale energy simulation are usually reflected via schedules that assume a normal behavior by all of the occupants. The normal behavior identifications are usually based on outdated surveys with disputable relevance today.

In an urban area with large numbers of building units, the impact of behavioral variances not being captured in the process of energy modeling only intensifies. However, unlike for small scale simulation, predicting the behavior of a city population is logically impossible. Currently IUMAT takes physical parameters such as floor space, type of use, location, etc., and augments the framework by pseudo-behavioral models that take into account a set of socio-economic parameters in order to predict the diurnal consumption of resources and the traffic that a given building absorbs and generates in a bottom-up analysis framework. Factors such as age, employment status, gender, occupation, income, highest level of education are some of the socio-economic variables that determine environmental behavior of urban agents and still, different people, even at the same income and literacy level, do not respond similarly to the incentives and environmental knowledge. IUMAT looks for sets of socio-economic indicators that are determinants of behaviors with environmentally significant consequences to establish the individual/attitudinal backbone of the model. Results of the energy model, form an evidence-based structure of calculative assessment that atones for the current lack of urban behavior-configuration integration in strategic governmental and industrial policy making and development programs. The energy model is designed to help understand the extent to which the procurement of more efficient energy appliances, using renewable energy sources, and energy conservation and recycling habits are influenced by socio-economic factors.

Flows of consumption span a long path form the source to their end-use site. Another advantage of the overall framework designed for IUMAT is the disaggregated approach it takes to indexing these passages that complicate allocation of the flows to specific sectors or activities.

Therefore, the immediate impacts of project landscaping as an example that includes energy, water and material use for construction, and operation and maintenance of the landscape are separately calculated by the water and materials use models, not the energy model. This is similar to the way irrigation water usage, energy use for water treatment and distribution, sewage disposal, roads and infrastructure material use, materials transportation and disposal energy consumption are calculated on a project basis.

There is a wide variety of strategies for controlling the urban energy demand and the associated GHG demands including dissemination of building energy efficiency measures, improving the technologies, optimizing the energy generation and distribution cycles, land use and spatial urban form management, and reducing carbon intensity of the grid electricity. For establishing a reliable city level energy modeling method and setting a baseline for urban GHG emission accounting, performance of building systems, equipment and appliances should be considered at the same time with distribution and generation systems in relation to urban form. The impact analysis module within the residential energy model enables drawing comparisons within a wide spectrum of sustainable energy production technologies for urban areas ranging from on-site renewable generation to higher efficiency fuel use methods such as cogeneration in terms of carbon emissions.

Energy master-planning, harvesting renewable sources and integrating new capacity into the grid needs a thorough understanding of the spatial load profiles. High resolution topological and geospatial data on regional energy demand help to understand what the transmission and distribution technical and economic costs will be to the destinations that power demand usually peaks. Blending renewable electricity generation into the grid is not always straightforward. Viability of renewables integration plans also depends on the magnitude of demand and storage technologies available in cases of over-generation for the times that demand falls below supply.

Considering the fluctuating nature of renewable energy production technologies and their lower power capacity relative to other sources, more state of the art storing and management technologies and smarter grids might be required in order to maximizing the carbon emission benefits of renewables. Planning for renewable energy production by balancing the non-predictable fluctuating supply with relatively predictable demand is critical along with providing a certain level of generation system security to meet the hourly needs of various urban sectors. Calculative IUMAT framework allows assessing and comparing alternative energy plan options (e.g. centralized vs scattered renewable energy plan) with regards to need for new infrastructure, distribution losses and meeting the peak loads. IUMAT energy model provides the means for improved forecasting needed for successful and efficient integration of renewables into the energy network. But, additional improvements to the transmission lines, storage facilities, and mobility systems are usually required in addition to operational enhancements such as establishing virtual power plant frameworks (central-holistic control systems) or integrating cogeneration district heating plans with non-dispatchable energy sources.

The energy model projects the environmental consequences of alternative energy technologies by simulating regional energy demand profiles corresponding to supply systems. It also calculates water use, waste and sewage production, as well as carbon emissions and transmission losses associated with the energy source and generation technology and takes into account appliances at the same time with energy sources. Electric vehicles are not always environmentally beneficial and can even lead to higher CO_2 emissions in cases of carbon intensive electricity for battery charging. IUMAT's other models (such as the materials model) upon completion would be able to estimate the amount of resources that go into developing and providing the infrastructure for the new renewable plants. So, for any proposed development of an energy plant or a building zone, planning authorities based on the IUMAT models' outputs will be able to compare the magnitude of material use, energy consumption, and the net emissions difference of the proposed plans. They can also use the spatial demand profiles and create aggregate neighborhood energy figures and get a better understanding of the distance of the supplying sites to peak demand generation zones. However, politics around the suggested development scenarios, opinion of the public on the projects, and cultural aspects of any kind of change can be very region specific and the final proper decision making would highly depend on the community needs, foresight of the policy makers and the vision they have for their communities. Furthermore, there sometimes exists a competition between categories of saving with sustainable scenarios. As an example, densification of communities could moderate solar energy harvesting potentials and IUMAT's energy model enables drawing comparisons between alternative conservation measures using a net sustainability index analysis mode.

Based on RECS data, there has not been a significant rise in average household energy use, despite a 30% increase in average home size over the past three decades suggesting effectiveness of conservation measures and more stringent construction codes in countering higher air conditioning and other energy use by cutting the space heating loads. IUMAT provides the tools necessary for relating the energy use and variables that characterize it over time for example, how price sensitivity of consumers has been decreasing since 1980, pointing out the need for new public policy directions rather than market-control-only approaches. Sustainable urban planning should have trepidations about population projection subject matters, as economic developments, housing issues, providing facilities and public services, environmental impacts, and accordingly sustainable development are all highly correlated with nose counts. Not only the magnitude of the population, but also demographic characteristics of it such as race, age and gender distribution can be of concern depending on the specificity of the study. Both demographic and non-demographic parameters can impact the trends of population growth and the decision making process of the population. Chapter 3 explains how factors such as size of the household are related to residential energy use and how population projections and demographic characteristics can be implemented in planning for future energy. Breaking down the categories of consumption shows that greatest opportunities for energy saving are in water heating and lighting/electronic/appliances and therefore, less achievable with more strict building codes or rigorous energy market regulations. The presented framework is distinctive in the way that it has the capability to specify for every region which of the behavioral change, community densification or physical alterations of the building stock should be the priority of energy conservation master planners.

The quantile regression method indicates how other partial models acting within the greater EWM model can implement actual data to draw patterns of change in regional demand profiles and calculate distribution losses and carbon emissions accordingly. Although IUMAT takes a non-deterministic approach by reporting the results via confidence intervals, next steps of the framework development should include some robust validation procedures by using other independent national surveys that are randomly sampled. Commercial and manufacturing energy models should take the same approach using CBECS, MECS and analogous regional datasets. However, the goal of the holistic framework for projecting the full picture of environmental consequences will depend on the accomplishment of all IUMAT models that represent the urban area as a mixed use and interconnected community.

For the intended comprehensive microscale analysis of different categories of consumption, a diverse range of spatial and temporal data collection methods may be appropriate. The suggested method for large-scale simulation depends on laying out the simulation framework geared towards maximizing the practical opportunities for methodological surveying improvements as well as providing modeling flexibility for employing engineering methods in absence of data with desired quality. IUMAT models use, generate and assign locational variables and unravel relationships between parameters of interest and observed patterns in the data. Every model should demonstrate a unique approach that considers the impacts of dynamics and socio-economic factors on the environmental footprint of an intertwined network of urban energy/water/materials use, transportation and land use. This complex city network is represented by buildings as individual agents that determine the performance and form the patterns of change within the wider urban context. The proposed structure's point of strength for planning disciplines beyond its all-inclusive nature, is the adaptability quality it has to perform in both urban and rural settings.

4.3 Future Steps

Formulating convenient responses to the environmental consequences of rapid urbanization requires a full understanding of all of the contributing parameters. The platform designed for IUMAT relies on actual data for unraveling the relationships between the built environment characteristics and flows of resource consumption in an extended platform of urban metabolism analysis. This could be an opportunity to expand urban planners' scope of work and provide a comprehensive perspective of inter-connected urban sectors for policy makers at community, regional and national levels. The Residential Energy Model explained in the previous chapter provides a template on how real data can be employed by bottom-up modeling structures to construct an integrated system of urban activity. Although currently the most developed IUMAT models are the Residential Energy and Land Use models, a brief description of how the current models can be improved and other models will be built and linked within the existing framework is presented next.

4.3.1 Improving the Residential Energy Model

4.3.1.1 Urban Form Influence

Built environment has lots of intricacies and inputs to urban models at their best cases are good estimates. Measuring the geometry, envelope properties, system efficiencies and occupant characteristics is not uncomplicated for small projects and impossible throughout the entire stock. In addition to site-specific qualities, consumption rates within the built environment are also highly dependent on the climate condition in which they operate in. Climate differences caused by urban architecture and activity change the natural balance of flows and resources in cities compared to untouched lands. Urban function and morphology have spatial and temporal aspects that especially influence energy performance of urban buildings and are rarely taken into account by conventional building energy performance analysis tools. The discrepancies between the actuality and energy modeling simulation results is often partially attributed to the micro climate differences between weather stations and the actual construction sites. Most of the buildings are exposed to a modified urban climate that is itself the product of many micro-scale climate exchanges between so many units and surfaces that create the urban structure. Mainstream energy simulation tools, by default, assume that all buildings are stand-alone entities interacting with a non-urban environment, unrealistically disregarding the impact of the micro-climate in the energy performance calculations. Decisions made at building level, whether about the structural format and choice of materials for the envelope, or about the type of activity that the building is supporting produce and engage with the neighborhood climate that is overlooked in most of the building performance analysis tool scripts.

One factor that is not adequately explored by the current residential model is the impact of urban landscape. Urban landscape is comprised of roads, buildings, trees, open space, water, etc. and their configuration and composition (spatial and non-spatial attributes) determines the mechanism by which land use elements influence resource consumption patterns (Zhou et al., 2011). Since the utility of IUMAT is to assist urban planners and policy makers as a decision tool, incorporating the connections between land-cover, regional building standards, and building site characteristics in the modeling process is necessary for comparing detailed site-specific design solutions. At this stage of development, the impact of landscape function is accounted for by defining different groups of space activity and building use. But the dynamic impacts of landscape elements on resource consumption is not trivial and should be addressed directly. The structure of a particular type of landscape surrounding a building influences its energy and water performance in many direct and indirect ways. The urban composition around a building, for instance, the existence of recreation areas or shopping centers, affects the number of trips generated by a household and the overall transportation energy use as a consequence. Also, the land cover class of the surrounding lots impacts the urban surface energy balance as low albedo paved surfaces slow down the night time cooling process compared to naturally covered land, resulting in higher summer power peak demand and lower winter heating loads (Lenzholzer and Brown, 2013). Heat sources are less concentrated in sprawling urban areas, but transportation requirements are more than high-rise areas at the same time, leading to more emissions. Clearly, the impact of urban landscape composition is a vital and critical factor in urban areas.

It is both physical form and function that urban planners aim to efficiently manage for an efficient, productive interaction of a given population. Neighborhood and street characteristics influence choices made by residents as well as the natural urban energy flows. Urban form affects the residential energy in many ways including transmission efficiency and distribution loss, housing stocks energy requirements, and cooling and heating needs due to the UHI effect. Urban morphology modifies air patterns and flows around buildings, reduces solar gains due to overshadowing effect by adjacent units, and controls patterns of heat gain from radiation exchange between different exposed surfaces. For instance, the mutual shading effect among buildings in a block can interact with both outdoor and indoor microclimates and building energy systems. Even minimal reductions in minimizing heating and cooling loads produced by improved energy management and zoning regulations can have significant impacts when applied to large metropolitan areas, and most commercial energy modeling software do not have a way to account for zoning strategies. These interactions are not easy to track. As an example, aerial imagery has been partially effective in enhancing the Urban Heat Island effect analysis models, but this technique only reflects the two dimensional heat gradient for the urban surface, and the 3D context which includes the urban canopy and the buildings' exterior walls is substantially more complicated and difficult to measure. IUMAT energy model's use of actual data in the modeling process serves as a starting point for linking urban climatology and building performance analysis. As more comprehensive methods for geometry, energy balance and form data collection are developed, improved strategies for operational energy modeling in the energy management process will emerge.

Another obstacle to incorporating urban configuration parameters in resource use modeling is the difficulties of defining and measuring urban form. It is not simple to exactly delineate indicators of urban form such as density, concentration, proximity, continuity, centrality, accessibility and compactness with consensus. These terms are mostly neutral and very objective (Churchman, 1999). For instance, some planners use the number of people per square mile as an index of density, and some use the recorded number of vehicles between urban centers. The correlation between these figures is not strong. Better urban form indicators that enable bringing together population, physical environment, and the generated traffic are yet to be defined to inform the integrated metabolism analysis framework.

For specific cases where more geometry and neighborhood qualities are known, the suggested statistical inference method can be coupled with engineering modeling tools to improve the predicting power of the models. IUMAT models are aimed to be as inclusive as possible by accounting for a relatively large number of variables in the modeling process. Nevertheless, there needs to be a balance between data inputs' level of detail, the accuracy of the simulation results and the cost and time of the simulation process. Another compromise is needed between indoor-based and outdoor based modeling techniques. After careful consideration of the literature on urban form, for a bottom-up method employing tool such as IUMAT, with myriad of input parameters to be considered, height-to-width ratio (H/W) is the only urban configuration feature that IUMAT aims to add to the current framework. Height of the building divided by the street width (height to width ratio) is a commonly used morphological description of urban canyon for airflow and energy analysis at the street level, but usually overlooked as a potential form indicator in urban scale building energy demand analyses. However, making some basic assumptions is necessary for the applicability of the model. IUMAT would need to assume that the factors affecting energy consumption are independent and its analysis builds upon an assumption that there are no connections between building forms, system efficiencies, occupancy schedules, and urban texture until extended inquiries and advanced surveying methods enable confirming otherwise.

4.3.1.2 Impact of Trees

The other factor that needs to be added to the current framework is the impact of urban tree canopy. Inclusion of the relationship between city parks/street trees and neighborhood energy and water consumption increases the precision and applicability of the models to energy, water and storm water management practices. Tree canopy reduces the heat island effect in urban areas as well as reducing the cooling loads by providing shading (Solecki et al., 2005; Shashua-Bar et al., 2009). But planting and maintenance of trees are not free of energy and cost. The optimal selection of tree species towards serving the cooling reduction goal, requires planting types with high shading coefficients and reasonable crown size to minimize the maintenance costs (Akamphon and Akamphon, 2014). Trees also act as shading elements depending on their relative location to the building. Donavan and Burty 2009 imply trees are more effective in reducing unwanted solar heat gain and thus peak air-conditioning electric demand, when planted on west side of the building. In order to assess the benefits of a tree from the energy savings standpoint, the analysis needs to be extended to integrate cost/energy modeling of maintenance and planting of surrounding trees into building energy and water use calculations. Computing the tree energy benefits or irrigation demand would require capturing growth rates and shading coefficients by using tree shading and geometry models that are linked to tree maintenance and building energy analysis frameworks.

Energy modeling optimization efforts usually do not include external shading in the HVAC design and system sizing process, although studies show considerable differences between shaded and non-shaded facades in terms of air and wall temperatures, humidity, heat transfer rates through the façade and wind speed (Gómez-Muñoz et al., 2010). In addition, the evaporative cooling resulting from the plants has the potential to reduce the temperature around shaded facades. Some studies (e.g. Wilkinson, 1995) suggest the use of geometric solid shapes instead of tree crowns to simulate the shading provided by trees. However, capturing the impact of tree shadows on energy saving can be complex since tree configuration (height, species and positioning), density and number on trees, building characteristics (size, glazing area and placement, insulation properties, orientation, adjacent buildings) and local climate conditions can affect the direction and magnitude of savings thus the feasibility of shading (Balogan et al., 2014). IUMAT is currently incapable of quantifying energy saving from trees for the building sector, but the water and energy models allow incorporation of planting and maintenance energy and water use. Although most of the case studies so far are done for a handful of species and specific building types, upon availability of national data on the impact of surrounding trees on cooling loads reduction, empirical correlation can be found and used by the framework. Linking the current framework to tools such as i-Tree Eco (www.itreetools.org) could be a starting point. i-Tree Eco is a tool based on the UFORE (Urban Forest Effects) models, for assessing the properties and the environmental benefits of community trees (Nowak et al., 2008). It should also be noted that the influence of tree shading on reducing cooling loads decreases as the number of building floors rises, and accordingly, inclusion of trees in the modeling gets less beneficial.

4.3.2 Commercial Energy

Commercial activities are usually defined as businesses established out of residential, industrial and transportation sectors (EIA[c] , 2016). In the residential sector, location and size are the key elements of energy use. Among the next decisive factors are design, mechanical systems and socio-economic household characteristics. Within the non-domestic sector, activity is the key determinant of energy consumption. However, due to the lack of consensus in classification, assessing the relationship between type of use and energy consumption is not as straightforward as in the residential sector. Based on EIA International Energy Outlook 2016, global residential, commercial, industrial and transportation sectors are projected to grow by 48%, 54%, 39% and 49% from 2012 to 2040 (EIA[d] , 2016). Demand growth is fastest for the commercial sector which is currently responsible for 18% of the U.S. national energy use. Better understanding of the available data will benefit the research community as well as policy makers to regulate the expanding demand and control the unwanted environmental impacts.

Buildings are the main contributors to energy consumption within the commercial sector, while only a small fraction goes to non-building services such as street lighting and city water systems (EIA, 2013). In fact, residential and commercial sectors have this quality in common that in both sectors, energy consumption can be attributed mainly to end-use building level consumption. As estimated by CBECS 2012, United States has 87 billion square feet of commercial building floor space, comprised of 5.6 million buildings. There were 3.8 million buildings making up 55 billion square feet in 1979, indicating increased building size for the new commercial stock (EIA[e], 2016). In fact, the top 2% of the buildings in terms of size, represent 35% of the total square footage. Since 2003, the energy end-use has been increased by 7% despite a 22% growth in the total commercial floor space, suggesting the effectiveness of newer construction standards. (Of course, the location of major developments and type of activity in the new buildings need to be considered in attributing partial causes of the performance improvement). By and large, expansion of the commercial building sector is impacted more by economic conditions compared to residential. Cultural aspects of design are also key factors, as per capita office space in the U.S. ($4m^2$) is two times the Europe figure (Pérez-Lombard et al., 2008). In most of the countries, retail and office are the most energy intensive activity types within the commercial buildings.

RECS and CBECS are among the most reliable sets of data available on the energy consumption of U.S. residential and commercial building stock. They are both annual snapshots in time and do not provide temporal information such as peak demand details or daily distributions. In the same way that RECS data was used to show the implications of actual data in residential energy modeling, the base for IUMAT commercial energy model will be drawn from the Commercial Building Energy Consumption Survey (CBECS) data. CBECS 2012 (the most recent update) contains 6,721 observations for buildings from fifty three specific building activity types. 1,120 variables are reported for each observation including capacity, percent occupancy, number of employees, weekly operating hours, imputed square footage and basic construction information for nine Census divisions.

In the same way that RECS 2005 was used to validate the prediction power of the model based on RECS 2009, CBECS 2003 can be used for validating the commercial energy model results. CBECS 2003 contains the data for 5,216 buildings, grouped in 51 categories of primary activity. The commercial energy model aims to predict the demand data for ten categories of energy services (heating, cooling, ventilation, hot water, lighting, cooking, refrigeration, office equipment, computing and miscellaneous). Some location variables such as HDD and CDD, form variables (e.g. number of floors, floor to ceiling height, building shape, total floor area), fabric variables (e.g. window glass type, floors-roof-exterior wall construction material), and equipment variables (e.g. lighting, HVAC, refrigeration and water heating systems) will be included within different activity type categories. At the next stage, based on spatial distribution of the generated demand profiles, geographical information can be used to assign the energy supply technology that satisfies the predicted demand.

Other CBECS-based approaches have been used by researchers for commercial energy modeling as well. For instance, in a report published by National Renewable Energy Laboratory (NREL), Griffith et al., (2008) used building descriptions of CBECS 2003 for EnergyPlus simulations and compared the results from 4,820 unique energy models to the 2003 survey. The risk of creating prototype models based on large data sets such as CBECS are a few. There is no question that considering the level of details provided by CBECS on building characteristics, the individual energy models that take them as inputs, are not going to be sophisticated enough. In addition, it is relatively easy to produce results within 15-20% of the actual mean of such large data set for each subsector, which is usually considered the threshold for determining the validity of methodologies. Their method only allows making projections for the future end-use for the major sub-sectors (such as education and food sales), assuming certain growth rates for those sub-sectors. However, since the method validation is based on average end-use figures, no credible comparison can be made regarding alternative scenarios of development within each sub-sector. Furthermore, CBECS buildings' exterior wall and roof compositions, HVAC systems features, equipment performance levels and schedules are basically assumptions and not suitable for non-comparative deterministic analyses. The discrepancy gets more problematic when dealing with parameters from big datasets with relatively large standard deviation and non-normal distribution that make the 20% proximity of the results and actual data even a less significant measure of analysis robustness.

Another advantage of the proposed method over prototype approaches is related to simulation run time. Usually, prototype styles of modeling that build on large datasets require thousands of energy models and take hundreds of hours to produce results for each scenario, and yet, in some categories fall short to meet the 20% error threshold, while reducing the number of prototypes reduces the accuracy of the predictions. Though, they are still quite reliable for smaller sectors and reference data set productions.

IUMAT energy models and similar structures, underscore the practical challenges of working with large datasets as well as developing nationally representative surveys. Improved understanding of the residential and commercial end use energy and better evaluation of energy saving potential with specific design and technology require advancement of data collection methods. RECS and CBECS data are the most comprehensive datasets of their own kind of detailed data on the residential and commercial building sectors. Yet, there is room for improvement. More detailed identification of the building sector is necessary to modify simplification such as describing major buildings as full air conditioned or not conditioned at all. Schedules are not realistically portrayed in the CBECS that confines to reporting weekly hours of operation and whether the facility is open on weekends. Although CBECS 2012 includes building shape, roof shape and floor to ceiling height, more building form features such as orientation and height to width ratio can still be added. The scope of future EIA energy consumption surveys could justifiably expand to include more accurate building site measurements, sub-metering the end uses, and measurement of the air quality and water use and lighting levels. Reporting monthly energy use data and peak information would greatly enhance possibilities for validation and calibration of bottom-up energy models, and make the model results applicable to energy management practices.

4.3.3 Water Consumption

As a result of migration from rural to urban areas starting at the end of the Second World War (Greenwood, 2014), larger energy and water supply systems are needed in order to respond to the growing demand created by households and industries in the urban areas. In the case of urban water, being able to predict the hourly demand in relation to climate change uncertainties is the key supply management factor of the future (Herrara et al., 2010). Design and operation of regional and municipal water supply systems require long-term understanding of industrial and residential demand as well as natural stream flows and aquifers (Runfola et al., 2013). Securing the water supply for urban population at desired quality and pressure is becoming more vital with a changing climate in addition to the rapidly growing population numbers (Pingale et al., 2014). As a result, decentralized supply systems and water re-use innovations are increasingly more favorable practical solutions every day. However, budget issues, regulatory barriers and behavioral resistance have delayed quicker adaptation of those practices (Krozer et al., 2010; Giurco et al., 2011).

United States Geological Survey (USGS) operating within the Department of the Interior maintains a nationwide ground water and surface water withdrawal data set at county level resolution that is updated every five years (USGS, 2016). According to USGS data, despite the economic growth and the population rise, national water use has been in decline during the past thirty years with a steeper drop since 2005. Total water consumption (saline and freshwater) has been reported as 440, 400 and 350 billion gallons per day (bgd) in 1980, 1985 and 2010 respectively. Per capita water use peaked at 1,900 gallons per day in 1980, and shrunk by 17% between 2005 and 2010, dropping to 1,100 gallons per capita per day (gpcd). Thermoelectric power is the major consumer of water (saline and fresh), ranging from 0.4-75 gallons/kWh from Arizona to Rhode Island. In 2010, water consumption by municipal/industrial, agriculture and thermoelectric sectors were 268, 480 and 640 gpcs respectively. Residential sector that is a subset of municipal/industry category used 88 gpcd in 2010, ranging from 50 to 170 gpcd from Wisconsin to Idaho (Donnelly and Cooley, 2015). As reported by EPA, of the 300 gallons of water that an average American family uses every day, 70% occurs indoors (EPA, 2016), however, this varies a lot in different climate zones across the country based on irrigation and landscaping water requirements. Studies suggest that replacement and retrofitting of residential appliances and devices have the potential to reduce the per capita urban indoor water use by up to 50% (Inman and Jeffrey, 2006; Mayer et al., 2004).

Reducing end use water demand eases the pressure on natural water sources and reduces the life cycle cost of city water provision and the carbon footprint by lowering energy consumption for distribution and waste water treatment. The fact that the correlation between population growth and water has been getting smaller over the last decades is encouraging, but makes water use modeling and planning for the future more challenging since more demographic/technological information and process details are required for the accuracy of water use simulation.

A major step for linking sub-categories of water use to physical and socio-economic variables is accurate water end-use metering. Overall, developing technologically advanced water use measurement methods have not gained the same attraction from the planning community as compared to energy metering, due to unmatched prices of water and energy. As an example, for residential water use, conventional water metering usually reports the annual water consumption based on two or four data points throughout the year (Britton et al., 2008). Quarterly recorded water use data not only fails to portray a complete description of weekly or monthly data, it does not enable breaking the aggregate figure that is usually in a unit of volume, into different end use categories (such as showers, toilets, garden irrigation, dish washers and laundry). Smart metering technologies, in contrast, provide comprehensive insight into water-use patterns, and enable analyzing the influence of socio-economic parameter on categories of water use. Also, reliable evaluation of the effectiveness of water reduction measures depends on availability of high quality data produced via automated sub-metering technologies and smart end use analyses methods.

Location specific research needs to occur regarding pricing structures, consumption behaviors, government regulations, efficiency profiles of water appliance stock, public environmental literacy and other factors that can impact the validity of water saving strategies. Reliable data sets and nation-wide surveys are required for identifying the categories of water consumption and assess the influence of water saving measures on different socio-economic clusters. For instance, Willis et al., 2013 recruited 151 homes in Gold Coast City in Australia with distinct socio-economic makeups to investigate the impact of factors such as family size, age of infrastructure and ownership status on differing end use categories. They used data loggers to gather pulse counts for 10 second intervals as a part of a smart metering network and used surveys to investigate water behavior as well as the appliance stock and found correlations between household makeup, income and appliances efficiency of residential end use. For large scale simulation of water use, IUMAT needs to rely on similar datasets that cover larger geographical spreads. Residential end-use water data such as the Aquacraft, Inc. survey commissioned by EPA (DeOreo, 2011) that was created with participation of nine water utilities across the nation can be used to simulate household water use profiles and calibrate the hot water models based on energy data.

In addition, water sector is a major consumer of energy. Due to high energy-water interdependences, most of the water related energy use inside homes is consumed by large groups of small individual users (Reffold et al., 2008). Most of these energy and water related GHG emissions are associated with residential hot water use, that is influenced by climate conditions, pricing regimes, household makeup, appliances efficiency and behavioral parameters (Arbués et al., 2003). RECS 2009 is basically an energy database, and it is difficult to find its counterpart for residential water consumption. However, RECS includes information for residential water heating energy use. Engineering methods can be used by the IUMAT water model to convert water heating energy use to actual amount (gallons) of hot water use. Total energy used for providing hot water can be estimated in accordance to variables such as water heater size/age, type/number of water heaters and number of tank-less/storage heaters. RECS also includes valuable information regarding water use behavior of households. Type of dish washer and washing machines and the frequency of use based on basic household characteristics can be obtained from RECS 2005 and 2009.

Although benchmarking and continuous measurement are crucial to any sector of business or industry that relies on optimized management practices for improvement, water end-use surveys for commercial and industrial sectors are much less frequent compared to residential sector and the available surveys are usually conducted for cities or smaller subsectors (e.g. Northcutt and Jones, 2004). CBECS 2012 only reports water for heating and cooling purposes and its 2007 data release only includes water data for large hospitals. Building Performance Database (BPD) administered by the U.S. Department of Energy provides a web-based energy explorer of residential and commercial buildings across the United States. The dataset it relies on is the largest in the nation, but the explorer mostly supplies adjustable distribution charts and basic statistical characteristics regarding energy consumption in different commercial and residential sub-groups. However, the BPD has made public relatively large Benchmarking Ordinance datasets for seven metropolitan areas (Boston, Chicago, Minneapolis, New York City, Philadelphia, San Francisco and Washington D.C.) that encompasses total energy/water use and square footage information. Although detailed building characteristics are not provided, the datasets could be very insightful on total energy use figures and beneficial for commercial water consumption modeling purposes (BPD, 2016).

Commercial end-use water simulation needs reliable information about building footprint, lot size and equipment features as well as consumption information for domestic uses, commercial kitchens, landscaping and outdoor uses, heating and cooling, processes, and sanitation and washing. Industrial water demand models have mostly been relying on econometric and statistic regression methods aiming at making projections regarding the whole stock demand rather than taking bottom-up disaggregated approaches (e.g. Wei et al., 2010) or similar to commercial water models, are based on surveys that target a particular industry (e.g. Saha et al., 2005). Therefore, obtaining data for non-domestic water simulation in a way that a diverse group of businesses and industries are represented is not uncomplicated and needs integration of scattered sub-sector specific studies and datasets to create a stronger base for large scale water consumption simulation.

4.3.4 Manufacturing Energy

In the United States, end-use delivered energy to industrial sector has been 24.5, compared to 11 and 8.8 quadrillion Btu for residential and commercial sectors in 2015 (EIA[f], 2016). According to Manufacturing Energy Consumption Survey (MECS 2010), although the aggregate energy demand of the manufacturing sector has reduced by almost 17% over the past decade, the gross output of the sector has dropped merely 3% over the same span. This indicates an improved overall energy efficiency for the whole sector. The 14 quadrillion Btu 2010 fuel consumption of the industrial sector can be mostly (over 80%) attributed to the five most energy intensive industries (petroleum and coal, chemicals, paper, primary metals and food) (MECS, 2014).

Similar to the commercial energy sector, most of the existing energy models operate in regional and national scales and the datasets with finer resolutions are only available for particular industries or plants. Subsector specific energy and water models (e.g. Worrell et al., 1997) enable incorporating detailed factors that are overlooked in other simulation contexts, and provide templates that can inspire new vision for other sectors integration and larger scope modeling frameworks. These surveys allow development of analysis tools for risk assessment of capital energy investments and finding optimized solutions for the environment and economy. They are useful for more accurate allocation of emissions and other environmental impacts to particular production stages or activity subsets. However, due to the lack of interaction between the models based on subsector specific surveys and other businesses and the broader economic backdrop, the scope of analyses is not extendable to other areas.

MECS dataset reports the energy consumption data for 84 type of industrial subsectors and manufacturing establishments for eight categories of fuel type. The aggregated MECS data does not represent technological and process details and therefore, can have limited implication for energy services simulation or any other non-economic policy modeling. In the absence of higher levels of disaggregation in the data, general equilibrium or input-output methods can be applied to the data in order to characterize macro-economy interplays between market issues, energy consumption and industrial subsectors' total output. The models that can be established using MECS type of data can have implications for analyzing overall interactions between energy consumption, environmental policy and economic growth.

Bottom-up structures similar to the IUMAT residential energy model and other hybrid engineering and statistical models lay out instruments for high resolution inquiries in favor of behavioral intelligence and equilibrium responses. Although such simulation frameworks require high quality detailed data, as compensation, by recognition of particular mechanisms and technologies and identifying different energy market scenarios and policy platforms, they allow for consideration of energy source/price/demand changes as well as penetration of new technologies in the modeling process. Therefore, bottom-up structures can have more implications in resolving cost effective directions for mitigation programs and projecting future technological and market energy trends.

4.3.5 Material Flows

Material Flow Analysis (MFA) techniques are suitable to evaluate flows and stocks of materials through different systems and provide a good basis for system control in view of sustainable development (Hendriks et al., 2000). MFA is a means for understanding the metabolic performance of urban activities and processes in a materials input-output context that links different sectors in a city. However, an important step for analyzing the flow of substances and goods into and out of the system, as well as processes and stocks within the system is to carefully identify time and space boundaries of the system.

Overall, MFA-related analyses are specific to substances, materials or products over the scope of single firms/households, sectors or regions (Bringezu and Moriguchi, 2002). For the scope of IUMAT material use model, obtaining detailed data for raw materials or substances further complicates the platform. However, incorporating the environmental impacts of specific products, not only is associated with easier consumption data collection, but also is more comprehensive in terms of capturing the bigger picture. This precisely mirrors the Life Cycle Assessment (LCA) approach. The primary interest of IUMAT, rooted in its inherent bottom-up structure, is the flow of products through limited scope of specific firms or households.

The application of MFA to planning has been very limited compared to its high influence in the field of industrial ecology. The integration of MFA into policy has remained challenging due to scarcity of models that are capable of mapping and disaggregating the flows of materials in sub-regional scales or linking these flows to regional and national data (Sinclair et al., 2005). There are few examples (e.g. Druckman and Jackson, 2009) where disaggregated input-output models are employed to assign carbon footprint at household level. MFA further needs to be combined with spatial allocation (Roy et al., 2015) to enable community-level policy analysis pertaining to the distribution of material consumption flows. Although tracking the flows and data collection for products is more straightforward than it is for materials and substances at fine resolutions, the limited scope of the end units in bottom-up structure such as IUMAT may occasionally require adjusting the study method to take broader systems approaches (such as LCA), confining to inclusion of specific major products, or rescaling the study to neighborhood, county or regional economies. These details will get clearer in later stages of IUMAT development as more models and data frameworks become available.

4.3.6 Land Use

IUMAT Land Use Model (IUMAT-LUM) that is being developed parallel to the energy model, is a major step towards the goal of geographical resource use allocation. The model uses GIS, Remote Sensing and Artificial Neural Networks (ANNs) to make projections on land use change and urban growth. The current focus of the land use model is to generate building-form variables by obtaining Light Detection and Ranging (LIDAR) data using normal equations and Density-Based Spatial Clustering and use the form variables as the new determinant factor of land-use change. Currently the model is able to predict non-urban to urban transitions and transformations between urban categories of land use type based on form and spatial variables in addition to proximity variables such as distance to commercial, industrial, residential and educational zones and some density variables. The results from IUMAT-LUM have shown that inclusion of form variables improves the prediction power of the land use change models by up to 11% and 19% for non-urban and urban case study areas respectively.

IUMAT-LUM converts land cover estimates, building forms information, transportation arteries and other physical attributes into a spatial grid system with a high cell resolution (6x6 meters). GIS and LIDAR data are used by the building form generator in order to detect geometric clusters using Mean Shift, Density-Based Spatial and Fuzzy clustering algorithms. Three pre-defined normal equation models are fitted for form identification. In future steps, a more comprehensive archive of predefined geometry models should be developed to enable identifying more complex geometries. Due to the predictive nature of the IUMAT-LUM, it can act as the medium for incorporating dynamics into the overall IUMAT framework. Also, the prediction of geometry and form variables such as height, number of floors and gross area can be used by other modeling units (e.g. energy model) in combination with socio-economic and environmental factors.

4.3.7 Developing Data Harmonization Methods

Surveys that are used for data collection by the EWM model potentially contain very diverse types of categorical and numerical variables. The energy model follows a measurement algorithm that enables statistical inference to relate energy use to physical, demographic, behavioral and attitudinal parameters. It relies on regression patterns to find the associations between variables for making observational inference (causal inference is not possible since the results are usually not from randomized control experiments). Square matrices of regression variables are employed to prevent multicollinearity of the variables from skewing the estimations and complicate the analysis. Residential energy modeling using RECS data depicts implications of reliable regional datasets in the policy making process as well as some major shortcomings and challenges of big-data-based urban modeling. In some cases, confidence intervals based on national data may not be applicable to specific locations. Fragmentary portrayal of detailed location specifications in nation-wide datasets such as RECS further complicates high confidence localized policy analysis. In addition, most of the large datasets published by public organizations are cross sectional observations that do not allow tracking of marginal changes over time. The residential model results suggest that conditional analysis methods such as quantile regression are capable of providing means for assessment of marginal impacts of behavioral and physical transitions on resource use and carbon emissions with improved panel data collection methods.

There are more imperfections to the common data collection methods other than their usually static approach. Although there is a multitude of building datasets available to researchers, most of the public or privately funded surveying efforts are uncoordinated and fragmented, focusing primarily on energy related issues and information on water or material flows are more scarce and laborious to find at household, business or plant level. Yet, these usually do not provide systems, operational, geometry, envelope and occupant detailed characteristics that are required for a fundamental analysis that aims to piece together sub-systems of urban resources use.

For the energy and water consumption in the commercial and industrial sectors the surveys are usually very location specific and stripped of important details that are required for setting up reliable modeling structures. As an example, California Energy Commission (CEC) produced a randomly sampled survey (California Commercial End-use Survey known as CEUS) of 2,790 commercial buildings located in California (CEC, 2006), but the micro-data is not made available to public due to non-anonymity in the survey's design and the finest grain of information provided is the aggregated energy results. Building Energy Data Book is another dataset (last updated in 2011) on residential and commercial energy use with statistics of building technology/construction, energy use and physical building attributes. However, it also does not go beyond sector end-use fuel types or average household/firm by region (Building Energy Data Book, 2012).

Surveys that do not report necessary physical and attitudinal information limit the forecasting capability of modeling to regional levels. For instance, National Energy Modeling System (NEMS) is a large scale energy model of the EIA that generates projection reports on energy supply, demand, market pricing and technological advancements and is used for environmental policy making and energy perspective evaluation (Wilkerson et al., 2013) and its Commercial Demand Module (CDM) makes projection for energy consumption at division level for eleven categories of commercial buildings, based on engineering and macro-economic relationships.

Datasets that are specific to businesses/industries or miss detailed building characteristics are not the best kind of IUMAT input material. Still, they are valuable on explaining general direction and aggregate outcomes of change. IUMAT EWM structural design needs to get more advanced to handle connecting datasets from different sources, and more flexible to allow adjusting to the quality and scope of the available data for EWM modeling of non-domestic sectors. Therefore, the challenging diversity in scope and style of the surveys on consumption of resources, can at the same time be an opportunity in disguise for model enhancement. The implementation of the actual data for analyzing environmental consequences of urban activity can also address the definitive needs for data updates and parameter refinements.

4.3.8 Completing the Holistic IUMAT Model

IUMAT's central research goal is to provide quantitative support for understanding the collective environmental impacts caused from collaborative decisions of a population of human beings within specifically drawn borders for urban regions. The carried out literature review on simulation towards sustainability evaluation at large scales points out wide knowledge and methodological gaps within the existing frameworks and the need for introducing evaluative/calculative structures that integrate urban subsystems and the interrelations between different sectors of urban activity/life. The results from the residential model that functions as a prototype for commercial and manufacturing energy models provide further evidence that calculating the environmental footprint of transportation, EWM (energy, water and materials use), and land use needs to go beyond seeing urban sub-sectors as stand-alone entities, or solely including physical variables.

Increasing concerns for the environment coupled with the massive projected growth of the global urban sector, underline the immediate need for development of reliable planning and policy analysis tools. Tools with stronger quantitative capabilities and focus are yet to be initiated despite significant achievements of planning and design researchers in devising guidelines and protocols towards building more sustainable communities. The notion of urban metabolism can facilitate quantitative measurement of sustainable performance for urban areas. Such analysis would require inclusion of social, economic and environmental capitals of urban life within an integrated analysis structure that studies physiological and morphological aspects of urban metabolism. Most of the tools in use today apply equilibrium, cross sectional approaches to singled-out aspects of urban life such as energy consumption, land use and transportation and therefore, do not go far enough in reflecting the interdependencies and combined consequences of change in urban systems. IUMAT aims at laying out the foundations required for monitoring and evaluating the trajectory and alternative design and planning scenarios in a holistic platform that considers the inter-relationships between various urban flows and sub-sectors. This would require completion of the separate, but connected models that are designated to land use, transportation, energy, water and material use simulation.

APPENDIX A

MARGINAL IMPACTS ON QUANTILES OF 2009 DATA

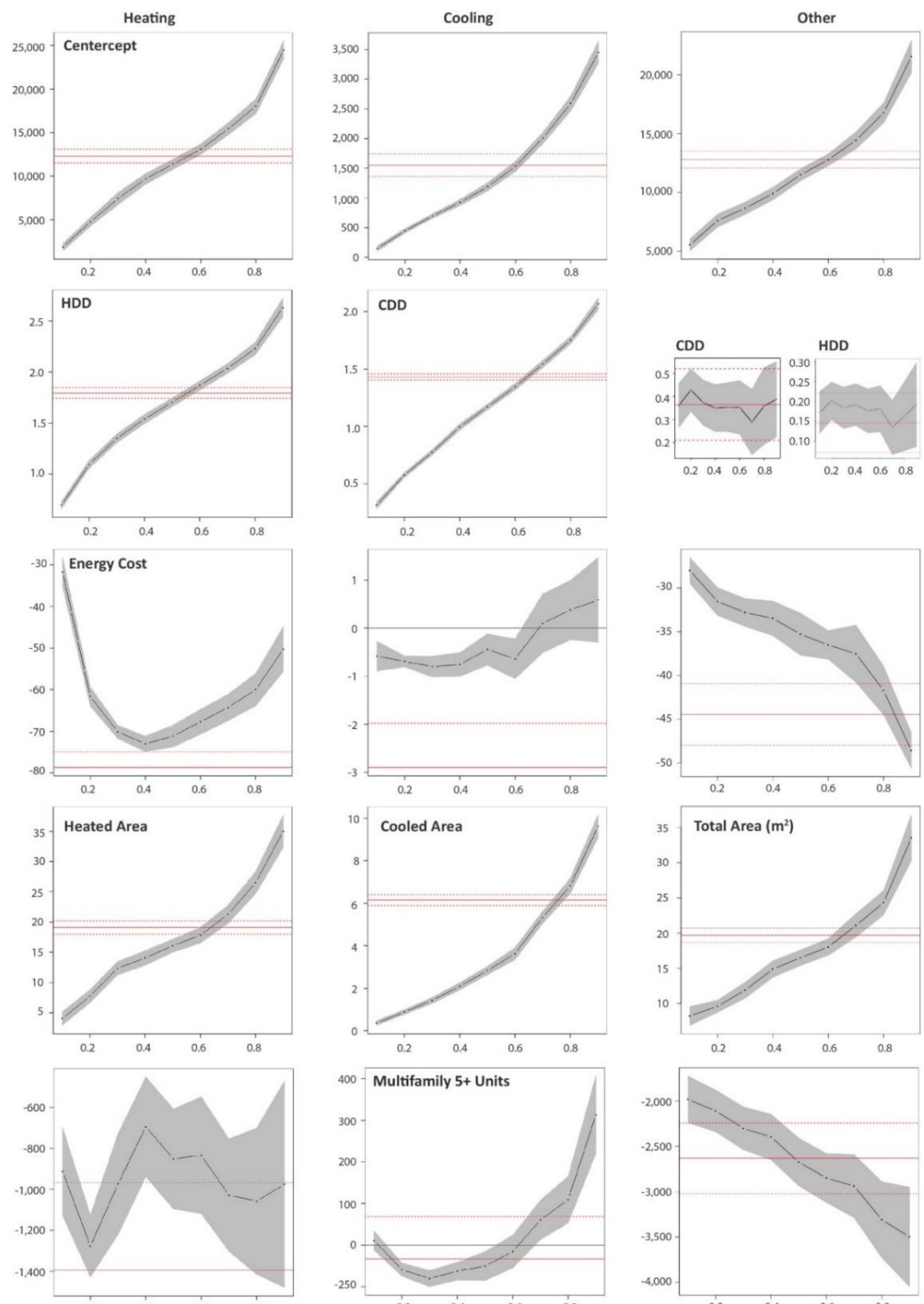


Figure A.1: Marginal impacts of some physical, weather and market variables (non-household) on different quantiles of residential energy use distribution

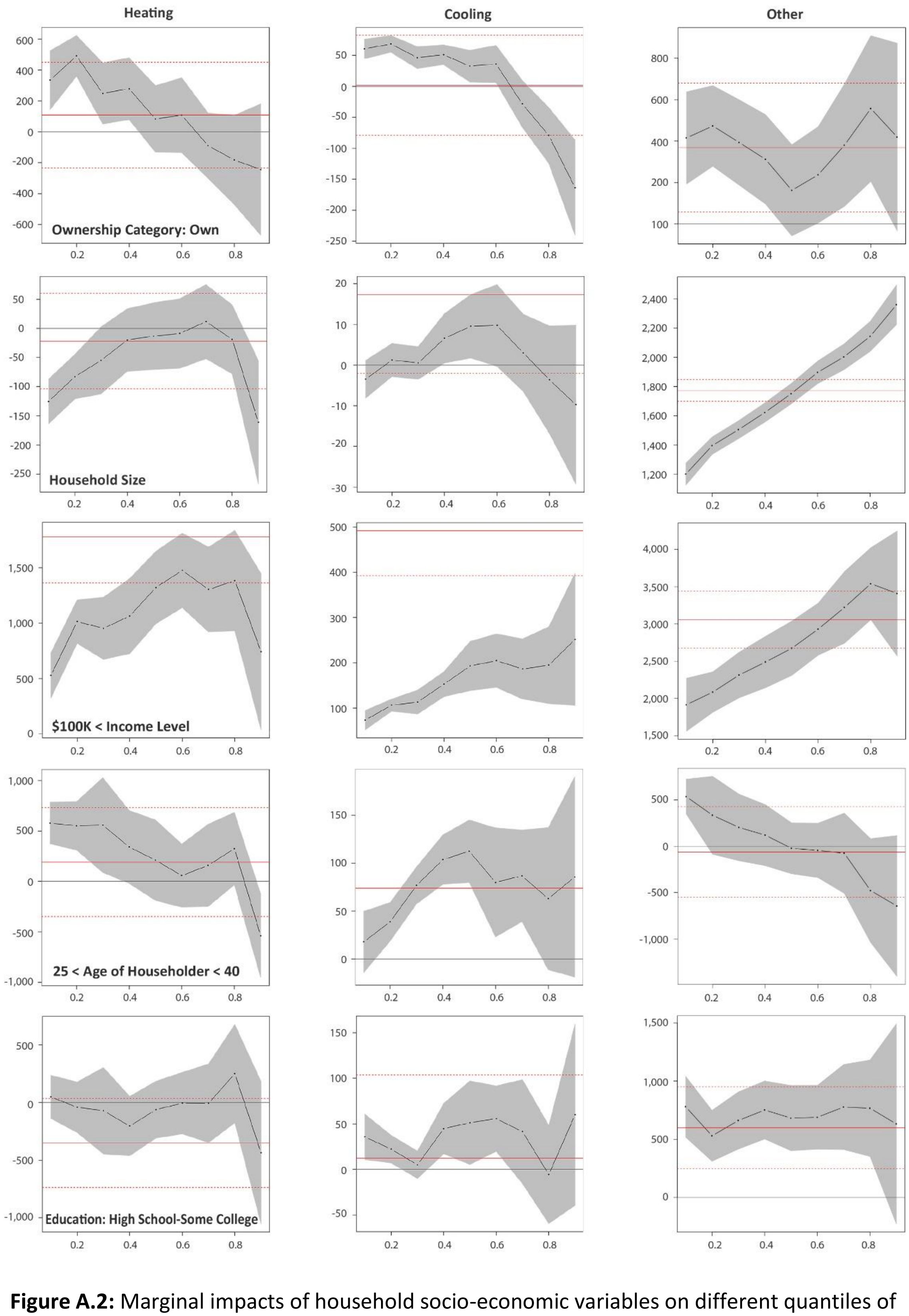


Figure A.2: Marginal impacts of household socio-economic variables on different quantiles of residential energy use distribution

The figures show conditional quantile estimates of energy consumption measures. The Y-axis represents the conditional influence of a specific variable of interest against quantiles of the response variable (heating, cooling or other energy use) on the X-axis. The gray area shows the 90% confidence interval. Accordingly, one unit of increase in heating degree days (HDD) will result in 0.66 kWh and 2.67 kWh higher space heating energy use for the 10th and 90th percentiles. While the extreme ends of the spectrum respond very differently to HDD increase, the OLS average estimate is constantly 1.79 kWh across the entire distribution (horizontal lines). An upward slope reflects that the positive impact of the intended variable on the energy use increases from the lower to the upper quantiles. A U-shaped graph indicates strongest effect in the middle (either negative or positive). A horizontal line or alternating change of direction suggests that the OLS estimates would be robust for the analysis.

APPENDIX B

SUMMARY OF QR RESULTS

Table B.1: Conditional Quantile and OLS estimates of household energy use based on 2009 RECS data.

Coefficients	Type	Tau= 0.1	Tau=0.3	Tau=0.5	Tau=0.7	Tau=0.9	OLS
Centercept	**CE**	433.2 (23.8)***	1015.9 (23.3)***	1609.6 (33.2)***	2321.9 (50.1)***	3370.8 (84.4)***	2024.1 (102.8)***
	HE	2251.5 (301.4)***	7816.8 (388.6)***	11658.6 (362.2)***	16035.2 (427.3)***	24866.5 (729.2)***	12650 (483.9)***
	OE	5536.4 (309.1)***	8654.7 (317.5)***	11506.3 (313.9)***	14435.1 (442.7)***	21563.9 (844.8)***	12790 (438.6)***
Cooling Degree Days	**CE**	0.3 (0)***	0.6 (0)***	0.9 (0)***	1.2 (0)***	1.4 (0)***	1.2 (0)***
	HE	0.0	0.0	0.0	0.0	0.0	0.0
	OE	0.4 (0.1)***	0.4 (0.1)***	0.4 (0.1)***	0.3 (0.1)***	0.4 (0.1)***	0.4 (0.1)***
Heating Degree Days	**CE**	0.0	0.0	0.0	0.0	0.0	0.0
	HE	0.7 (0)***	1.3 (0)***	1.7 (0)***	2.1 (0)***	2.7 (0.1)***	1.8 (0)***
	OE	0.2 (0)***	0.2 (0)***	0.2 (0)***	0.1 (0)**	0.2 (0.1)**	0.1 (0)**
Household Size	**CE**	-1.9 (2.3)	-1.8 (2)	3.8 (3.8)	10.9 (4.3)*	3.4 (9.2)	11.7 (10.5)
	HE	-146.5 (21.5)***	-55.2 (31.5)	-19.4 (36.8)	53.2 (27.2)	-108.5 (63.9)	-2.4 (49.9)
	OE	1201.9 (45.7)***	1505.5 (37.2)***	1751.5 (42.5)***	2002.8 (53.5)***	2359.6 (82.4)***	1774 (45.3)***
Total Area (m^2)	**CE**	3.1 (0.1)***	4.7 (0.1)***	6.6 (0.1)***	8.6 (0.2)***	13.4 (0.3)***	10.3 (0.2)***
	HE	7.4 (0.5)***	14.8 (0.7)***	17.5 (0.6)***	21.2 (0.8)***	32.6 (1.4)***	20.6 (0.8)***
	OE	8.2 (0.8)***	11.9 (0.7)***	16.5 (0.7)***	21.1 (1)***	33.5 (2)***	19.7 (0.6)***
Average Energy Cost	**CE**	0.2 (0.1)	0.5 (0.1)***	0.9 (0.1)***	0.6 (0.3)*	0.3 (0.4)	-0.5 (0.5)
	HE	-33.3 (1.9)***	-71.1 (1.3)***	-70.9 (1.8)***	-62.7 (1.8)***	-42.1 (3.5)***	-77.8 (2.3)***
	OE	-28 (0.9)***	-32.8 (1)***	-35.3 (1.5)***	-37.5 (2)***	-48.6 (1.2)***	-44.5 (2.1)***
$25K < Income Level < $50K (Baseline < $25k)	**CE**	16.7 (7.4)*	16.6 (6.7)*	-1.7 (10.5)	-49.9 (15.8)**	-49 (34.9)	-9.8 (40)
	HE	135.3 (99.3)	197.7 (104.9)	211.8 (125.2)	-137.9 (128.7)	-76.9 (246.8)	134.8 (188.1)
	OE	293.9 (113.2)**	300.4 (100.7)**	184.1 (111.6)	0.9 (158.1)	-387.5 (204.6)	-39.5 (170.6)
$50K < Income Level < $75K (Baseline < $25k)	**CE**	30.6 (10.6)**	54.9 (8.1)***	52.2 (12.6)***	6.2 (19.3)	-43 (48.2)	76.2 (47.4)
	HE	73.9 (124.1)	-22 (116.7)	42.1 (157.8)	-367.4 (155.2)*	-309.5 (256.2)	-124.6 (222.8)
	OE	640.3 (152.6)***	670.5 (139.4)***	528.3 (130.2)***	356.1 (182.3)	-281.1 (272.2)	379.8 (202.1)
$75K < Income Level < $100K (Baseline < $25k)	**CE**	45.4 (14.3)**	78.4 (10.2)***	80.5 (15.6)***	53.6 (32.7)	47.3 (33.3)	179.3 (55.9)**
	HE	81.1 (137.8)	402.1 (181.6)*	357.6 (158.1)*	224.4 (206.2)	1063.1 (327.2)**	643.8 (263.1)*
	OE	1102.6 (253.8)***	1034.4 (165.8)***	1109.2 (207.8)***	1248.8 (217.2)***	892.2 (449.5)*	1064 (238.8)***
$100K < Income Level (Baseline < $25k)	**CE**	46.2 (10.3)***	67.9 (10.9)***	94.3 (14.8)***	137 (34.5)***	209.2 (50.8)***	351.9 (53.9)***
	HE	477.6 (156.1)**	971.6 (161.2)***	1380.7 (195)***	1579.1 (235.7)***	2324.2 (377.2)***	1968.2 (254.8)***
	OE	1915.6 (216.2)***	2314.1 (186.2)***	2673.6 (221.6)***	3221.4 (292.5)***	3407.8 (510.2)***	3057 (232.6)***

Mobile House (Baseline : SFD)	**CE**	85.2 (19.3)***	44.9 (20.7)*	7.4 (19.9)	51.4 (49.1)	94.1 (78.1)	113.8 (72.3)
	HE	613.8 (157.9)***	702.9 (150.2)***	590.2 (243.1)*	59 (248.1)	-773.8 (443.3)	150.9 (341.7)
	OE	-253.6 (253.1)	-26 (250)	425.4 (212.8)*	252.4 (351.5)	69.1 (296.4)	189.9 (313.6)
Single Family Attached (Baseline : SFD)	**CE**	-0.1 (12.2)	-60.2 (13.7)***	-107.9 (17.1)***	-200.7 (26.4)***	-107.4 (76.2)	-157.7 (57.3)**
	HE	-222.6 (148.3)	-515.5 (131.2)***	-692.4 (150.4)***	-794.6 (258.4)**	-1256.4 (365.2)***	-816.2 (270.2)**
	OE	-1236.9 (204.4)***	-1623.5 (183.3)***	-1775 (186.7)***	-1947.1 (270.2)***	-2166.9 (492.5)***	-1620 (246.1)***
Multifamily 2-4 Units (Baseline : SFD)	**CE**	6.3 (9.1)	-59.2 (11.4)***	-70.7 (13.9)***	-136.9 (27.6)***	-124.1 (38.8)**	-119.5 (63)
	HE	-299.1 (138.8)*	-631.7 (195.1)**	-372.3 (232.4)	-231.5 (198.6)	225.1 (335.8)	-21.6 (297.3)
	OE	-1642.1 (181.4)***	-1724 (171.5)***	-1787.7 (181.5)***	-1909.5 (271.3)***	-1319.2 (428.8)**	-1296 (272.1)***
Multifamily 5+ Units (Baseline : SFD)	**CE**	19.3 (8.9)*	-120.4 (10.5)***	-137.4 (14.9)***	-217.9 (22.3)***	-212.1 (43.3)***	-243.2 (53.9)***
	HE	-948.1 (126.7)***	-1164.1 (125.8)***	-1384.2 (160.5)***	-1796.5 (160.9)***	-2549.7 (293.8)***	-2074.3 (256)***
	OE	-1983.1 (156.6)***	-2301.9 (143.8)***	-2673.2 (160.2)***	-2939 (212.1)***	-3499.6 (333.9)***	-2633 (237.3)***
Year Built 1950-1969 (Baseline: before 1950)	**CE**	-25.6 (6.9)***	-52.2 (6.4)***	-78.5 (9.9)***	-94.2 (16.9)***	-70.8 (29.8)*	-168.9 (45)***
	HE	-301.8 (222.8)	-1845.3 (245.2)***	-2758.4 (187.1)***	-3443.5 (273.6)***	-5458.5 (416.3)***	-2795.8 (212.2)***
	OE	798.1 (168.2)***	710 (124.4)***	523.7 (157.2)***	600 (199.2)**	330 (398.8)	667.4 (192.7)***
Year Built 1970-1989 (Baseline: before 1950)	**CE**	-43.9 (7.8)***	-61.4 (7.1)***	-65.7 (10.6)***	-44.9 (17.5)*	-33 (32.2)	-229.4 (43.7)***
	HE	-721.5 (208.3)***	-3014.7 (233.9)***	-4203.7 (173.9)***	-5116.7 (266.3)***	-8118.8 (366.7)***	-4803.9 (204.6)***
	OE	965.7 (150.2)***	634.2 (113.2)***	350.5 (140.8)*	165.9 (194)	-497 (410.1)	330.2 (185.4)
Year Built 1989-2000 (Baseline: before 1950)	**CE**	-21.6 (9.8)*	16.9 (13.9)	16.6 (15.1)	14.2 (39.1)	25.7 (63.9)	-161.9 (53.5)**
	HE	-763.3 (214)***	-3225.8 (239.8)***	-4512.2 (209)***	-5918.1 (279.5)***	-8983.2 (449.9)***	-5266.8 (248.6)***
	OE	1334.8 (193.3)***	750.1 (129.7)***	338.5 (169.2)*	204.9 (225.2)	-1126.7 (420.1)**	130.5 (224.8)
Year Built 2000+ (Baseline: before 1950)	**CE**	-37.4 (9.8)***	-11.1 (16.7)	-35.6 (17.8)*	-52.1 (30.6)	-61.7 (52.9)	-280 (55.2)***
	HE	-839.1 (221.1)***	-3460.4 (241.8)***	-4638.5 (191.8)***	-5924.5 (275.9)***	-9536.1 (439.1)***	-5565.5 (255.6)***
	OE	286.7 (193.1)	228.7 (160.1)	-152.6 (168.4)	-611.3 (236.4)**	-1558.6 (471.5)***	-272.8 (231.5)
Urbanization Category: Urban (Baseline: rural)	**CE**	-42.5 (10.5)***	-109.1 (9.1)***	-164.5 (12.9)***	-213.5 (22.1)***	-184.8 (32.9)***	-235.9 (38.4)***
	HE	999.3 (93.2)***	1366.5 (117.4)***	1295.1 (145.7)***	1023.1 (169.1)***	580.3 (343.5)	1573.2 (182)***
	OE	-108.2 (148.5)	119.1 (126.6)	-26.3 (146.9)	-335.6 (203.7)	-597.9 (285)*	-262.5 (164.9)
Ownership Category: Own (Baseline: rent)	**CE**	20.4 (7.3)**	-9.8 (9.5)	-11.6 (12.4)	-88.8 (20.4)***	-75.8 (31.8)*	-65.2 (44.2)
	HE	145.5 (104)	217 (107.4)*	154.4 (141.1)	86.3 (147.7)	-87.5 (265.8)	177.3 (208.5)
	OE	415.1 (135.4)**	393.3 (125.3)**	162.2 (133.8)	380.3 (179.6)*	419.4 (275.5)	368.6 (189.2)*
Occupied Without Rent (Baseline: rent)	**CE**	-3 (60.5)	18.2 (81.2)	45.5 (69.8)	50.1 (72)	134.7 (40.5)***	94.9 (133.6)
	HE	689.1 (199.2)***	703.6 (538.2)	508.6 (348.6)	-53.2 (763.6)	-1081.2 (685.6)	79.7 (629)
	OE	-222.2 (147.8)	542.2 (211.7)*	936.9 (657.1)	532.3 (679.6)	1873.3 (2510.5)	1051 (570.4)*
Education: K-12 (Baseline: MSc or PhD)	**CE**	-34.8 (15.4)*	-38.2 (10.8)***	-59 (17.9)***	-25.1 (31.7)	-122.1 (52.2)*	-79.4 (67.1)
	HE	-452.9 (161.9)**	-831.9 (239.9)***	-782.8 (248.3)**	-549.7 (246)*	-55.5 (487.3)	-884.9 (315.9)**
	OE	268 (202.8)	180.7 (182.4)	89.1 (213.8)	273.9 (279.9)	440.6 (586.2)	82.9 (286.8)
Education: High School-Some College (Baseline: MSc or PhD)	**CE**	39.4 (13.1)**	42.3 (8.4)***	20.2 (14.7)	16.5 (20.6)	-59.5 (47.4)	5.7 (49.9)
	HE	139.2 (121.4)	-144.6 (211.7)	-200 (171.1)	-314.5 (179.4)	-373.2 (410.6)	-503.6 (235.2)*
	O	779.8 (159)***	661.7 (149.4)***	682.4 (170.6)***	777.6 (222.2)***	632 (522.9)	599.1 (213.7)**
	CE	16.6 (12.9)	25.9 (9.3)**	-8.6 (14.6)	39.4 (21.3)	26.9 (49.7)	-0.4 (50.1)

Associate's or Bachelor's Degree	HE	117.7 (123.4)	-0.4 (213.2)	-166.7 (168)	-286.5 (175.9)	-527 (396.6)	-495.2 (235.9)*
(Baseline: MSc or PhD)	OE	318 (162.4)	271.3 (147.3)	454.7 (176.1)**	416.3 (226.5)	10.6 (521.7)	-1.4 (213.9)
25 < Age of Householder < 40	CE	20.6 (13.2)	60.2 (8.4)***	87.4 (16.5)***	24.7 (32.8)	36.9 (51.9)	13.4 (69.8)
(Baseline < 25 years)	HE	443.5 (149)**	379.5 (194.4)	176 (231.4)	14.4 (226.2)	-490 (341.4)	122.3 (328.5)
	OE	536.7 (114.3)***	203.6 (219)	-22.1 (167.3)	-75.2 (263.4)	-645.2 (462.9)	-61.3 (297.9)
40 < Age of Householder < 60	CE	7.4 (14)	43.8 (7.3)***	69.2 (16.4)***	49.6 (33.5)	87.1 (53)	57.5 (69.3)
(Baseline < 25 years)	HE	513.2 (149.3)***	657.9 (194.3)***	631 (236.2)**	502.6 (228.4)*	-149.1 (366.6)	808.8 (326.3)*
	OE	1000.8 (141)***	913.3 (225.3)***	880.9 (169.6)***	870.9 (259.1)***	92 (456.6)	792.7 (295.9)**
60 < Age of Householder < 80	CE	-13.9 (15.3)	19 (9.5)*	69.3 (17.2)***	62.5 (36.8)	104 (54.4)	60.5 (73.3)
(Baseline < 25 years)	HE	645 (160)***	1029.7 (206.7)***	994.4 (242.8)***	1030.2 (232.1)***	1331.6 (433.1)**	1606.1 (345.4)***
	OE	867.8 (154.8)***	591.4 (233.3)*	611.6 (184.5)***	536.8 (276.9)	369.9 (478.1)	656 (313.3)*
80 < Age of Householder	CE	-3 (15.7)	-27.4 (8.3)***	-9.9 (21.8)	-84.1 (42.5)*	19.2 (90.5)	-98.1 (90.9)
(Baseline < 25 years)	HE	791.1 (239.2)***	1899.3 (330.3)***	2058.8 (380.1)***	2297.5 (328.7)***	2616.1 (575.7)***	3038.8 (428.5)***
	OE	252.2 (157.1)	165.6 (276.4)	45.1 (213.7)	-232.6 (348.2)	-1546.7 (563.4)**	-373.9 (388.6)

(CE: Cooling Energy, HE: Heating Energy, OE: Other Energy)

*(p: 0 <***< 0.001 <**' 0.01 <*< 0.05)*

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