Urban metabolism and land use modeling for urban designers and planners: A land use model for the Integrated Urban Metabolism Analysis Tool

URBAN METABOLISM AND LAND USE MODELING FOR URBAN DESIGNERS AND PLANNERS:
A LAND USE MODEL FOR THE INTEGRATED URBAN METABOLISM ANALYSIS TOOL

A Dissertation Presented

by

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To my Loving Mom and Dad

And

my love and best friend Sheema

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ABSTRACT

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Predicting the resource consumption in the built environment and its associated environmental consequences (urban metabolism analysis) is one of the core challenges facing policy-makers and planners seeking to increase the sustainability of urban areas. There is a critical need for a single integrated framework to analyze the consequences of urban growth and eventually predict the impacts of sustainable policies on the urbanscape.

This dissertation presents the development of an Integrated Urban Metabolism Analysis Tool (IUMAT) – an analytical framework that simulates urban metabolism by integrating urban subsystems in a single comprehensive computational environment. It reviews the existing literature on urban sustainability, urban metabolism, as well as introducing the general framework for IUMAT. IUMAT uses three separate models for quantifying environmental impacts of land-use transition, consumption of resources, and transportation. This work outlines the development of IUMAT Land-Use Model that uses Remote Sensing, GIS, and Artificial Neural Networks (ANNs) to predict land use change patterns. By using Density-Based Spatial Clustering and normal equations, this dissertation

introduces a method for generating building-form variables from Light Detection and Ranging (LIDAR) data, which can be used as a new determinant factor in land-use change modeling. The proposed Land-use Model, within IUMAT or other analytical models, can be useful to local planning officials in understanding the complexity of land-use change and developing enhanced land-use policies.

TABLE OF CONTENTS

LIST OF TABLES

Table Page

LIST OF FIGURES

Figure Page

CHAPTER 1

INTRODUCTION

1.1 Sustainable Cities

In the next decade and a half, a majority of the world's population will be living in urban areas, and cities in developing countries are expected to have the fastest growth (UN Population Fund, 2007). Cities are major consumers of the world's primary energy and produce 71 percent of greenhouse gas (GHG) emissions (International Energy Agency, 2008). After World War II, cities faced critical social, economic, and environmental problems due to rapid urban renewal and expansion. Growing public awareness about economic, social, and environmental crises in US urban and suburban areas (Babcock, 1966) precipitated the establishment of the National Environmental Act (NEPA 1970) mandating all federal agencies and major projects funded by the federal government to prepare environmental assessments (Fischer, 2003). In 1987, the United Nations World Commission on Environment and Development published a report that provided a now widely-accepted definition of "sustainable development". The definition of sustainable development is to respond to current human needs without compromising the ability of future generations to meet their own needs (Butlin, 1989). The UN also published Agenda 21 (a UN Action Plan) as an outcome of the 1992 UN summit in Rio, Brazil, outlining strategies for sustainable development and growth (Doyle, 1998). Since then, creating sustainable communities, reducing resource consumption, and minimizing negative environmental impacts have become a key goal of the urban planning and design community.

Agenda 21 outlines strategies for sustainable development, but does not provide a direct application for cities in particular (Doyle, 1998; Newman, 1999). Since ecological footprints of cities extend far from their territories, to create a truly sustainable ecosystem,

the concept of sustainable development has to be integrated into different scales and sectors of urban and suburban areas (Lenzen & Peters, 2010; Næss, 2001).

Sustaining human life means creating a balance between humans and nature while also satisfying the economic and social needs of current and future generations (Fiksel & Frederickson, 2012). The balance between society, economy, and environment (three aspects of sustainable development), is necessary for the creation of this harmony. Scholars have investigated design methods and urban policies to identify key parameters of this balance. Wheeler & Beatley (2004) proposed land-use, urban design, transportation, economic development, environmental justice, social equity, resource use, urban restoration, and green architecture as critical dimensions for sustainable urban development.

In many cases, the complexity and intertwined aspect of urban systems are reflected in solutions developed by researchers. For example to address commuter based transportation-driven air pollution, strategies ranging from improving public transportation to mixed land-use regulations are introduced. Some scholars like Cervero (2004) propose flexible suggestions for promoting sustainable development. Cervero suggests a concept of "*Adaptive cities*" or "*adaptive transit*" for encouraging the public to use public transportation. In his proposal, planners either control urban development by more restricted land-use regulation to create an adaptive urbanscapes within an existing transit system (light railway and subway), or they implement combined transportation systems that are suitable for low-density development. Other researchers such as Gehl (2014) and Pucher et al. (1999) promote cheap and pollution-free alternatives for the same planning problem. Creating walkable and bike-friendly urbanscapes requires implementing strategies that favor compactness, density, and pedestrian infrastructure as well as modifying social behaviors and norms (Pucher et al., 1999).

There are two major driving forces behind creating a balance between environment and society. One is to reduce resource consumption while the other is focused on social-environmental equality. The first effort falls within the context of urban metabolism: to quantify flows of energy, natural resources, and waste into and out of cities in order to advance policies for sustainable urban development. Some scholars like Calthorpe (1993), suggested redefining urbanscape by increasing density in residential areas, improving network connectivity, protecting open space, and promoting Transit-Oriented Development to conserve energy and water. One alternative for resources conservation is controlling urban sprawl by promoting smart growth and regulating restrictive land-use policies. Infill development could encourage construction within municipal boundaries instead of urbanization on green land outside cities. There are many advantages to this approach such as infrastructure cost reductions, improvement of density, and diversification (Wheeler & Beatley, 2004). Expanding energy efficiency building codes and decreasing the cost of renewables may reduce urban energy usage. And to address limited natural resources, sustainable development policies promote recycling and re-manufacturing to replace a 'one-way loop' with a 'closed resource loop cycle' to decrease landfills. In addition, changing social behavior is another key factor in this regard (Girardet, 2004).

The social-environmental equality movement surfaced in the 1980s, when the idea of environmental justice emerged in response to concerns about the fairness of decision process in selections of hazardous sites. Since then, the concept of social-environmental equality expanded, ranging from equitable public places to diversified urban policies. Social-environmental equality includes all citizens regardless of gender or race in the decision-making process of developing and implementing fair policies and regulations. Organizing, educating, and empowering citizens especially by grassroots organizations became part of the

urban sustainability movement to combat social segregation, racial tensions, crime, congestion, and poor environmental quality (Bullard & Johnson, 2000).

Balancing between economic systems and other aspects of sustainable urban development is a challenge. Most economic development approaches do not account for environmental and social factors. The long-term cost of environmental pollution, excessive use of resources, and destruction of the natural environment are absent from most calculations of economic growth (Wheeler & Beatley, 2004). While some scholars (e.g. Hawken et al., 2013; Pearce & Turner, 1990) suggest changing the whole economic structure as a solution, others (e.g., Roseland & Soots, 2007; Shuman, 1998) propose solutions to replace the global economy with local economies and self-reliant communities. Pearce & Turner (1990) developed the concept of environmental economics to integrate these concerns in financial analysis, and Hawken et al., (2013) promoted changing incentives and subsidies to reward sustainable business practices.

Many parameters in urban systems are complexly intertwined. Most of the existing urban problems are outcomes of unbalanced and inclined decisions toward one or multiple variables in urban development such as income inequality in economic development (Trotter, 2004), race specific public policy (Wilson, 2012), social segregation in housing policy (Nelson et al., 2004; Keating, 2000; Sugrue, 2014), displacement of poor minorities in urban renewal (Teitz, 1996), environmental impacts of urban developments (Johnson, 2001), and social injustice in environmental regulation (Nabalamba & Warriner, 1998). Urban planning decisions at different scales influence each other, and success or failure of a decision or a policy often depends on the participation of a wide range of stakeholders in cities (Frey, 2003; Wheeler & Beatley, 2004).

One of the critical concerns of the urban planners and designers is to move toward creating sustainable communities by minimizing resource consumption and negative

environmental impacts. City counselors have implemented policies from neo-traditional development, compact city, urban containment, and eco-city principles to manage the environmental consequences of urban development. Although these efforts have had some positive impact on the urban environment, there are limitations to the ways that micro-scale environmental data can be used to measure and evaluate the social and economic parameters of large-scale sustainability indicators. Lack of empirical research evaluating the effectiveness of urban policy (Bengston et al., 2004), and the inadequacy of advanced methodological approaches for complex urban systems (Ellis, 2002; Gordon & Richardson, 1997) have given rise to mixed results about the effectiveness of these policies (Ellis, 2002; S. Handy, 2005; Jabareen, 2006). Subsequently, the consequences of sustainable policy efforts on urban environments are neither clear nor straightforward (Tanguay et al., 2010).

Planners need to consider interrelated social, economic, and environmental factors to formulate appropriate responses to increased demand for resources, growth in energy and material intensive industries, demographic transitions, urbanization and social disparities, and loss of habitat in rapidly expanding cities (Lehmann 2011). Implementing a reliable urban sustainability analysis tool that can properly address the environmental impacts of urban growth and development will be crucial in the following decades.

1.2 Sustainable Urban Form

In 2003, Frey linked the well-established planning goals of the 'good city', to sustainable development. The 'good city' provides necessities for urban life including housing, infrastructure, accessibility and employment in a safe, secure, aesthetically pleasing physical environment. A good city is a place free from crime, pollution, noise, and accidents. It has a sense of place, appropriate image, good reputation, and prestige for residences. Under a holistic approach to urban design and planning, even if all social, economic and

environmental policies and decisions work together, it is not possible to have a good city unless we consider urban form as a key parameter. There are many unsolved concerns about the relation between urban form and sustainability, however, without damaging natural and cultural resources, urban form can easily be adapted well to the requirements of change and growth (Okata & Murayama, 2011). The relation between urban form and sustainability of cities can be categorized into three sections: formulating indices for quantifying urban forms, investigating the association between urban forms and environmental/social/economic impacts, and exploring an optimum urban form in terms of environmental impacts.

Research on the development of an urban form index grew out of studies on formulating urban sprawl, as a reflection of public concern about racial segregation, resource consumption, and environmental pollution that are typically associated with urban sprawl in the United States. Sprawl is defined differently ranging from low-density development or separation of land-uses to automobile dependency. Lopez and Hynes (2003) defined an urban sprawl index in metropolitan areas by calculating the percentage of total population in high-density versus low-density census tracks. Sutton (2003) introduced a measurable urban sprawl index as a simple regression model between the natural logarithm of urban population and area to fairly compare Urban Sprawl in different districts. In 2003, Ewing et al. included other variables like residential density, land-use mix, concentration degree of activities, and street accessibility in a multi-dimensional sprawl index. This sprawl index is used as four dependent variables of travel and transportation for measuring average vehicles per household, percentage of commuting by public transportation, average of work-travel time, and walking duration.

In addition to urban sprawl, the degree of shape irregularity is another feature in quantifying urban form that shows the relation between the urban spatial pattern and ecological processes. The irregularity of shape is integrated into a shape complexity index by

calculating a fractal ratio of perimeter to area (Huang et al., 2007). This index can be combined with urban continuity that represents the degree of fragmentation among patches in an urbanscape measured as a ratio of the main contiguous to total built-up areas (Bechle et al., 2011). Other indices like compactness index, centrality (average distance of parts to city center), population density, open space ratio are also critical in the urban form analysis (Huang et al., 2007). In a comprehensive study for formulating urban form, Hamidi et al., (2015) redefined and validated the urban sprawl index (Ewing et al., 2003) and compactness by using principal component analysis. In that study, socio-economic parameters with urban form indices were explored in different categories such as land-use mix, development density, and activity centering. The activity centering variable indicates the decentralization of the population and associated activities. Handy and Clifton (2001) measured neighborhood accessibility in the district and urban scale by calculating weighted distributions of different activities based on distance, time, and cost.

For monitoring and assessing the environmental consequence of urbanization, quantifying the spatial pattern of urban form is essential. Urban planners usually employ urban form indices such as urban sprawl and degree of fragmentation in formulating different sustainable strategies. Most studies on the relation between urban forms and sustainability focus on public transportation, travel behavior, accessibility, energy consumption, lifecycle analysis, and ecological assessments. Among them, finding the relation between transportation and land-use pattern or urban form is common. Cervero and Gorham (2009) and Friedman et al. (1994) explore resident travel patterns by comparing different groups like auto-dependent versus pedestrian friendly neighborhoods, or suburban versus urban districts. The oversimplification of urban form parameters, ignoring control variables, and the multicollinearity between variables affects the validity of these studies. Other socioeconomic factors were added to the urban form indices in optimizing urban form and transportation

pattern. In 2006, Newman and Kenworthy investigated the relation between urban population and automobile density and defined the minimum density (population and employment) that would justify public transportation and amenities. Despite using sound empirical methodologies, that study ignored control variables such as environmental, and other urban form parameters.

In 2001, Ewing and Cervero found that travel behavior is a function of the built environment and the socio-economic characteristics of an urban area. However, the significance of this relation relies on different parameters. The study demonstrated that urban design features such as skylines, building facades, open space, and other micro-scale parameters have minimal impact on primary trips (home to work or home to others) but affect secondary trips within an activity district. The general assumption of Ewing and Cervero (2001) study is that urban design is simply focused on small-scale and aesthetic interventions. Scholars like Madanipour (1997) have a different perspective about the scale and scope of urban design. If certain urban features individually affect the travel behavior, it is probable that multiple variables collectively have different impacts on travel patterns. For example, improving sidewalks could improve walkability and accessibility of local roads, but have no impact on regional transit patterns. Creating composite parameters may be helpful in this respect. Cambridge Systematics (1994) combined twenty independent land-use and urban design variables into five principal components such as mixed land-use, availability of convenience services, accessibility of services, public safety, and aesthetically pleasing environment. On the other hand, most scholars believe single regression modeling is not enough for capturing the complex interactions between urban form and travel behavior. For example, in contrast to Ewing and Cervero (2001), Chao and Qing, (2011) suggest that urban form has no direct influence over VMT or transportation energy consumption. It indirectly affects the householder's behavior like the type of car they purchase.

Urban design impacts energy use in other ways as well. Green urban infrastructure promotes healthy ecosystems, clean air, recreation, urban cohesiveness by moderating local climate, and preserving natural environment (Alberti, 2000). Replacing the natural environment with built forms creates more constructed surfaces that absorb more solar radiation and reduce natural cooling effects such as evapotranspiration and tree shading. Transportation and building systems also generate more waste heat and increase the urban heat island index. Ewing and Rong (2008) propose a framework for understanding the relation between urban form and residential energy consumption by using the urban sprawl index introduced by Ewing et al., 2003. This study introduces housing choices and urban heat island effect (local temperature) as mediators for determining the association between urban form indices and residential energy use. Norman et al. (2006) investigate the relationship between urban density and energy use with GHG emissions by implementing Life Cycle Analysis (LCA) method. Despite oversimplification and many subjective assumptions about urban systems, their study shows low-density developments are more energy and GHG emissions intensive compared to high-density districts. It also shows that defining an appropriate unit of analysis can affect the conclusion in a study. For example, by changing the unit from GHG per square meter to GHG per person, differences between low and high-density districts increase significantly.

Glaeser and Kahn (2010) combine transportation and householder energy use in GHG emissions and found a negative association between land-use regulation and GHG emissions. This study concluded that more restricted land-use regulations push new developments from denser areas like city centers to places, which produce more GHG emissions like suburban areas. On the other hand, Stone and Rodgers (2001) show that higher density development contributes more radiant heat energy to heat island emissions compared to lower density development.

Until the last decade, it was generally accepted that a compact city is an optimum sustainable urban form. Researchers are investigating the difference between compact and dispersed developments for improving urban form (Williams et al., 2000). Newton (2000) studied the environmental impacts of edge cities, corridor cities, and fringe cities as alternative scenarios for future urban growth. The concept of compact cities, as an ideal sustainable urban form, has received both credit and critique. Improving social interactions, safety, energy efficiency, accessibility and affordable public transportation are a few positive arguments for the compact city. However, as congestion escalates, high financial incentives for social controls and limited open spaces are some negative arguments against this concept (Ellis, 2002; Frey, 2003; Gordon & Richardson, 1997). Researchers also investigate other parameters such as density, concentration, dispersal, and mixed use to find an effective balance between urban form and sustainability (Williams et al., 2000, Buxton, 2000; Newton et al., 2000).

There is no universal definition for sustainable urban form. Some researchers like Newman and Kenworthy (1989) suggest centralized urbanscape with higher density, while others like Owens and Rickaby (1992) list centralized and decentralized districts, as sustainable development patterns. In these examples, the primary difference is in selecting a homogenous monocentric pattern or polycentric development (Frey, 2003). Decentralized independent communities linked by public transportation are also suggested as another form of sustainable city structure (Haughton & Hunter, 2004). Frey (2003) studied four hypothetical alternatives (core, satellite, linear, and polycentric) of macro-structure for urban form with the same population and open space ratio. The study concluded that there is not a single urban form that fulfilled all sustainability criteria. Each model has advantages and disadvantages, depending on weighting and design priorities. Guy and Marvin (2000) argued

that instead of searching for one ideal sustainable urban form, multiple sustainable forms are needed based on diversified necessities and requirement of urban settlements.

Jabareen (2006) summarized the concept of sustainable urban forms into seven design strategies: high density, mixed land-uses, compactness, social and cultural diversity, passive solar strategies, increasing green infrastructure, and sustainable transportation. These approaches are categorized into four types of sustainable development: neo-traditional development, urban containment, compact city, and eco-city (Jabareen, 2006). Most attempts to achieve sustainable cities are focused not only on urban form but also on other sustainability aspects such as ecological footprint (Holden, 2004), political dimension (Bulkeley & Betsill, 2005), urban agriculture (Smith & Nasr, 1992), and quality of life (McMahon, 2002). Different urban forms can offer diverse qualities of sustainability (Frey, 2003, Burton et al., 2003), despite the fact that a single model of sustainable urban form is not applicable in all situations (Guy and Marvin, 2000), there are widely accepted principles of sustainable urban form that serve for evaluating different scenarios (Scheer & Scheer 2002). The overall urban fabric is still considered a powerful connector of the integrated, interlinked, and complex sustainability variables, and has direct impact on the success or failure of sustainability policies.

1.3 Sustainable Development Assessment in Cities

UN Commission on Sustainable Development (CSD) in 1992 published a list of indicators covering environmental, social, economic and institutional aspects of sustainable development. Later, CSD created a hierarchical framework for governmental assessment that grouped sustainable indicators in fifteen main topics and 38 sub-topics (Singh et al., 2009). Now, it has become common for city officials, state, regional governments, and even small organizations to implement models for Sustainable Development Assessment. These models

can also be used in decision-making processes or as public participatory tools. Using simple and visual techniques to present the results of complex quantitative analysis is helpful for officials and public to comprehend complicated and intertwined phenomena (Warhurst, 2002).

One of the challenges in formulating a Sustainable Development Assessment model is defining individual sustainability indicators and composite indicators. In 2005, Krajnc and Glavič used a framework of sustainability indicators and grouped them into social, economic, and environmental categories. Indicators were normalized and weighted using an analytic hierarchy process. By summing up the values from sub-indices, a sustainable composite index can be obtained. Selection and combination of indicators depend on organizational values, which could be altered depending on goals and conclusion about sustainable development (Singh et al., 2009). For example, Circle of Sustainability by Global Compact Cities Programme recommends understanding urban social life across an integrated series of economical, ecological, political and cultural indicators, while in ecosystem-based indices, the sustainability process index measures the process of production from raw material to accommodation and installation in the biosphere (Narodoslawsky & Krotscheck, 1995). Urban Sustainability Index, City Development Index, Sustainable Cities Index, Compass Index of Sustainability are some comprehensive indices developed for implementation in cities. In 2002, Zhang developed 22 individual indicators for calculating Urban Sustainability Index. By using an analytical hierarchy process, these indicators are weighted for providing scores for three urban sustainability areas: the urban coordination, development capacity, and urban development potential. City Development Index designed by UN Human Settlements (HABITAT) is composed of five weighted indices: infrastructure, waste, education, health, and production index. Normalization value of City Development Index ranging between zero to hundred is used to rank cities based on development level (Böhringer & Jochem, 2007).

Other examples are designed to deal with specific programs (such as Sustainable Seattle for confronting public health crises). This method operates in a broader context by covering issues such as resources and population change, environment, economy, and education.

Most sustainable assessment methods use the familiar triangular model with three vertices of environment, economy, and society for measuring a multitude of combinations of strategies and targets, in contrast, Ness et al. (2007) suggests a framework, which includes indicators, product-related assessment, and integrated assessment. Indicators are categorized into integrated (like ecological footprint and wellbeing index), regional flow indicators (like input and output analysis and substance flow analysis), and non-integrated variables. Product-related assessment consists of product/service related analysis for capturing energy flow of material or product and breaks into life cycle assessment, life cycle costing, material flow analysis, and energy flow analysis. And integrated assessment tool analyzes regional/local projects and policies based on system analysis approaches like Risk and Vulnerability Analysis. To account for uncertainties in the real world, Peterson et al. (2003) suggest contrasting hypothesis and scenario planning to explore the consequences of a decision. Combinations of scenario planning, incorporating qualitative, and quantitative information with sustainable assessment techniques can create a robust tool for measuring urban sustainability.

Despite scientific approaches applied to sustainable assessment methods, there is still a high degree of subjectivity in initial assumptions (Singh et al., 2009). Tanguay et al. (2010) analyzed local indicators for measuring the sustainability in cities. Around two hundred indicators from 17 different studies are categorized into three aspects of sustainability development: environmental, economic, and social dimensions. Tanguay et al. concluded that only 15% of indicators are used more than four times in different studies. This study reveals the lack of consensus on definition and standardization of sustainability indicators. In 2009,

Singh et al. provided an overview of sustainable indices and methodological approaches implemented to measure sustainable development. The study concluded that there are subjective judgments in normalizing and weighting these indicators. And few attempts considered an integrated approach for measuring economic, social and environmental aspects for creating composite indicators. The process of constructing composite indicators is also important, since, poorly designed composite indicators could provide misleading guidelines. Other challenges like lack of information at local or district level, uncertainty in the quality of data, and inconsistency in classification could affect the comparability of results (Pannell, 1997). Achieving sustainable communities cannot be feasible unless policies, decisions, and designs incorporating the complexity of urban systems are combined in a comprehensive approach. Sustainable assessment indicators are defined subjectively in relation to particular goals and organized in different analytical structures. For developing a robust methodology, it is necessary to define well-established goals towards sustainability that are selected by the appropriate communities of interest.

1.4 Urban Metabolism

In 1965, Wolman published a pioneering paper about the metabolism of cities. This research was a response to the shortage of water and pollution of air in American cities as a result of rapid urban growth and provides the fundamental basis for researchers working on the quantitative assessment of urban flows. In his analysis, Wolman calculates the overall flow of energy, material, water and waste in a hypothetical American urban district with a population over 1 million. This study mostly concentrated on sanitary water systems presents a simplified version of urban metabolism, and for the first time, Wolman introduced a holistic quantifying approach for capturing footprints of intertwined urban systems. Since then, researchers have explored urban metabolism analysis in real cities such as Tokyo (Hanya &

Ambe, 1976), Brussels (Duvigneaud & Denayeyer-De Smet, 1977), and Hong Kong (Newcombe et al., 1978). After four decades, the urban metabolism analysis is still prevalent in analyzing urban systems (Færge et al., 2001; Huang & Hsu, 2003; Zhang et al., 2009).

Urban metabolism is a metaphorical framework to study the interactions of natural and human systems in urban districts. Urban metabolism refers to "*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 of quantifying material, energy, water and waste flows in an urban area (Sahely et al., 2003). In 2011, Kennedy et al. proposed four applications of urban metabolism: defining sustainability indicators, urban GHG accounting, developing dynamic mathematical models for policy analysis, and creating design tools.

Qualitative and quantitative methods are two general approaches to urban metabolism analysis (Heynen et al., 2006 & Tarr, 2002). Qualitative method categorized under political science suggests urban political ecology to solve interconnected political, social, economic and ecological processes. Quantitative method considered urban metabolism under energy equivalents and mass flux (Material Flow Analysis) concerning flows of water, materials, and nutrients within urbanscape (e.g. Odum, 1983, Heynen et al., 2006 & Tarr, 2002). Implementing the thermodynamic approach in capturing ecology and ecological economics proposed by Odum (1996), and Brown & Ulgiati (1997) opened a new analytical framework for simulating interaction between natural and urban environments. In 1999, Newman furthered the idea of Urban Metabolism to "Extended Metabolism" by including livability factors in the analysis of the urban systems. The Extended Metabolism model employs additional indicators such as socioeconomic factors, health, and leisure to improve the quality of life in urbanscapes while reducing resource consumption and waste production.

Most of the empirical studies break down urban systems into a separate framework and develop individual models for one or multiple features of urbanscape (e.g. Sahely and Kennedy (2007) addressing water-related issues, Hammer and Giljum (2006) on material stocks and flows). Different tools have been developed for simulating urban metabolism. iTEAM (Integrated Transportation and Energy Activity-Based Model) employs micro-simulation agent-based for evaluating policies and predicts future energy consumption by converting agents' decisions to energy demands (Almeida et al., 2009). Other tools such as CitySim implements a normative methodology for optimizing urban resource flows instead of projecting their future state (Robinson et al., 2009). SynCity, integrated tool for modeling urban energy systems, simulates citizens' activities for calculating resource demands (Keirstead et al., 2010). A more comprehensive tool, UrbanSim, predicts behaviors of urban agents by integrating three interrelated urban systems; land-use, transportation and the environment (Vanegas et al., 2009). Despite some conceptual commonalities, these simulation tools are developed to capture a certain property of specific urban spaces with particular modeling targets (Mostafavi et al., 2014) and do not consider urban systems as a cohesive and interrelated structure. Existing urban metabolism analysis tools like CitySim (Robinson et al., 2009) and SynCity (Keirstead et al., 2010) simulate urbanscapes in a single scale and do not adjust modeling framework based on the essence of the phenomenon. Lack of robust methods in dealing with uncertainty and multidimensionality especially in capturing human behavior is still a significant problem in modeling urban systems. And finally, most existing simulation tools are relatively weak in visualizing mathematical results of urban simulations. This weakness might damage their practical implications in planning and design process.

Urban metabolism analysis is a comprehensive assessment tool for planners, designers, and policy makers and provides tangible perspective about energy efficiency,

emission control, material cycling, waste management, and effectiveness of infrastructure within urbanscape. In other words, urban metabolism analysis evaluates environmental impacts of policy and design scenarios. Designing an urban simulation tool that captures the complexities of an urban system is not trivial. Even assigning 'buildings' as the simplest unit in urbanscape is complicated when combined with other economic, social, and environmental factors. One way to account for urban complexity is to maximize the number of explanatory variables that affect the desired dependent variables. Even if we assumed that the changes in an urbanscape are regulated by a simple mechanism, due to numbers of possible options for the subsystem, the level of complexity is still high. Moreover, subsystem interdependency is dynamic and fluctuates between different states

1.5 Research Goals

There is a critical need for a single integrated framework to analyze the consequences of urban growth and eventually predict the impacts of sustainable policies on the urbanscape. Interrelation and complexity of urban systems require the simulation approach that simultaneously integrates socioeconomic, physical, and environmental features of urbanscape. This dissertation aims to address this need by developing a tool – an ***Integrated Urban Metabolism Analysis Tool (IUMAT)*** – an analytical framework that simulates urban metabolism by integrating urban subsystems in a single comprehensive computational environment.

IUMAT will quantify the environmental impacts driven by decisions/policies/designs within an urban region.

The IUMAT framework also includes livability factors such as health, employment, income, education, leisure activities and accessibility. IUMAT integrates different databases and creates statistical associations between socioeconomic parameters with other spatial

factors. IUMAT focuses on five major indicators of urban metabolism: land-use, energy consumption, water use, material resources, and air quality. The framework applies these indicators into three separate models: Land-Use Model, Transportation Model, and EMW (Energy, Material, and Water) Model. In the simulation process, these models work together, and one model may call for results of another model when it is necessary. My overall research questions are:

How to create a holistic framework that can assist city officials to understand the overall sustainability of a city? What are the parameters in land-use, physical, environmental, cultural, institutional, socioeconomic variables that can be implemented in urban metabolism analysis?

Within IUMAT framework, my research focuses on developing a framework for the Land-Use Model to assist urban designers and planners in policymaking. The body of scholarship on the relationship and environmental impacts of land-use and urban form is extensive. Most of the previous work (Friedman et al., 1994; Ewing & Cervero, 2001; Newman & Kenworthy, 2006; Cervero & Gorham, 2009) focused on the effects of urban sprawl on travel behavior and transportation trends in metropolitan areas. The recent versions of these studies (Chao & Qing, 2011) integrate socioeconomic factors in urban sprawl. Despite lingering questions about validity and accuracy, existing research (eg. Hamidi et al., 2015; Chao & Qing, 2011) indicates that integration of more variables into the analysis improves model predictions about human behavior and urban systems.

In the IUMAT Land-Use Model, the effects of different urban activity parameters that differ from one place to another can be explored, and different conclusions/planning decisions could be formulated based on various hypotheses and models. The IUMAT Land-Use Model uses an Artificial Neural Networks structure. The emergence, relation, and

interaction of urban units are governed by dynamic sets of algorithms that are generated through an automated learning process. My research goal is:

To test the effectiveness of using the Artificial Neural Networks and pattern recognition techniques to analyze land-use change and predict future development patterns

In this study, I develop a land-use model within IUMAT framework and examine different combinations of explanatory variables for predicting land-use transformation. I investigate research gaps in existing land-use models and propose alternatives within the IUMAT Land-use Model (IUMAT-LUM). Methodologically, I focus on identifying the appropriate computational approaches for optimizing of the interaction between involving parameters in predicting changes in land-use and building form. I also investigate weather unsupervised machine learning and pattern recognition techniques are appropriate in this area.

1.6 Dissertation Structure

The remainder of my dissertation is organized into five chapters. The second chapter defines the concept of the urban metabolism and its relations to sustainability. It reviews the empirical literature and the existing urban metabolism simulation tools. It outlines our methodology to metabolism analysis and introduces Integrated Urban Metabolism Analysis Tool (IUMAT). Chapter 3 specifies analytical models characterized the dynamics of choice, time, and scale in the IUMAT framework. It presents Land-Use, Transportation, and EMW (Energy, Water and Materials) models within IUMAT framework. This chapter describes the modeling structure as well as modeling methodologies. Chapter 4 defines the IUMAT-LUM modeling structure and describes emerging methods in modeling land-use changes. It outlines our approach to generating building form variables from LIDAR measurements and other explanatory variables from GIS vector databases. I present a case study, the implementation

of the proposed IUMAT-LUM framework to the town of Amherst in Massachusetts. Different scenarios are used for generating multiple land-use models. In the final and concluding chapter (5), I discuss what we have been able to accomplish with IUMAT-LUM and the limitations of the research as well as a discussion of future directions and goals for the IUMAT framework.

1.7 Roles and Responsibilities

In 2012, Dr. Simi Hoque introduced the idea of IUMAT, an urban scale analytical tool. IUMAT is a collaborative project developed by the Green Building research group in the UMass Building Systems graduate program over the last four years. In collaboration with Nariman Mostafavi, a Ph.D. candidate in Building Systems, we published two papers about IUMAT and the IUMAT framework in peer-reviewed journals (Mostafavi, Farzinmoghadam & Hoque, 2014; Mostafavi et al., 2014); these are chapters two and three, respectively. We also presented the IUMAT framework and energy modeling approach at the Association of Collegiate Schools of Planning (ACSP) conferences; 55th Annual ACSP Conference (Mostafavi, Farzinmoghadam, & Hoque, 2015) and 54th Annual ACSP Conference (Mostafavi, Farzinmoghadam, & Hoque, 2014). Dr. Hoque supervises the overall management and the timing of this project while providing research guidance to the team, which is supported by Urban Planning professors, Elisabeth Hamin and Henry Renski. Chapter 2 of this dissertation, Integrated Urban Metabolism Analysis Tool (IUMAT), is the first IUMAT project's publication. Chapter 3, a framework for integrated urban metabolism analysis tool (IUMAT), is about the IUMAT modeling structure. This interdisciplinary project represents a collaborative effort among faculty and students in the Regional Planning and Building Construction Technology programs. Table 1.1 presents my roles and responsibilities in the first two IUMAT papers. For the remainder of my Ph.D. studies, I was

solely responsible for research on IUMAT Land-Use Model, which is presented in the last three chapters of this dissertation.

Table 1.1: My roles and responsibilities for first two IUMAT papers

	Section	**Responsibility**
2.3	Background and Literature Review	Contributor for the section
2.4	Urban Metabolism and Sustainability	Leader for the section
		Prepared Graphic
2.5	Urban Metabolism Simulation Tools	Contributor for the section
2.6	IUMAT	Contributor for the section
		Prepared Graphic
2.7	Conclusion	Contributor for the section
3.2	Introduction	Contributor for the section
3.3	Background	Contributor for the section
3.4	Overview of IUMAT framework	Contributor for the section
3.5	Demographic Factor	Contributor for the section
3.7	Land cover	Leader for the section
3.8	Transportation	Leader for the section
		Prepare Graphic
3.9	Energy, water and materials	Contributor for the section
		Prepared Graphic
3.10	Aggregation	Leader for the section
		Prepared Graphic
3.11	Conclusion	Contributor for the section

CHAPTER 2

INTEGRATED URBAN METABOLISM ANALYSIS TOOL (IUMAT)

The following chapter was published in the Urban Policy and Research Journal, Volume 32(1), in October 2013; the text below is the same as that publication. Nariman Mostafavi, Dr. Simi Hoque (Corresponding Author), and Dr. Benjamin Weil are other coauthors in this published article. The following citation can be used for citing this paper:

Mostafavi, N., Farzinmoghadam, M., Hoque, S., & Weil, B. (2014). Integrated urban metabolism analysis tool (IUMAT). Urban Policy and Research, 32(1), 53-69.

2.1 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.

2.2 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 counselors 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.

2.3 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 & Ambe, 1976), Brussels (Duvigneaud & 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 timeframes 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 & Ulgiati, 1997). While Odum's method has not become mainstream, 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 low lands. 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 Hu¨ttler (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. The´riault 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 Burstro¨m et al. (2003) for Stockholm. Færge et al. developed a nutrient balance model considering the nitrogen and phosphorous cycle for Bangkok province. Burstro¨m 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, Bergba¨ck et al. (2001), SoKrme et al. (2001) and Svide´n 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 large scale 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 modeling 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 modeling 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 modeled. 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.

2.4 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 periurban areas in some analyses (Lenzen & 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 2.1).

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).

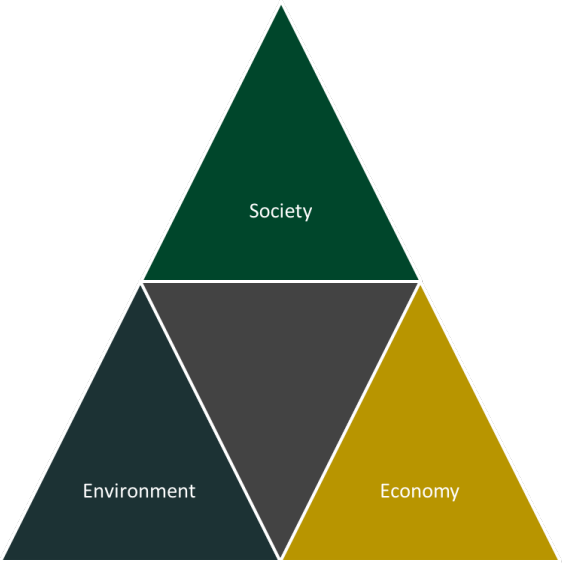

Figure 2.1: Triangular model of sustainable development

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 do 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.

2.5 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 & 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 modeling 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 modeling 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).

2.6 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 modeling 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–life style, needs approaches and methods that go beyond traditional boundaries between familiar disciplines. A new methodology and modeling 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 2.2).

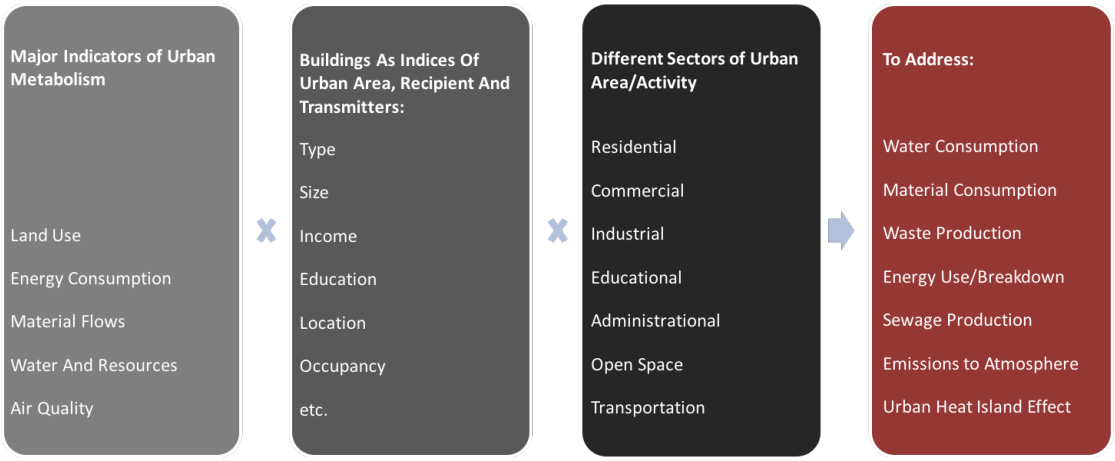

Figure 2.2: Variables and outcomes of the urban metabolism analysis tool

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 2.3, 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).

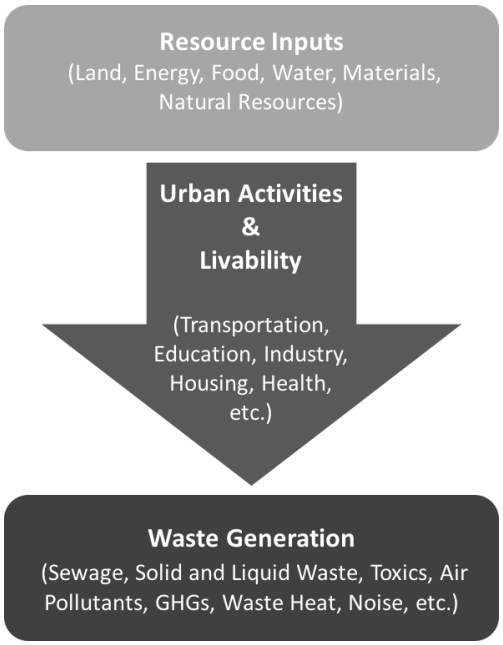

Figure 2.3: Trend from resources to livability and waste

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 2.4). 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 categorize 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.

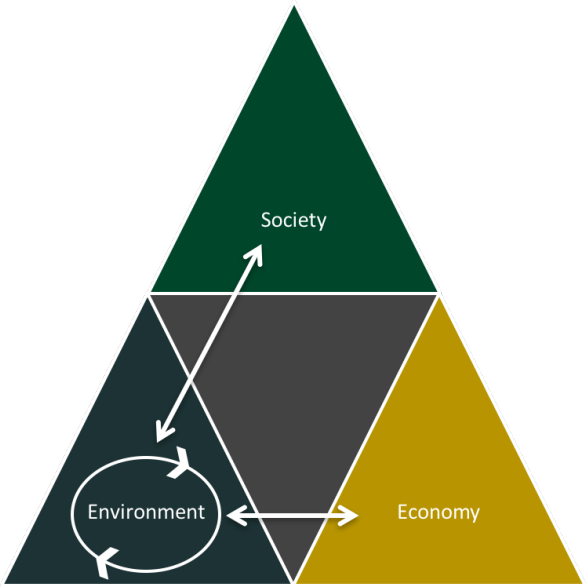

Figure 2.4: Inter-flows and intra-flows to be investigated by IUMAT

2.7 Conclusion

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 3

A FRAMEWORK FOR INTEGRATED URBAN METABOLISM ANALYSIS TOOL (IUMAT)

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3.1 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 models for land cover, transportation, and energy/water/resource use are described as well as the modality of connections between the models.

3.2 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 (P_erez-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.

3.3 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 & 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.

3.4 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.

3.4.1 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 prime 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.

3.4.2 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 & 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.

3.4.3 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.

3.5 Demographic Factor

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 & 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.

3.6 Economic Factor

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 & 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.

3.7 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 & 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 & 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 (Land based classification system, 2016). 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 3.1).

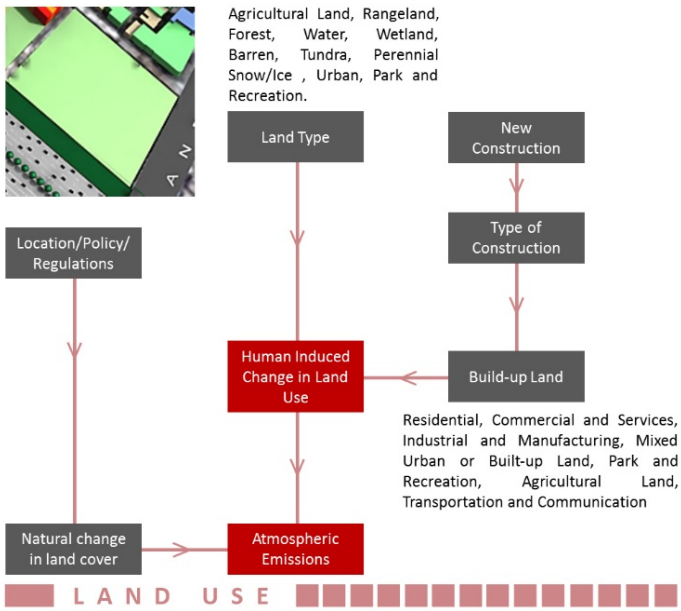

Figure 3.1: Land Use analysis algorithms for IUMAT

3.8 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 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 3.2).

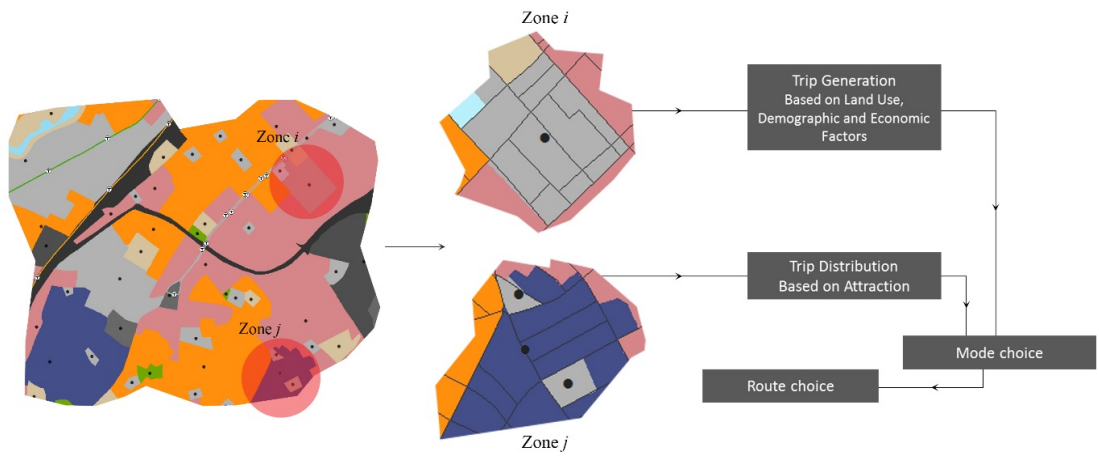

Figure 3.2: Four-step travel demand prediction model used by IUMAT

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 3.3).

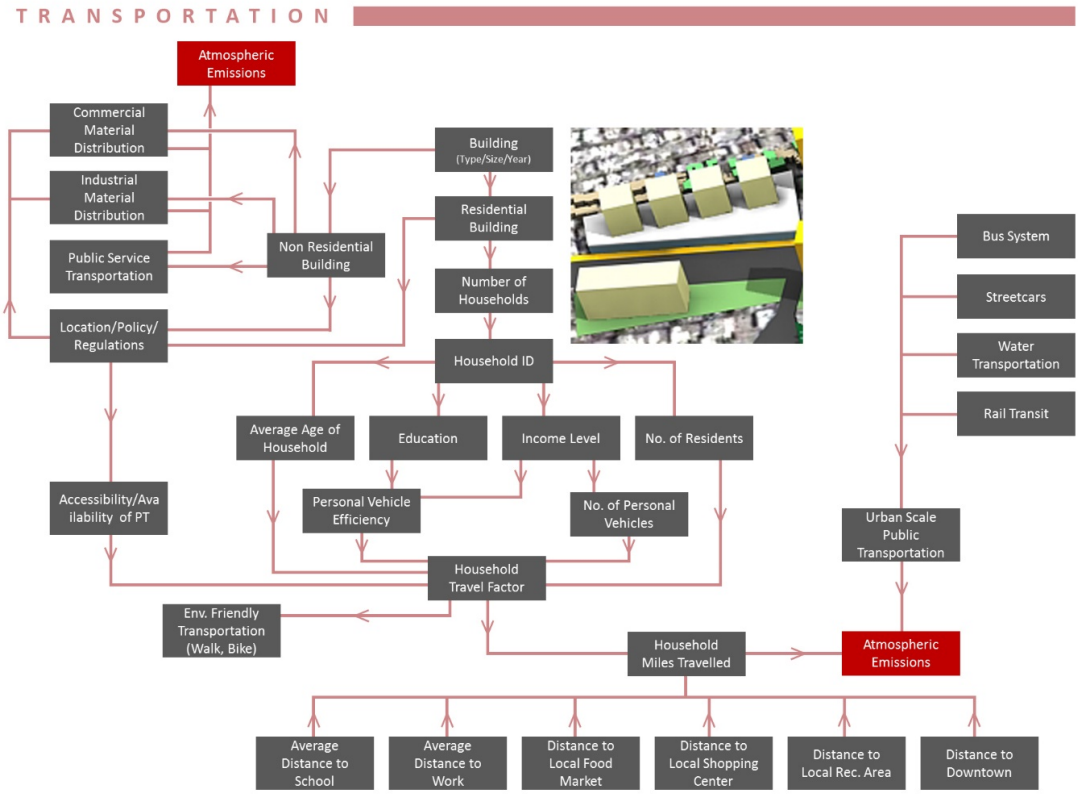

Figure 3.3: Transportation algorithms for IUMAT

3.9 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 Figure 3.4 and Figure 3.5.

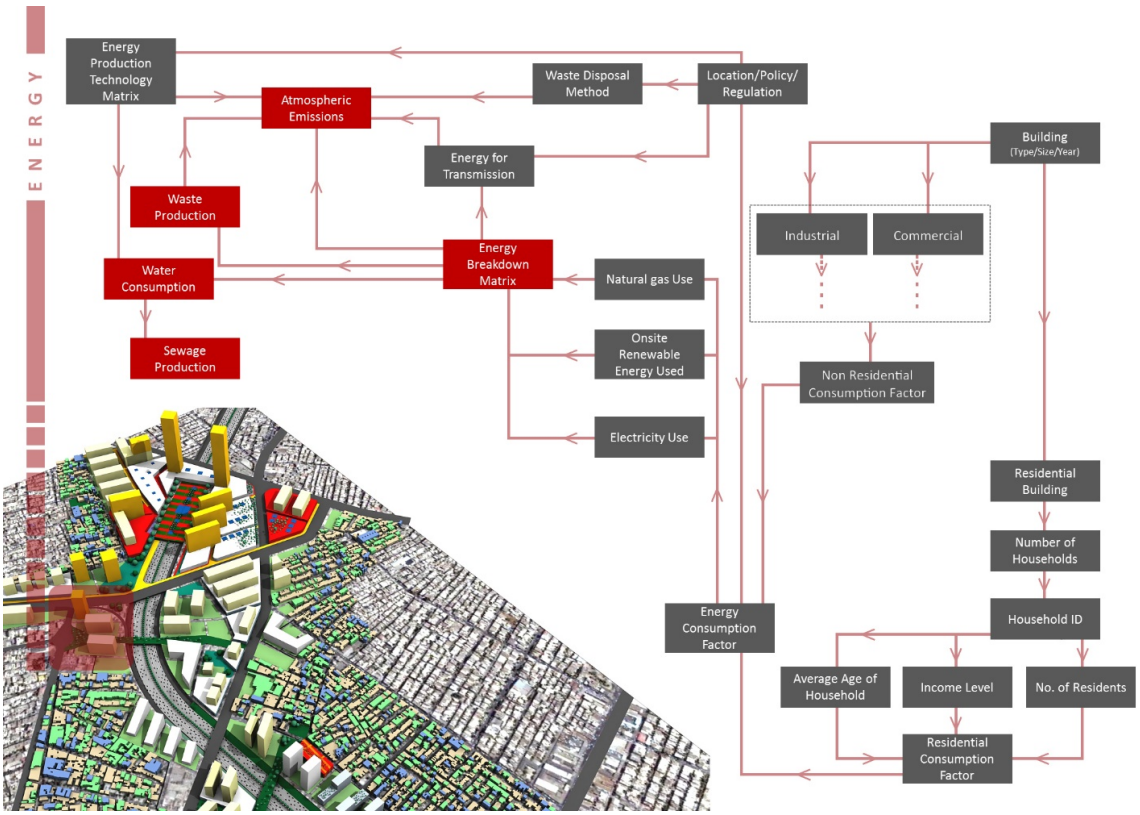

Figure 3.4: Energy use algorithms for IUMAT

For a list of organizations and manufacturing unit types the North American Industry Classification System (NAICS, 2016), which has replaced the Standard Industrial Classification (SIC) in 1997 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, 2016).

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 are is more likely to be of a $f(x) = \frac{ax^2}{b^2 + x^2}$ 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 $g(x) = cx^d$ ($0 < d < 1$) 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.

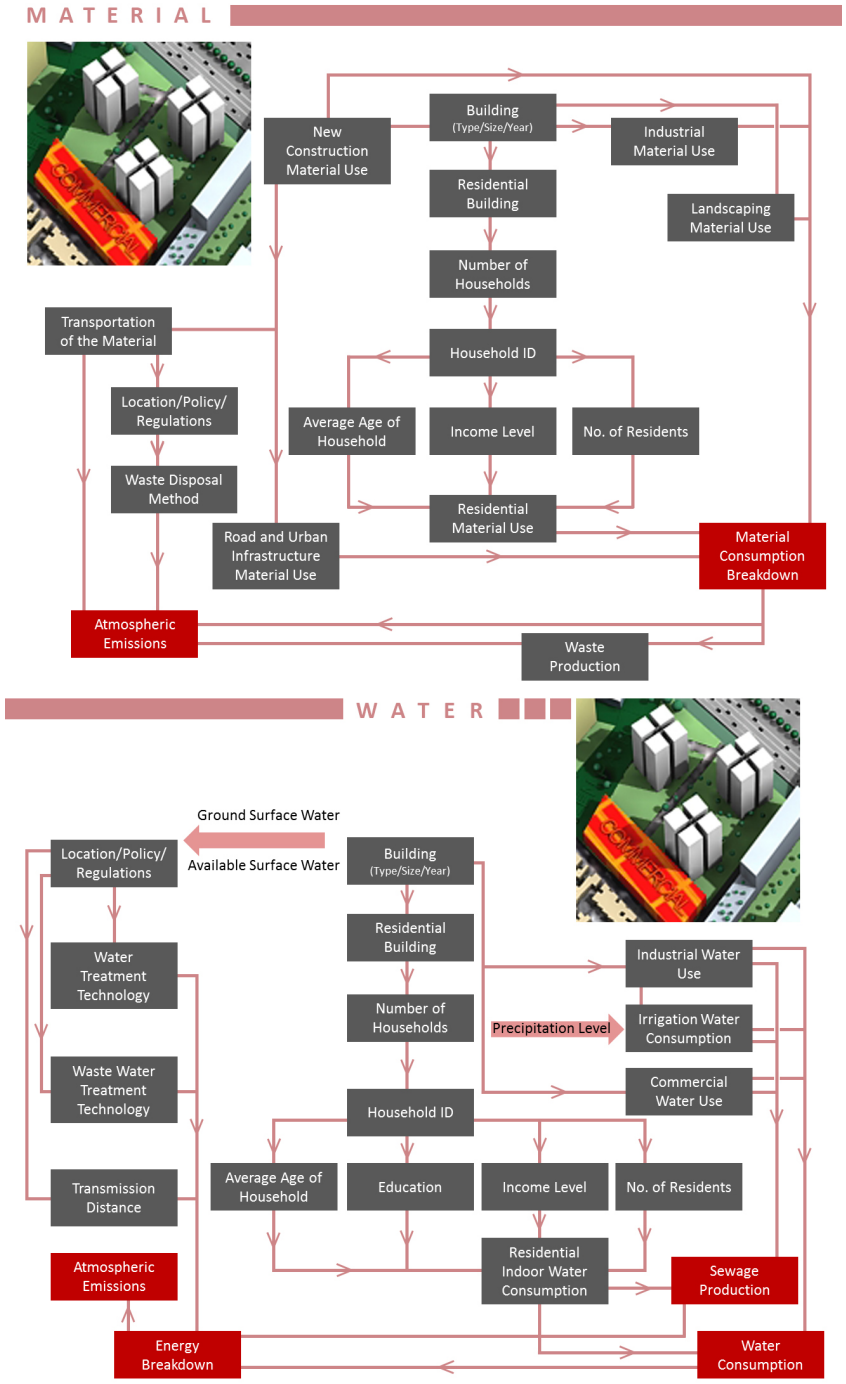

Figure 3.5: Water and material use algorithm

3.10 Aggregation

IUMAT holistic framework (Figure 3.6) 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. Models that are the main simulation engines for capturing the urban metabolism features.

d. Coordinators that are responsible for data distribution between the models.

Each of these components consists of different sub-units such as data generator model, spatial data store, IUMAT wizard connector, metabolism models, 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 Model (EMW Model), Transportation Model and Land Use Model 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 models. With respect to local regulations and policies, users are able to actively manage modeling coefficients and parameters within the models. The Wizard connector forwards projected data and real-time data to the Calibration Model that provides statistical comparison results and marginal errors for users' review. Based on statistical results, this Model also provides suggestions for calibration of the simulation models. The Result Aggregator Model 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.

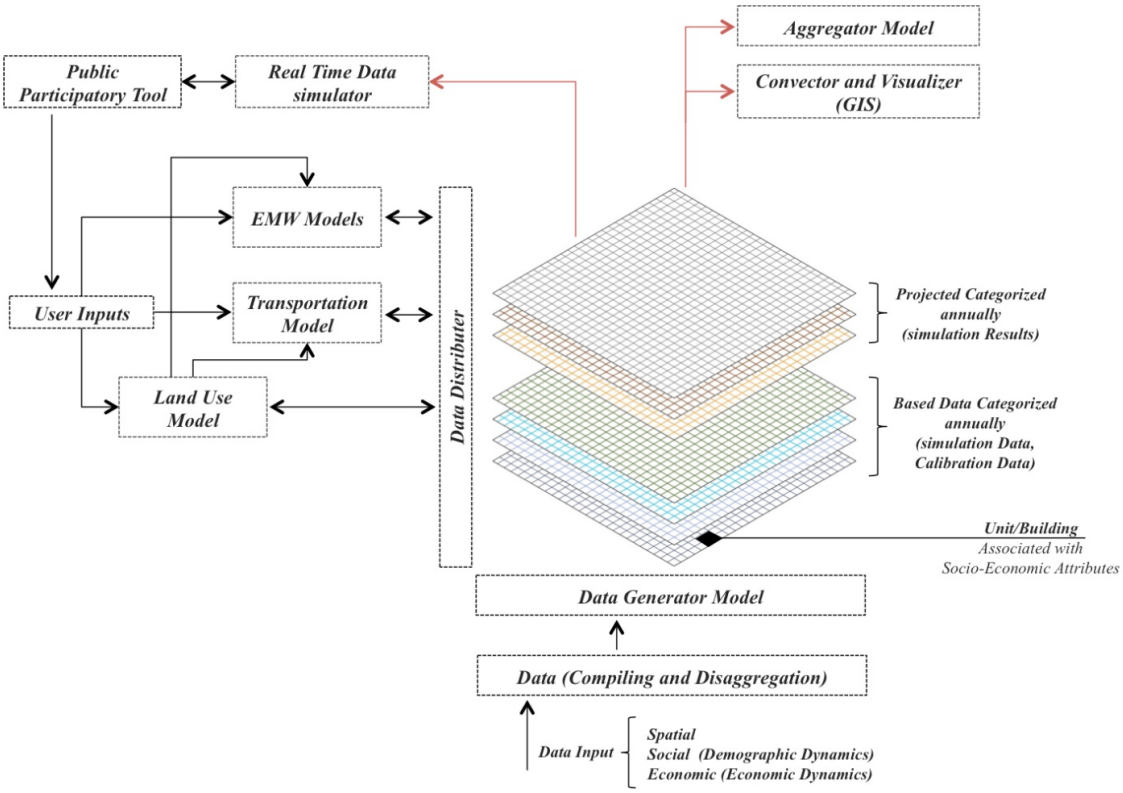

Figure 3.6: IUMAT holistic structure

3.11 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 4

DEVELOPING AN AUTOMATED METHOD FOR THE APPLICATION OF LIDAR IN IUMAT LAND-USE MODEL: ANALYSIS OF LAND-USE CHANGES USING BUILDING-FORM PARAMETERIZATION, GIS, AND ARTIFICIAL NEURAL NETWORKS

The following chapter will be submitted to the Computers, Environment and Urban systems Journal. Nariman Mostafavi and Dr. Simi Hoque (Corresponding Author) are other coauthors in this article.

4.1 Abstract

Predicting the resource consumption in the built environment and its associated environmental consequences (urban metabolism analysis) is one of the core challenges facing policy-makers and planners seeking to increase the sustainability of urban areas. The study of land-use change has many implications in infrastructure design, resource allocation, and urban metabolism simulation. This paper presents a Land-use Model that uses Remote Sensing, GIS, and Artificial Neural Networks (ANNs) to predict urban growth patterns within the IUMAT framework (Integrated Urban Metabolism Analysis Tool), which is an analytical platform for quantifying overall sustainability in the urbanscape.

Our work outlines a method for generating building-form variables from Light Detection and Ranging (LIDAR) data by using Density-Based Spatial Clustering and normal equations. In addition to physical, institutional, cultural, and environmental parameters commonly studied, building form is introduced as a new determinant factor in land-use change modeling. Land-use data, transportation arteries, physical and environmental characteristics, and building forms are converted into a spatial grid system with a 6x6 meters

cell resolution. We apply kernel density estimation techniques and Euclidean distance to the nearest neighboring cell (K-dimensional-tree algorithm) for generating explanatory variables such as density, proximity, and land cover estimates.

The Town of Amherst in Western Massachusetts for the period of 1971-2005 is used as a case study for testing the model. We employ a backpropagation method for training the ANNs models based on explanatory variables. A computer algorithm calibrates and statistically tests the ANNs models based on calibration and test data for selecting the optimum ANNs model with the lowest error on the calibration data. ANNs modeling is used to avoid the subjectivity of modelers or data format in the results. By isolating the weights of each explanatory variable in the models, this study highlights the influence of building geometry on future development scenarios. This Land-use Model, within IUMAT or other analytical models, may be useful to local planning officials in understanding the complexity of land-use change and developing enhanced land-use policies.

4.2 Introduction

Mountain snowpack declination (Mote et al., 2005), unprecedented drought in California (Mann & Gleick, 2015), and Atlantic Hurricane trends (Mann & Emanuel, 2006) are some examples of the changing climate and as the U.N. Climate Chief clearly expressed "This transformation is unstoppable" (UN releases draft agreement on climate change, 2015). Human activities and rapid urbanization are two major sources of GHG emissions (International Energy Agency, 2008, Grimm et al., 2008). While the world population living in the urban or suburban areas is expected to grow 25 percent between 2011 and 2050 (Crossette et al., 2011), more studies provide evidence highlighting strong association between land-use change and climate change (Melton et al., 2016, Heald & Spracklen, 2015,

Pielke et al., 2002). Planners develop policies for minimizing environmental impacts of land-use change like air pollution (Mage et al., 1996), waste (Kennedy et al., 2009), and soil erosion (Chen, 2007) in urban and suburban districts. However, understanding the processes and parameters involved in land-use transition remains one of the most challenging tasks in the planning community. To address this issue, planners have employed advanced methods such as Cellular Automata and Artificial Neural Networks to capture land-use change. Land-use models improve our perception of the causes and consequences of existing spatial pattern, and the extent of future changes (Verburg et al., 2004).

4.2.1 Existing Land-use Model and Modeling Approach

Early land-use models with deterministic approaches concentrated solely on modeling deforestation (Lambin, 1997). More recent methods implement dynamic methods to simulate complex land cover changes like urbanization (Carrero et al., 2014). Land-use and urban models can be categorized based on modeling approaches: spatial approaches, dynamics of time and scale, and planning applications (Silva & Wu, 2012). These models investigate the interaction of involved parameters at a micro scale (eg. TLUMIP (Weidner et al., 2009), UrbanSim (Waddell et al., 2003), ILUMASS (Wagner & Wegener, 2007)), or a macro scale (eg. LTM (Pijanowski et al., 2002)), or at multiple scales (eg. WiVsim (Spahn and Lenz, 2007)). Land-use changes and urban growth models in the long term (eg. FEARLUS, Cioffi-Revilla & Gotts, 2003), medium term (eg. CLUE-S (Verburg et al., 2002)), or short term are developed for different planning tasks (Silva & Wu, 2012).

Cellular Automata (CA) based models (eg. SLEUTH (Jantz et al., 2010), iCity (Stevens et al., 2007), Metronamica (van Delden et al., 2005)), Agent-Based Models (eg. STAU-Wien (Loibl & Toetzer, 2003), SIMPOP (Sanders et al., 1997)), Genetic Algorithms

(Tseng et al., 2008), and Artificial Neural Networks (eg. ART-MMAP (Liu & Seto, 2008; Omrani et al., 2012; Pijanowski et al., 2014) are four intelligent approaches to modeling land-use changes. CA models and Agent-Based Models work with spatial data while other methods need to be integrated with other spatial techniques (Carrero et al., 2014). CA is used for capturing long term conversion of non-urban to urban land in urban growth models. In this dynamic discrete modeling technique, each cell responds to the same set of rules based on states of neighboring cells while ignoring the global spatial context and characteristics of built environment (Vanegas et al., 2010). In contrast to CA, the interaction between agents in an urban context is included in Agent-Based Models. The latter method still applies simple behavioral rules influenced by localized context, in comparison to CA models, but there are limited attempts for validating models by observed data (Vanegas et al., 2010). Genetic Algorithms is a method used to generate and optimize a set of parameters for complex problems with high levels of uncertainty (Jenerette & Wu, 2001) However, the logic behind the rules is difficult to parse (Tseng et al., 2008).

Similar to Genetic Algorithms, Artificial Neural Networks (ANNs) apply *machines with the mathematical logic capacity like human neural systems* to solve sophisticated problems such as land-use changes and urban growth (Basse et al., 2014). ANNs are interconnected networks of neurons comprised of input, output, and hidden layers. Interrelational weights between nodes are updated by implementing different algorithms and an internal transfer function (Aisa et al., 2008). Users are responsible for defining the number of hidden layers, regularization value, learning rate, learning iteration numbers, and data encoding techniques (Tseng et al., 2008).

ANNs, with the aid of spatial analysis methods, are capable of simulating land-use and urban changes by integrating the variety of environmental, social, and political variables.

For example, in ART-MMAP, Liu & Seto (2008) predict urban growth by learning from past trends and regularized weights of socioeconomic variables. Tayyebi et al. (2011) use an ANNs-based model for predicting urban growth boundaries, based on variables such as built areas, accessibility to roads, green areas, and service stations. Maithani (2009) proposed coupling ANNs with GIS and remote sensing measurements for generating site variables and reducing subjectivity in urban growth modeling. The non-parametric characteristic of ANNs models may be considered an alternative to estimating land-use transition probabilities in CA simulation models (Almeida et al., 2008). Unlike common statistical methods, ANNs do not make assumptions about the data distribution and can reduce the subjectivity in modeling complex phenomena such as urban growth where there is high nonlinearity between variables (Maithani, 2009). ANNs also perform better in predicting land-use classes changes compared to other well-known non-linear models like Classification and Regression Trees (CART) and Multivariate Adaptive Regression Splines (Tayyebi & Pijanowski, 2014). Integration of Multiple Neural Networks in urban growth models could improve the modeling accuracy and enhance modeling capacity in capturing spatial heterogeneity (Wang & Mountrakis, 2011). However, calibration and validation of ANNs models remains a challenge (Basse et al., 2014). Although Triantakonstantis & Mountrakis (2012) believe there is no need for multicollinearity and spatial correlation assumption in ANNs analysis, others like Garg and Tai (2012) assume that ANNs models cannot automatically deal with data interrelationships in training data. One of the main weakness is the "black box" behavior of ANNs models where users cannot specifically extract rules or conclusions from the learning process (Triantakonstantis & Mountrakis 2012).

The integration of land-use vector data and urban form in urban simulation may improve our understanding of human behavior (Silva & Wu, 2012) in different areas such as

transportation and travel behavior (Chao & Qing, 2011; Ewing & Cervero, 2001; Newman & Kenworthy, 2006; Cervero & Gorham, 2009), accessibility (Handy & Clifton, 2001), energy use (Ewing & Rong, 2008), life cycle analysis (Norman et al., 2006), ecological assessments (Bereitschaft & Debbage, 2013), and environmental impacts (Anderson et al., 1996; Ellis, 2002; Ewing & Rong, 2008; Frey, 2003; Gordon & Richardson, 1997; Newton, 2000; Williams et al., 2000). These studies confirm that the integration of a comprehensive set of land-use and urban form variables (e.g. Hamidi et al., 2015; Chao & Qing, 2011) improve prediction of complex problems, and even provide results that contradict conventional wisdom. For example, Glaeser and Kahn (2010) found that more restrictive land-use regulations increase urban GHG emissions by promoting new developments in the periphery of cities. Urban form variables such as concentration, dispersal, mixed use (Buxton, 2000; Newton et al., 2000), urban continuity (Bechle et al., 2011), centrality, compactness index, and open space ratio (Huang et al., 2007), in combination with urban sprawl index (Lopez and Hynes, 2003; Sutton, 2003) are also used in analyzing the metabolic performance of cities. For example, Bereitschaft and Debbage (2013) study the relation between urban continuity and shape complexity indices with air pollution. These indices are also integrated into landscape metrics for exploring evolutions of land-use and urban growth (Ji et. al, 2006; Luck & Wu, 2002). In other studies, multi-dimensional sprawl indices (Hamidi et al., 2015, Ewing et al., 2003) integrated with socioeconomic variables and urban form indices are applied for measuring transportation.

Urban and building form indices play an essential role in modeling human behavior and urban systems. Three-dimensional urban geography research performs better when compared to two-dimensional analysis in capturing the complexity of built environment (Thill et al., 2011). Researchers have investigated the effects of a building's height on

different areas such as heat island, rainwater runoff, pollution, and habitability (Lin et al., 2014). For example building heights influence the rainfall run-off process in an urban environment. Integration of building heights in urban hydraulic models enhances modeling capacity for capturing the water run-off and plays a significant role in storm water management (Isidoro & Lima 2014). Combined with other morphological properties of buildings such as roof area and compactness, building height is used to extract urban land-use categories (Barnsley et al., 2003). The vertical aspect of urbanscape influences parameters such as humidity, wind direction and speed, and solar radiation; these effects create different microclimates and thermal comforts within urban districts (Palme & Ramírez, 2013). In addition to thermal property, building heights are critical in analyzing visual and acoustical effects of urbanscape. Ko et al. (2011) evaluated impacts of building heights on road traffic noise for identifying areas with excessive environmental noise. Moreover, the vertical growth of urbanscapes significantly influences "livability" in urbanscapes (Lin et al., 2014). Comprehensive 3D geospatial database of urbanscape not only is a valuable resource for analyzing different aspects of urban systems, but also is useful during emergencies by reducing the response time on multi-level structures (Lee & Zlatanova, 2008; Kwan & Lee, 2005).

While most urban models focus on horizontal growth patterns, few investigate the impacts of vertical characteristics of urbanscape into predicting land-use changes. In this study, we explore the possibility of using building form indices in land-use modeling. In contrast to environmental, physical, institutional, and cultural data, many planning and design agencies do not have the resources or knowledge to develop a comprehensive vectorized database of urban and building geometry. Parameterization of roof shape provides enough information about most of the architectural characteristics of a building such as geometric

prototype, footprints, site coverage, courtyard ratio, the number of floors, height, and building orientations. Therefore, building form is identified as roof shape in this study. LIDAR data, which is the 3-dimensional measurement of the built environment, is a valuable resource for creating building form parameters. Our research introduces an automated method for generating building form variables from LIDAR measurements.

This approach is integrated into the IUMAT Land-Use Model (IUMAT-LUM) with an ANNs modeling structure and is applied to and validated for the town of Amherst, Massachusetts. The IUMAT, Integrated Urban Metabolism Analysis Tool, is an analytical platform for quantifying overall sustainability in the urbanscape. Unlike other urban metabolism studies, IUMAT analyzes an urban area as a single entity and simulates urban metabolism by taking all urban subsystems in modeling without directly dividing them. Unit of analysis in IUMAT is buildings, which serve as key indicators in all sectors of urban activities. IUMAT evaluate the environmental impacts in an urbanscape by measuring land-use change, transportation, and consumption of energy and water (Mostafavi et al., 2014). IUMAT Land-Use Model (IUMAT-LUM) is one of three IUMAT models that simulates urban growth and future development patterns.

4.2.2 Chapter Structure and Research Questions

The Town of Amherst is selected as a case study because of its steady growth of the built environment and the availability of geospatial and LIDAR databases essential for modeling land-use transitions. Our research questions are:

1. How can Light Detection and Ranging data (LIDAR) be transformed into a determinant factor (building form indices) in land-use modeling?

2. Does building form indices in combination with other spatial explanatory variables improve the predictive power of land-use modeling?

The remainder of this paper is organized into three additional sections. The Methodology section (2) outlines our approach for generating building form variables from LIDAR measurements and other explanatory variables from GIS vectorized databases that are usually available through public agencies or town planning boards. It summarizes the Artificial Neural Network (ANNs) embedded in the structure of IUMAT-LUM. Section 3 (Implementation and Results) describes the study area and databases applied in this study. We explain the implementation of the proposed IUMAT-LUM framework to the town of Amherst. Different combinations of explanatory variables are combined and used for generating multiple land-use models. The impacts of the building form variables in predicting changes in the pattern of the built environment are also explored. In the final and concluding section (4), we discuss IUMAT-LUM results and its potential for integrating into other urban metabolism and land-use policy studies.

4.3 Methodology

4.3.1 Data Preparation Process

Land-use models are used to investigate the relationships between socioeconomic characteristics and the built environment in order to analyze and predict land-use change. In addition to physical, institutional, cultural, and environmental parameters commonly studied, in this paper, we integrate building and urban form as a new determinant factor for modeling land-use change. We investigate the influence of building form indices extracted from LIDAR measurements on patterns of new developments. The three main components of the IUMAT-LUM framework are the Building Form Generator, the Spatial Variables Generator,

and the Simulator (Figure 4.1 and 6). The Building Form Generator applies different algorithms for extracting building form variables from LIDAR data. The Spatial Variables Generator compiles these variables and GIS vector data into a spatial grid system and employs spatial functions for calculating density, proximity, and land cover estimates. Generated explanatory variables are split into training, calibration, and test data for training and calibrating ANNs models in the Simulator. And finally, optimized ANNs training weights are applied to simulate land-use change. The algorithms of IUMAT-LUM are written in Python to generate, process, and analyze data.

4.3.2 Building Form Generator

Airborne LIDAR is a remote survey technology, which generates 3D points with coordinates (x and y) and elevation information (z) about the natural and built environment without any projection and shadow distortions (Yan et al., 2015). Compared to aerial and satellite images, LIDAR data is more useful for extracting building 3D models especially when dealing with large sets of objects (Zhang et al., 2006). Building and urban 3D models have many applications in planning and urban design such as measuring energy performance, creating virtual urban models, and assessing urban heat island (Jensen, 2009). For the last decade, researchers have developed several algorithms for converting LIDAR data to building 3D models at the urban scale (Grammatikopoulos et al., 2015; Yan et al., 2015; Palmer & Shan, 2005; You et. al, 2003). Schwalbe et al. (2005) categorized these algorithms into model-driven and data-driven methods. Data-driven algorithms identify planes in cloud points or combine LIDAR measurements with other data sources like imagery to extract building 3D models, while in model-driven approaches, limited predefined geometry models are fitted to the LIDAR measurements.

The Building Form Generator in IUMAT-LUM integrates a model-driven approach in its framework and employs five steps towards converting LIDAR measurements to building variables (Figure 4.1). In the first step, the Building Clusters Detector applies a Density-Based Spatial Clustering of Applications with Noise (DBSCAN) algorithm introduced by Ester et al. (1996). LIDAR points provided by public agencies can have a classification type such as *ground*, *low vegetation*, or *building* assigned to it, which define the type of object represented by that point. The Clusters Detector selects LIDAR points in the *building* class within an urban block, classifies points with higher density together as buildings, and sets low-density regions as outliers. The DBSCAN algorithm is suitable for detecting arbitrary shapes with high efficiency on large databases without specifying numbers of clusters for the algorithm. The Cluster Detector uses the DBSCAN algorithm in a Scikit-learn library (Python). Users are responsible for adjusting *min_samples* and *eps* parameters, which define minimum density of points in clusters (of buildings). The *min-sample* specifies the minimum number of points in a region and the *eps* parameter represents the maximum distance allowed by the algorithm between points in each cluster.

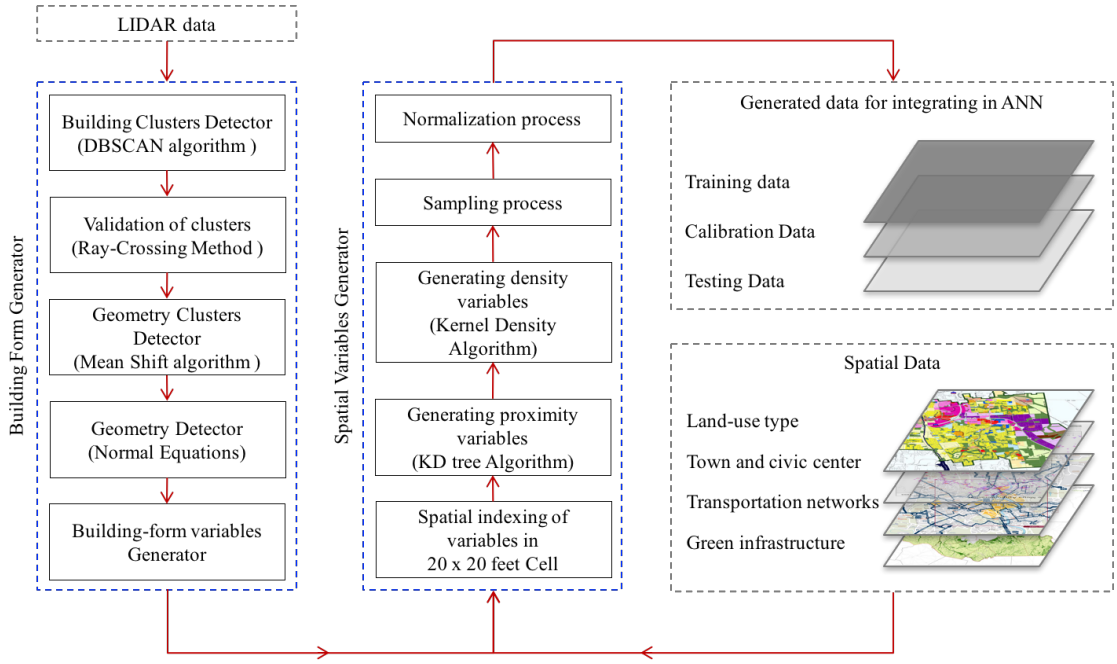

Figure 4.1: Conceptual framework of IUMAT-LUM data preparation process

If building boundary vector data exists in spatial databases, the Building Form Generator checks the positions of cluster points relative to those boundaries. In step 2, using a Ray Crossing Number method (Shimrat, 1962), the model assigns zero to points inside a building footprint and one to points outside. The Cluster Detector outcomes are then used in the Geometry Cluster Detector (Step 3), which applies Mean Shift and Fuzzy clustering algorithms for identifying geometric components in each building cluster. Mean shift is a non-parametric technique for detecting modes of a density (Eq. 1 and Eq. 2) and was originally proposed for image segmentation and analysis of multidimensional spaces (Comaniciu & Meer, 2002). Within a given building cluster, the algorithm initially selects centroid candidates and updates candidates' positions to be the means of points in each iteration.

$$m(x) = \frac{\sum_{i=1}^{n} K(x-x_i)\, x_i}{\sum_{i=1}^{n} K(x-x_i)} \qquad (1)$$

$$K(x) = exp\,(-||\,x\,||^2) \qquad (2)$$

where K is a Gaussian kernel density estimation function of squared distances between points and the cluster centroid. The algorithm ends when the difference between m(x) and x is small (m(x) → x). The numbers of geometric components are defined based on the size of a building and examined by Fuzzy Clustering. This soft clustering method gives each point a degree of belonging to different clusters instead of assigning concretely to a particular group. If the fuzzy partition coefficient is more than 0.9, the Cluster Detector breaks a building component down into multiple ones (Figure 4.2).

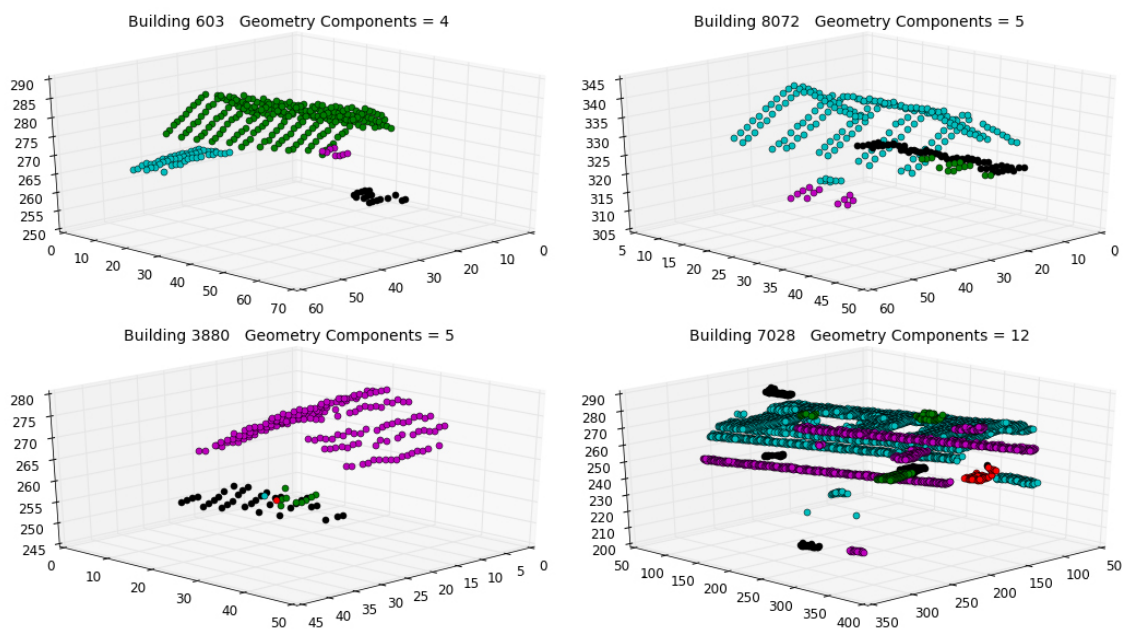

Figure 4.2: Examples of the Cluster Detector results in Amherst: Mean shift and Fuzzy Clustering algorithms are used for grouping LIDAR points in each building and defining geometry components. Each color represents one geometry component

In the step 4, the Geometry Detector uses three predefined geometry models to identify geometric types for each building component: one linear model for a flat roof, two linear models for a gable and single sloped roof, and one non-linear model for gambrel roof

(Figure 4.3 and Figure 4.4). For each component, the algorithm fits three predefined models and selects a model with the lowest mean squared error (MSE). For the optimization of computing performance, we use the normal equations that perform faster compared to other non-vectorize least square regression techniques. The normal equations apply matrix derivatives for minimizing the model's error to calculate the fitting parameters (Eq. 3 and Eq.4).

$$\theta = (X^T \times X)^{-1} \times X^T \times y \qquad (3)$$

$$MSE = \frac{1}{m} \sum_{i=1}^{m} (y - (\theta \times X^T)^{-1})^2 \qquad (4)$$

where X is a matrix $M^{m \times n+1}$ of coordinates (x and y values), y is a m-dimensional vector V^m of elevation information. θ is a n+1-dimensional vector V^{n+1} of fitting parameters, m is number of points in each geometric components, and n is number of coordinates (two in our study).

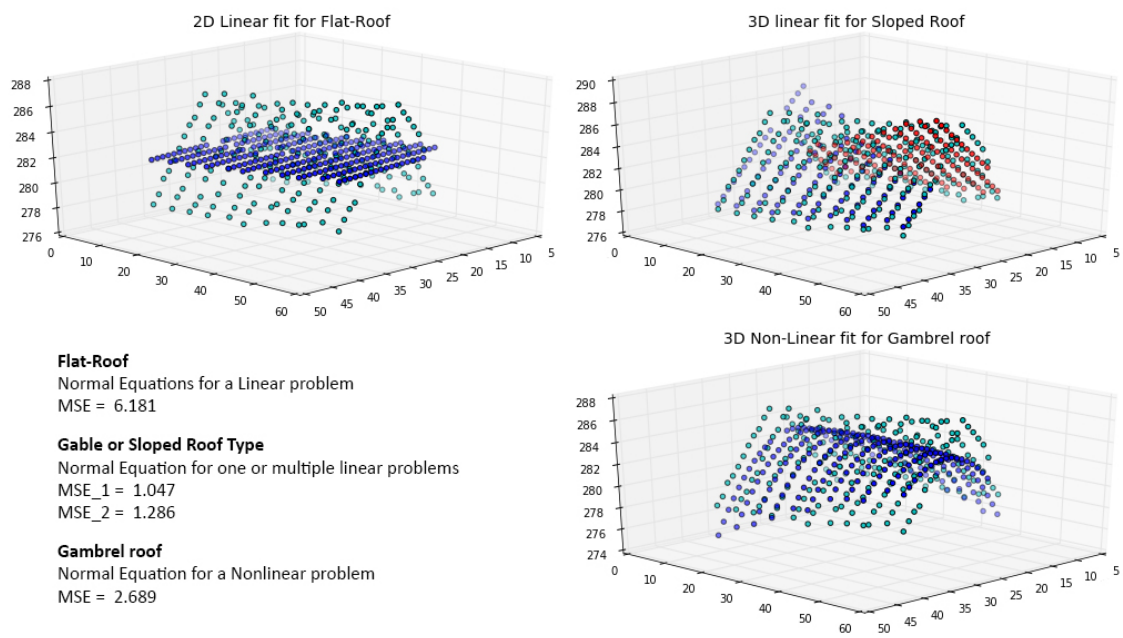

Figure 4.3: Example of Geometry Detector fitting results: three predefined models fitted to a building component and the algorithm selects a model with lowest MSE value

In the final step, for each building, the Building Form Variables Generator calculates building form variables (Eq. 5) and generates building information variables such as area, number of floors, and height.

$$C_{pv} = n_{cluster} + \sum_{i=1}^{n}(cl\_type_i \times cl\_p_i) + (if\ cl\_ext_i\ , 1) \qquad (5)$$

where $n_{cluster}$ is the number of geometric components in a building, cl_type_i is a categorical value for each geometry type, cl_p_i is the portion of building for each type, and cl_ext_i is binary value for the existence of overhang. C_{pv} is a continuous variable indicating the complexity level for a building's geometry. Higher C_{pv} values specify that a building has diverse cluster types, more overhangs, and complex components.

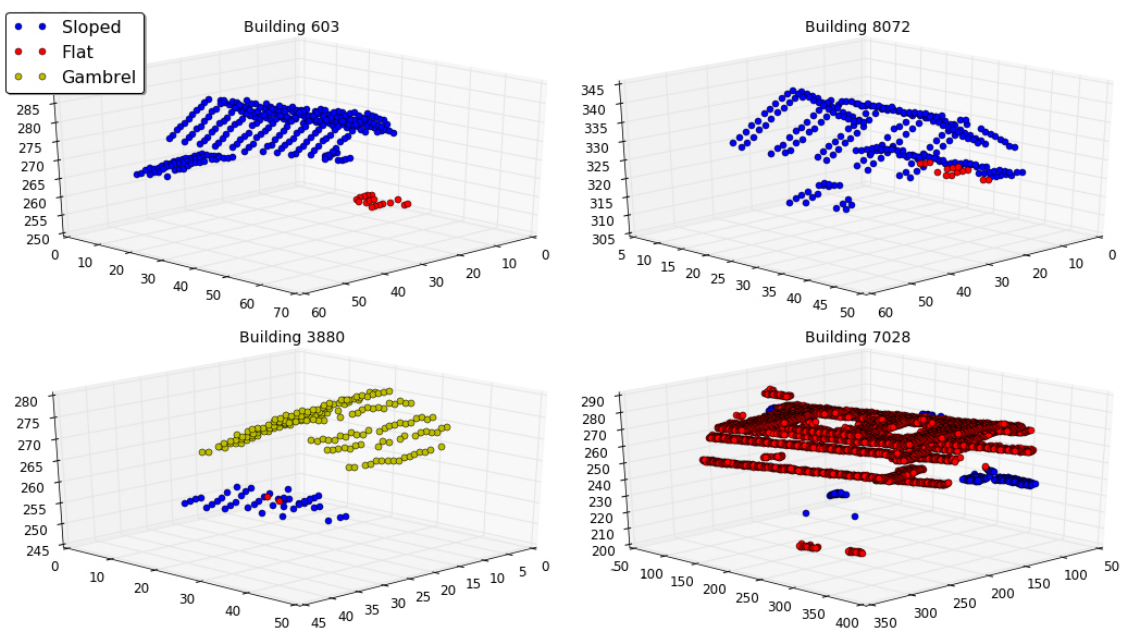

Figure 4.4: Examples of the Geometry Detector outcomes in Amherst: algorithm fits three predefined models to each geometry component and detects roof types.

4.3.3 Spatial Variables Generator

Once the Building Form Generator has completed the five step process to generate building form variables, the next phase involves the selection of different sets of site-specific, proximity, or neighboring indicators as external and internal driving forces for land-use changes. The algorithm converts building form variables, which have coordinate information to GIS vector data and combines it with spatial databases. IUMAT-LUM Spatial Variables Generator employs five steps in coding the GIS vector data to the input data required for training ANNs models (see Figure 4.1). The Spatial Variables Generator converts building form variables in addition to other physical, institutional, cultural, and environmental parameters into the same projection and then into spatial grid system with a 6x6 meters cell resolution. For example, the adopted system in Amherst has the total of 1,933,022 cells (71.9 km2) that defines the simulation domain. The Spatial Variables Generator creates ten descriptive variables (Table 4.1) that include a land-use type of each cell. Similar to other studies (Almeida et al., 2008), we convert related land-use types into one category, e.g. different residential densities are transformed into one. In doing so, we reclassified 21 land-use classes into 8 groups: residential, commercial, educational, industrial, recreational, urban infrastructure, and non-urban. The Spatial Variables Generator uses the k-dimensional tree algorithm or KD tree (Bentley, 1975) for searching the nearest neighborhood and calculating the proximity variables (Table 4.2). KD tree is suitable for avoiding inefficiencies in brute-force computations as the required number of calculations are reduced by encoding the k-dimensional data into new partitioned regions. The algorithm then calculates Euclidean distance between each cell and nearest neighboring cell (Pijanowski et al. 2002) for each parameter (e.g. commercial).

Table 4.1: Summary of descriptive variables

	Variable	Description
1	x	Latitude converted to feet
2	y	Longitude converted to feet
3	z	Elevation in feet
4-9	conservation, vegetation, water, recreational, railroad, educational	Binary variables
10	Trans	Binary variable: impermeable surfaces related to transportation network (Paved road, parking, driveway)

Next, the Spatial Variables Generator produces eleven candidate parameters for density variables (Table 4.3 and Table 4.4) using Kernel density estimation (Scott, 2015) with Gaussian function. Kernel density estimation is a nonparametric spatial agglomeration for pre-smoothing data, especially with large samples and variables. The algorithm uses a specified distance from a cell's center to estimate the probability density variables. These variables indicate relations of each cell with local actions and global patterns. For maximizing computing performance, the Spatial Variables Generator normalizes all descriptive, proximity, and density variables (ranging from 0.00 to 1.00) by subtracting each variable from the minimum value and dividing the product by the maximum value. In the final step, the algorithm creates a binary transition variable for phase transition from one state to another. It detects land-use changes in different periods and assigns zero to non-change conditions and one to land-use changes. In most cases, we might have an unbalanced database due to the small ratio of land-use changes compared to stable states, which results in skewed model outcomes. In IUMAT-LUM, we use a downsampling method (Provost, 2000) to deal with unbalanced databases, which is explained later in this paper.

Table 4.2: Proximity variables (Euclidean distance)

	Variable	Description
11	d_residential	Distance to nearest residential areas (Land-use class: multi-family residential, high density residential, medium density residential, and low density residential)
12	d_commercial	Distance to nearest commercial areas (Land-use class: commercial)
13	d_m_comercial	Distance to main commercial district
14	d_city_center	Distance to nearest city center
15	d_rec	Distance to recreation spaces (Land-use class: participation recreation, spectator recreation, and water-based recreation)
16	d_ind	Distance to industries (Land-use class: mining, industrial, and waste disposal)
17	d_edu	Distance to educational (University, college, and school)
18	water	Distance to water bodies
19	d_m_road	Distance to primary roads (Transportation networks: paved road, tunnel, and bridge)
20	d_s_road	Distance to roads (Transportation networks: Unpaved road)
21	d_busstop	Distance to public transportation (In Amherst case, bus stops)

Table 4.3: Summary of density variables (Kernel density estimation)

	Variable	Description
22	agri_kde	Kernel density of agricultural (Land-use class: cropland, pasture)
23	forest_kde	Kernel density of forest (Land-use code: forest and non-forested Wetland)
24	water_kde	Kernel density of water bodies
25	res_kde	Kernel density of residential districts
26	com_kde	Kernel density of commercial areas
27	rec_kde	Kernel density of recreational regions
28	ind_kde	Kernel density industrial areas
29	edu_kde	Kernel density of educational spaces (University, college, and school)
30	trans_kde	Kernel density of paved surface (Transportation networks including driveway and parking Lot)
31	walk_kde	Kernel density of sidewalks & bike-path (Transportation networks type: bike or walk path, lead walk, detach sidewalks, and attached sidewalks)

Table 4.4: Building-form variables extracted from LIDAR measurements and converted to density variable (Kernel density estimation)

	Variable	Description
32	b_height_kde	Kernel density of building height
33	comp_v_kde	Kernel density of Building-form complexity index

4.3.4 Artificial Neural Network

IUMAT-LUM employs an ANNs-based land-use change model, which is a robust machine learning tool for recognizing complex patterns in data (Skapura, 1996). There are four major multi-layer network architectures; Backpropagation (Rumelhart et al., 1986), Hopfield (Hopfield, 1982), Counter propagation (Hecht-Nielsen, 1987), and LAMSTAR network (Graupe, 1999). In the IUMAT-LUM framework, we employ the backpropagation algorithm, which is the most common. Drawing from biological neural networks, ANNs are composed of several layers of nodes called multi-layer perceptrons- an input layer, one or multiple hidden layers, and an output layer (Figure 4). Associated weights control mapping from one node to connected nodes and the activation operation or squashing function is a nonlinear function, which regulates relations between nodes and keeps cell output between certain limits (Graupe, 2013).

Training is a procedure for updating the weights and bias in ANNs until a specified Mean Squared Error (MSE) is reached, i.e. the optimum difference between expected values and predicted results. Each training iteration involves three phases, which include forward propagation, backpropagation, and adjustment of weights (Rumelhart et al., 1986). The algorithm randomly initializes a matrix of weights to ANNs' nodes; in each cycle, it runs the inputs through the network using activation functions and generates output hypothesis (forward propagation). Each hidden node sums the input values with different weights,

calculates output by applying the assigned activation function, and sends output value to next layer nodes. In backpropagation, the algorithm then updates the weights by calculating partial derivatives to minimize the error function.

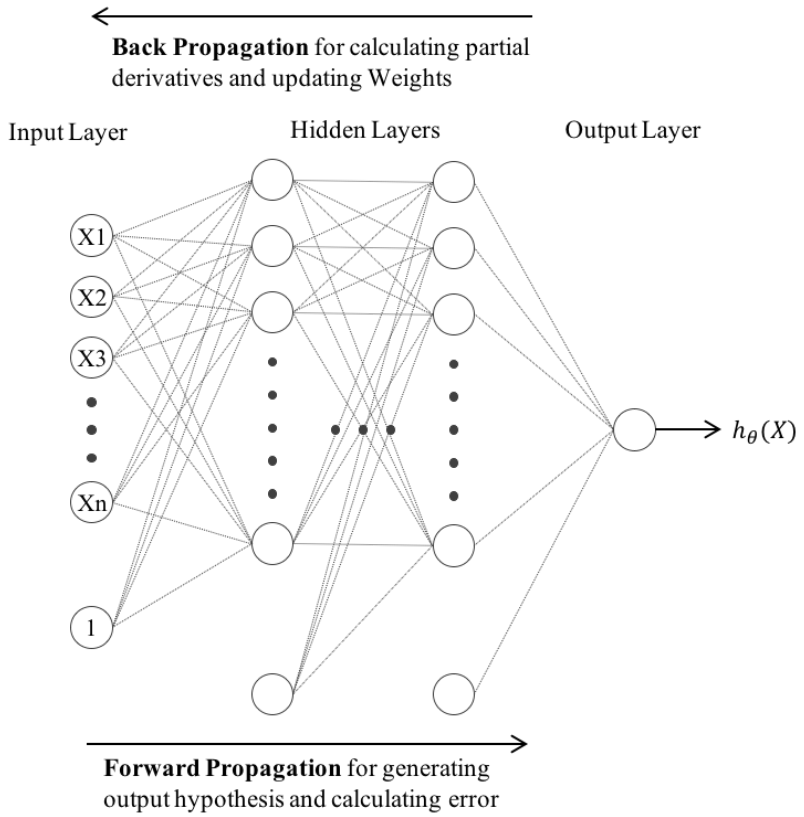

Figure 4.5: ANNs architecture with Back Propagation learning procedure

The number of hidden layers and nodes in ANNs models are critical parameters (Huang & Huang, 1991) that could affect the modeling performance and goodness of fit. For optimization purposes, IUMAT-LUM updates ANNs models over training data, in each cycle, as numbers of hidden layers and nodes increase until validation errors, F1 score, and iteration time satisfy the initial condition for optimization. F1 score is a statistical method for evaluating the accuracy of a classification model by integrating precision and recall (Raghavanet al., 1989). Precision, positive predictive values, indicates the fraction of correct positive outcomes from all predicted positives. Recall, sensitivity values, shows the portion

of valid positives out of expected positives. A higher F1 score value ranging from zero to one indicates the better prediction of an ANNs-Cl model.

Since ANNs has the tendency for overfitting to training data (Triantakonstantis & Mountrakis, 2012), in the IUMAT-LUM framework, we divide a given dataset into three sections of training, validation, and test sets. The ANNs Model Builder runs a learning process over the training data, and validates models by calculating the MSE over a calibration set. In doing so, the algorithm selects an optimal ANNs model that is not overfitted to the training data. And finally, the Land-use Simulator runs the optimized ANNs model over test data for simulating changes over time specified by users (Figure 4.6).

Multicollinearity refers to the strong correlation between dependent variables and is one of the main challenges in machine learning, especially in ANNs algorithms, which cannot automatically exclude relevant parameters (Garg & Tai, 2012). To deal with multicollinearity, instead of using data transformation methods like Principal Component Analysis, in IUMAT-LUM, we evaluate the correlation between variables and select those with no strong correlation. Since Pearson's r method only controls the linear relation between variables, we use Spearman's rank-order correlation to evaluate the monotonic relationship between parameters.

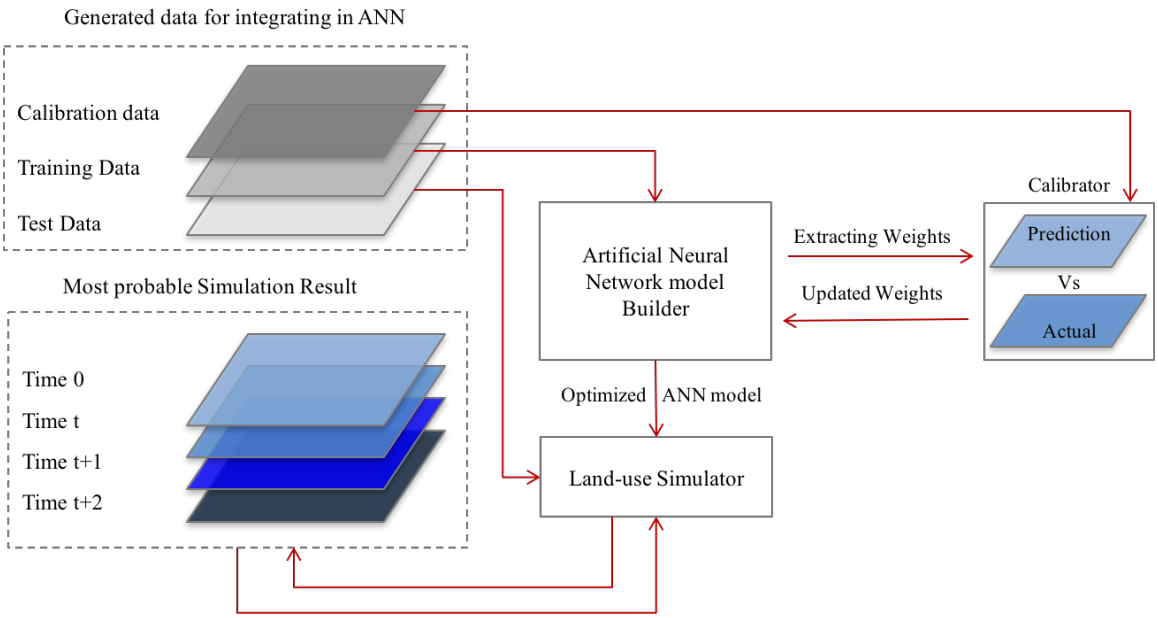

Figure 4.6: Conceptual structure of IUMAT-LUM Simulator

4.4 Implementation and Results

4.4.1 Study area and Databases

Amherst, Massachusetts for the period of 1971-2005 is used to test the IUMAT-LUM framework. Located in the Connecticut River Valley, Amherst has three institution of higher education - the University of Massachusetts, Hampshire College, and Amherst College. The town has an area of 71.9 km2 and has experienced a steady population growth, from 26,331 total population in 1970 to 37,819 in 2010. Amherst has diverse land-use classes ranging from relatively high-density commercial to forest and cropland. A random distribution of urban and non-urban lands as well as a consistent trend of land-use changes since 1971 are valuable resources for generating and testing the land-use model. Additionally, the Amherst Planning Board in collaboration with UMass Campus Planning has comprehensive remote sensing and GIS vector data available. LIDAR measurements provided by the Town of Amherst are used to generate the building form variables. Zoning, vegetation, hydro system,

building boundaries produced by the town, as well as transportation networks, land-use (1971-2005), topography, educational institutes boundaries provided by MassGIS are compiled in Spatial Variable Generator for producing explanatory variables (Figure 4.7).

In most urban areas, the number of cells without change is usually more than ones with land-use change. One common approach to deal with imbalanced data is to alter the balance artificially by upsampling or downsampling datasets (Provost, 2000). Dividing the Amherst dataset into three time-intervals (e.g. 1971-1985, 1985-1999, and 1999-2005), we downsampled (Huang, B. et al., 2009) or ignored cells from the majority. In each set, the algorithm assigns a value of one to cells that change in that time interval and zero to those that do not. The algorithm then measures the number of cells with changes and resamples from the no-change cells (Figure 4.8). In doing so, the adopted 6x6 meters cell resolution in Amherst with a total of 1,933,022 cells is adjusted in different datasets (Table 4.5). For example, in the 1971-1985 set, 20,132 cells were selected from the land-use map where 10,066 cells (assigned a value of one) belong to the cells that transitioned from non-urban in 1971 to built-up in 1985 while another half (assigned a value of zero) are sampled from non-urban cells in both 1971 and 1985. We also check the balance at different intervals by measuring transition probabilities of datasets. Rather than using discrete sets, the algorithm combines three datasets and randomly divides it into 60% data as a training set, 20% data for a cross-validation, and 20% data as a testing set (Raj et al., 2010). In this way, the ANNs model is trained based on a continuous historical trend (from 1971 to 2005), not a discrete snapshot and can simulate future patterns with higher accuracy. Calibration and testing datasets are used for checking overfitting and determining if the ANNs model predictions over untrained data are reliable.

4.4.2 ANNs Structure, Calibration, and Validation

In our study, we also assess ANNs classification model (ANNs-Cl) and ANNs regression model (ANNs-Rg) performances in predicting land-use change in Amherst by comparing MSE values. In the IUMAT-LUM Simulator, ANNs-Cl has three hidden layers; each has nodes equal to numbers of dependent variables, with one rectifier, two sigmoid activation functions. The normalized exponential function is applied to the output layer, so ANNs-Cl generates a zero or one value for outcomes. With a similar structure, ANNs-Rg uses a sigmoid activation function for the output layer, so the outcomes range between zero and one, which determines probabilities of land-use change for cells. A value of one indicates a maximum potential for a future change while a value of zero indicates a low probability. The algorithm initially runs ANNs models over the training datasets for a hundred iterations and updates the weights. After initial training, weights and bias are used in a separate computational loop, which uses training data for updating weights and the calibration set for calculating the MSE. Once it identifies a specified MSE value, the training process is halted. The optimum ANNs model with the lowest error on the calibration data is checked with the test dataset for over-fitting and under-fitting of the ANNs model. Higher MSE of the test data indicates that the model is over-fitted to the training data, while lower MSE of the test data demonstrates the reliability of the model in predicting untrained data.

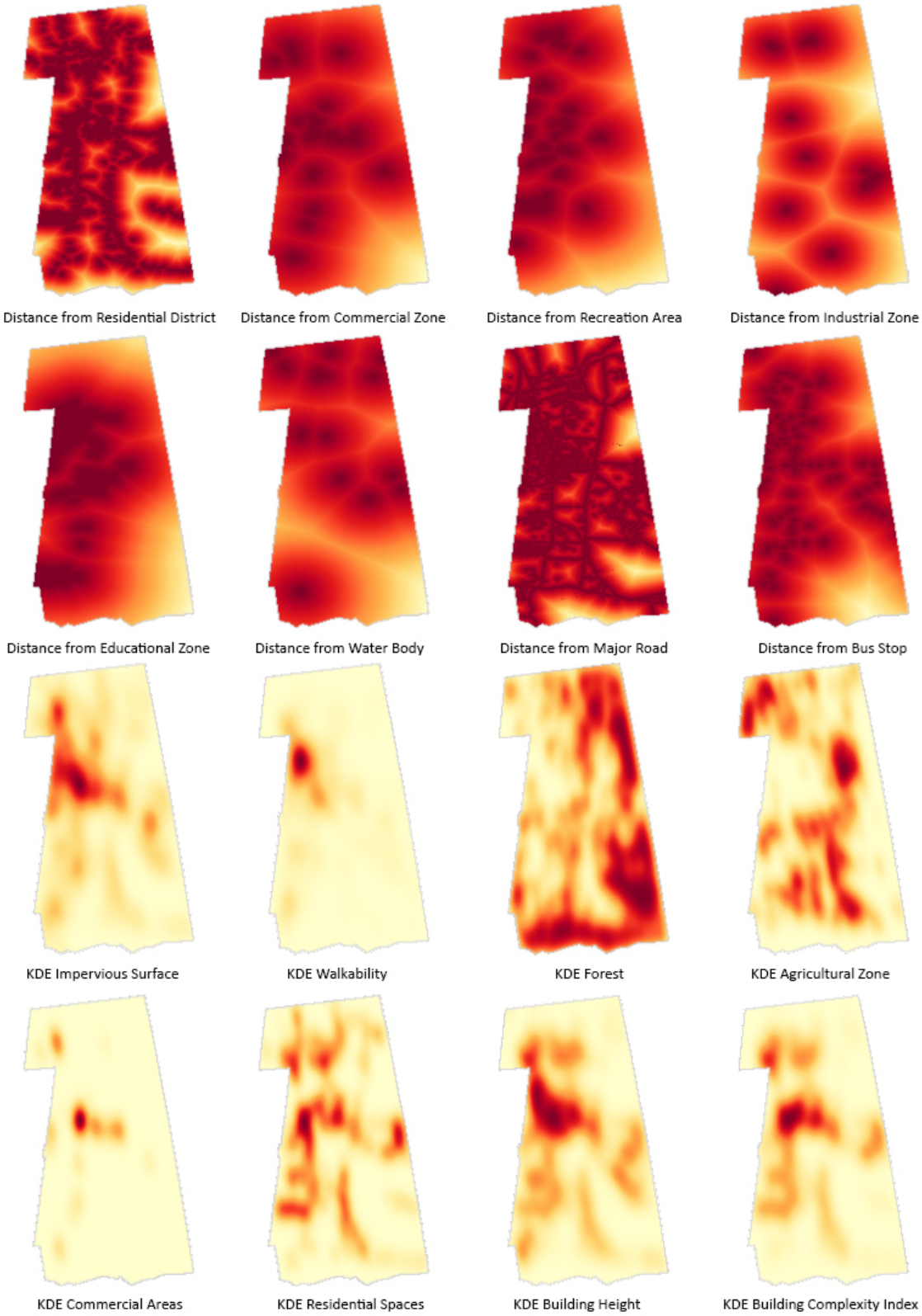

Figure 4.7: Maps of proximity and density variables in Amherst (1971-1985)

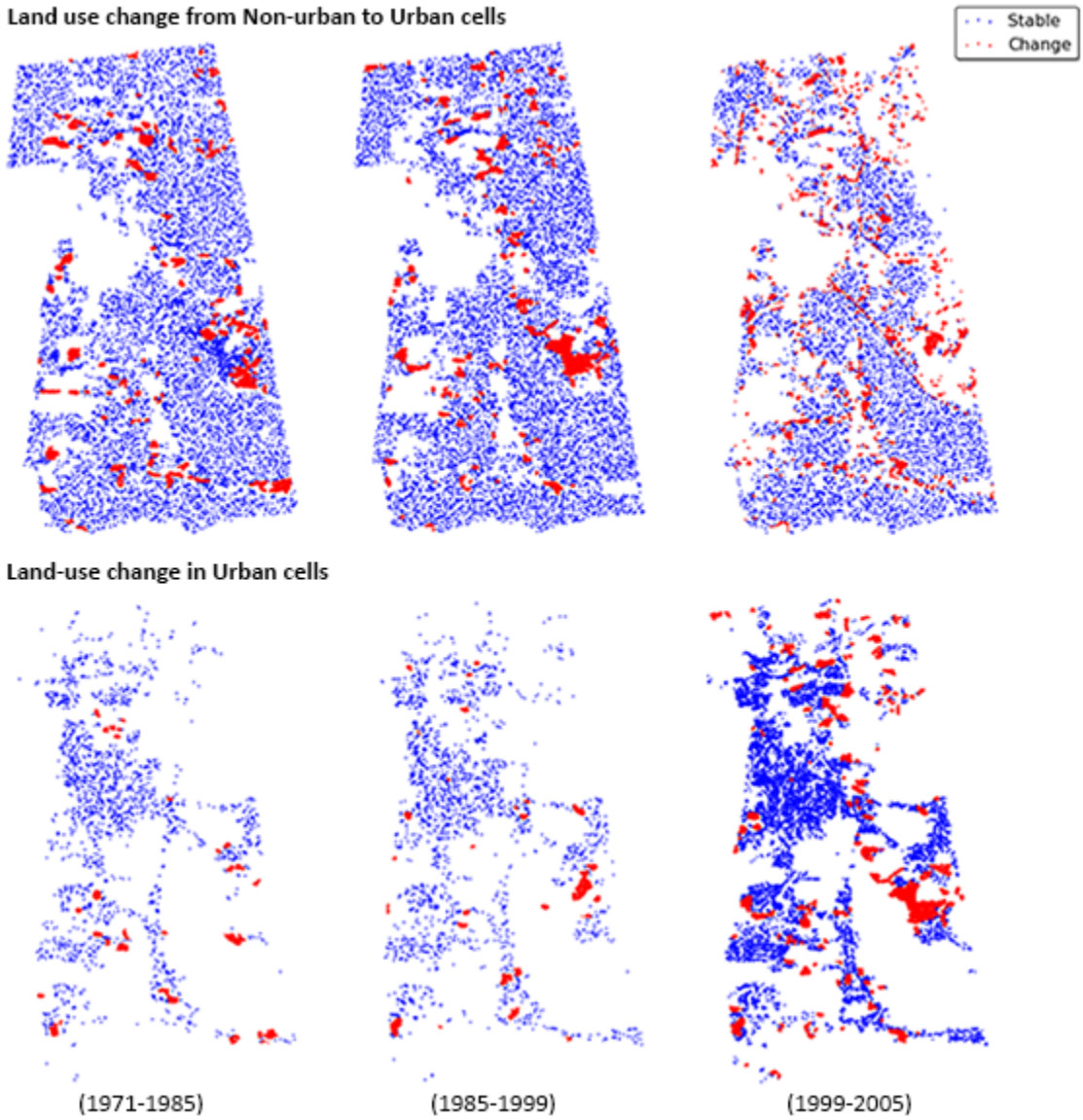

Figure 4.8: Maps of downsampled datasets present patterns of land-use change in Amherst from 1971 to 2005. Top: Transition pattern from non-urban to urban types in different time intervals. Bottom: Land-use change patterns within different urban classes.

Table 4.5: Transition probabilities in ANNs datasets for Amherst

	Number of cells	Global Transition probabilities	Global Transition probabilities Urban Cells	Global Transition probabilities Non-Urban Cells
Training	20,132	0.0451	0.0318	0.0496
Calibration	21,308	0.0497	0.0306	0.0574
Test	12,758	0.1187	0.2252	0.0583

For isolating the effect of each explanatory variable in the land-use model, we use the inverse version of the "drop one out" approach (Washington et al., 2010, Tayyebi et al., 2011). We run a series of normal equations for measuring variable effects in modeling land-use change within all six databases. For each iteration, the algorithm adds a new variable to matrix X, updates theta (Eq. 3), and measures the MSE value (Eq. 4). Figure 4.9 shows the trend of MSE values. For the first run, latitude (x), longitude (y), and height (z) are initially used in matrix X. For the second iteration, the binary variable of conservation is added to the matrix X. All independent variables listed in Table 4.1 -Table 4.4 have positive impacts on model MSE values that vary from a dataset to a dataset (Figure 4.9). For example, the distance to residential has more impact in land-use transformation of non-urban transition data compared to urban data. In urban databases, residential districts, educational institute, and the forestlands improve the predictability of the model, while in non-urban datasets agricultural lands, green infrastructure, and transportation networks have significant effects on land-use transformation. In another analysis, the relative effect of building form variables on land-use modeling is separately explored. After the first run with basic variables (x, y, z), building height and building complexity indices are added to the list of variables for the next two iterations (Table 4.6). In Amherst, these building indices improve prediction of the land-use model by 11% in non-urban and 19% in urban datasets.

Table 4.6: Mean squared error of land-use models with included variables for the statistical analysis. x, y, and z as basic variables are used for the initial run and dependent variables (Table 4.1 - Table 4.4) are included in the final run.

	Initial Run	Building Height	Building Complexity Index	All dependent variables included
Non-urban Training set	0.2436	0.2378	0.2158	0.1540
Non-urban Calibration set	0.2442	0.2395	0.2191	0.1524
Non-urban Testing set	0.2442	0.2376	0.2142	0.1526
Urban Training set	0.2316	0.2310	0.1884	0.1391
Urban Calibration set	0.2294	0.2289	0.1909	0.1421
Urban Testing set	0.2322	0.2316	0.1885	0.1381

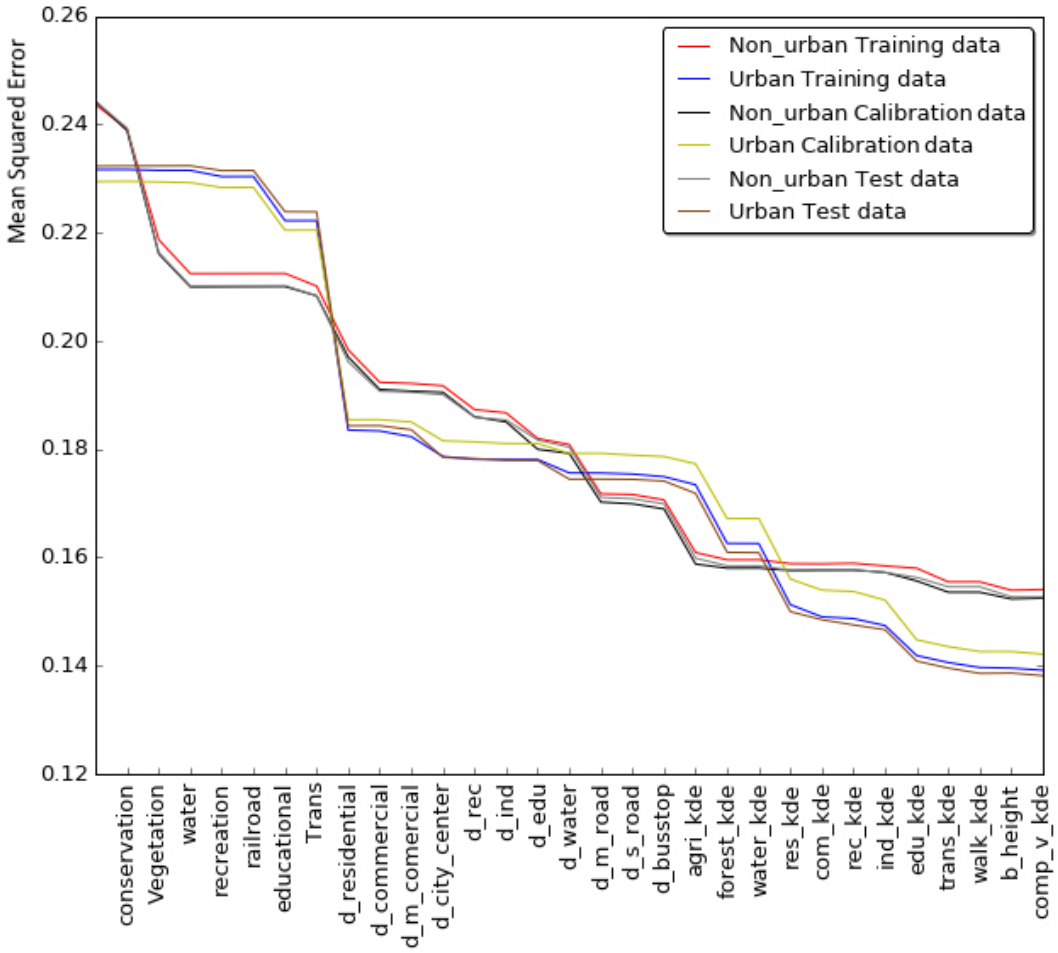

Figure 4.9: Improvement trend of model MSE values in predicting land-use change while adding one independent variable in each iteration

4.4.3 ANNs Simulation Results

After successful training and calibration, bias and weights of ANNs models are used for forecasting land-use change in the test data. The accuracy value of each model is measured by comparing predicted outcomes applied to the test data versus expected values. In non-urban datasets, overall testing data accuracy for the best fit simulation is 90% in ANNs regression model and 92% in ANNs classification model with 0.65 F1 Score. While in urban datasets, ANNs models have better predictions where overall testing data accuracy for both models is 98% and F1 score for classification model is 0.66 (Figure 4.10). It is observed that Simulator performs better in predicting state changes in urban cells and differences between MSE values of ANN classification and regression models steadily decrease till they reach to the global minimum. However, for non-urban sets, the models arrive at global optimum more quickly and have higher differences between MSE values of ANNs-Cl and ANNs-Rg models.

For visual comparison, model simulation outcomes for Amherst were converted into color-coded maps, while in ANNs-Rg models, which generate local transition probabilities ranging from zero to one, the outcomes were transformed into thematic maps for better visualization (Figure 4.11). The results indicate that the IUMAT-LUM can produce satisfactory predictions about patterns and scope of changes with slight differences between simulated results and the observed situation. One reason for these discrepancies is the complex spatial interactions and behavioral differences of land-use classes within urban systems like green infrastructure or transport networks. Another reason is the interaction between land-use types that are not included in IUMAT-LUM. The emergence or evolution of a particular class in a region creates different situations for neighboring cells, which results in changing ultimate land-use pattern (Basse et al., 2014). In addition, socioeconomic

characteristics are another deterministic parameter, which has not been integrated into IUMAT-LUM framework at this stage.

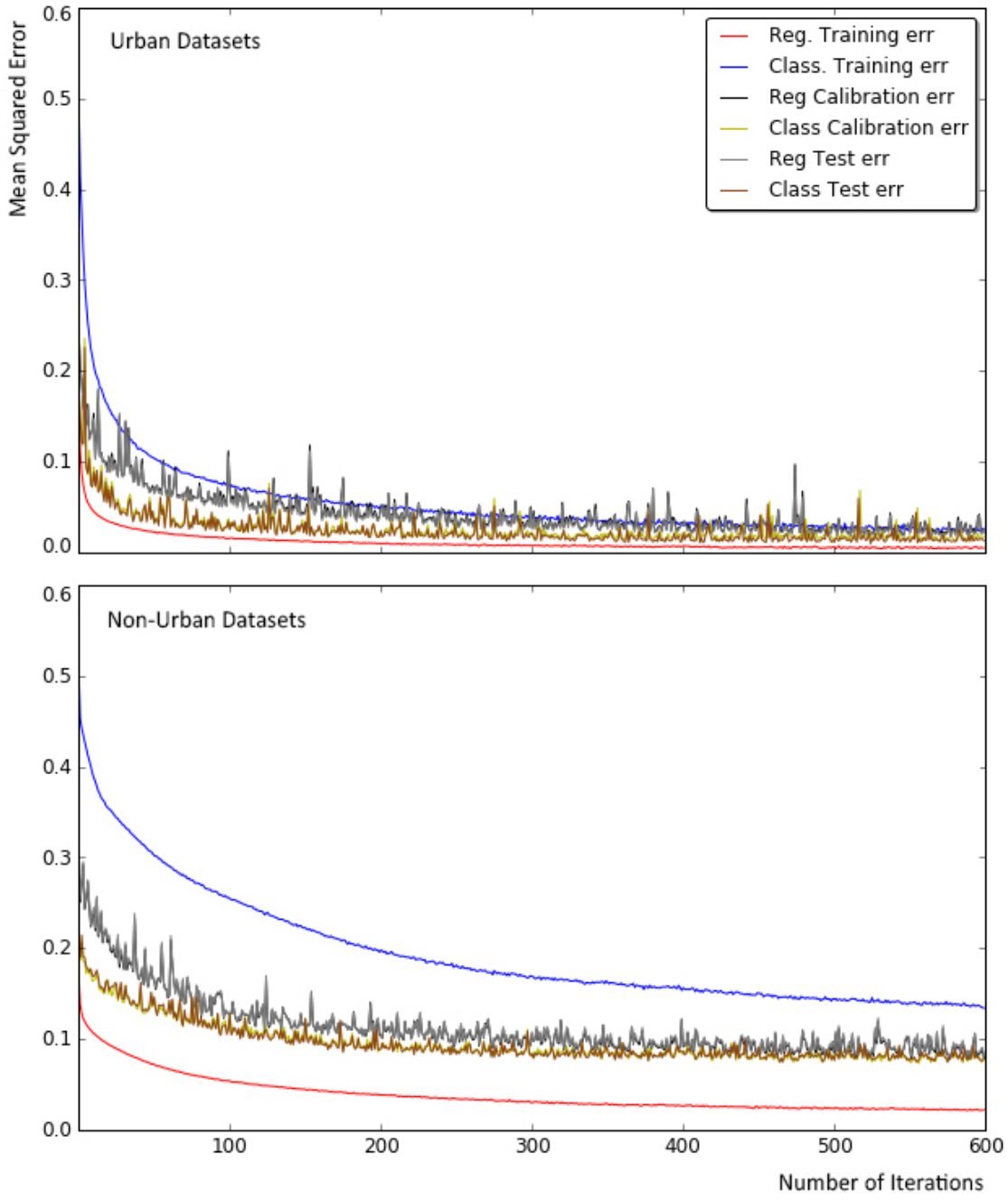

Figure 4.10: Mean Squared Error decay curve regarding the IUMAT-LUM ANNs models after 600 iterations. Top: MSE trend of ANNs classification and regression models in non-urban datasets. Bottom: MSE trend of ANNs models in urban datasets.

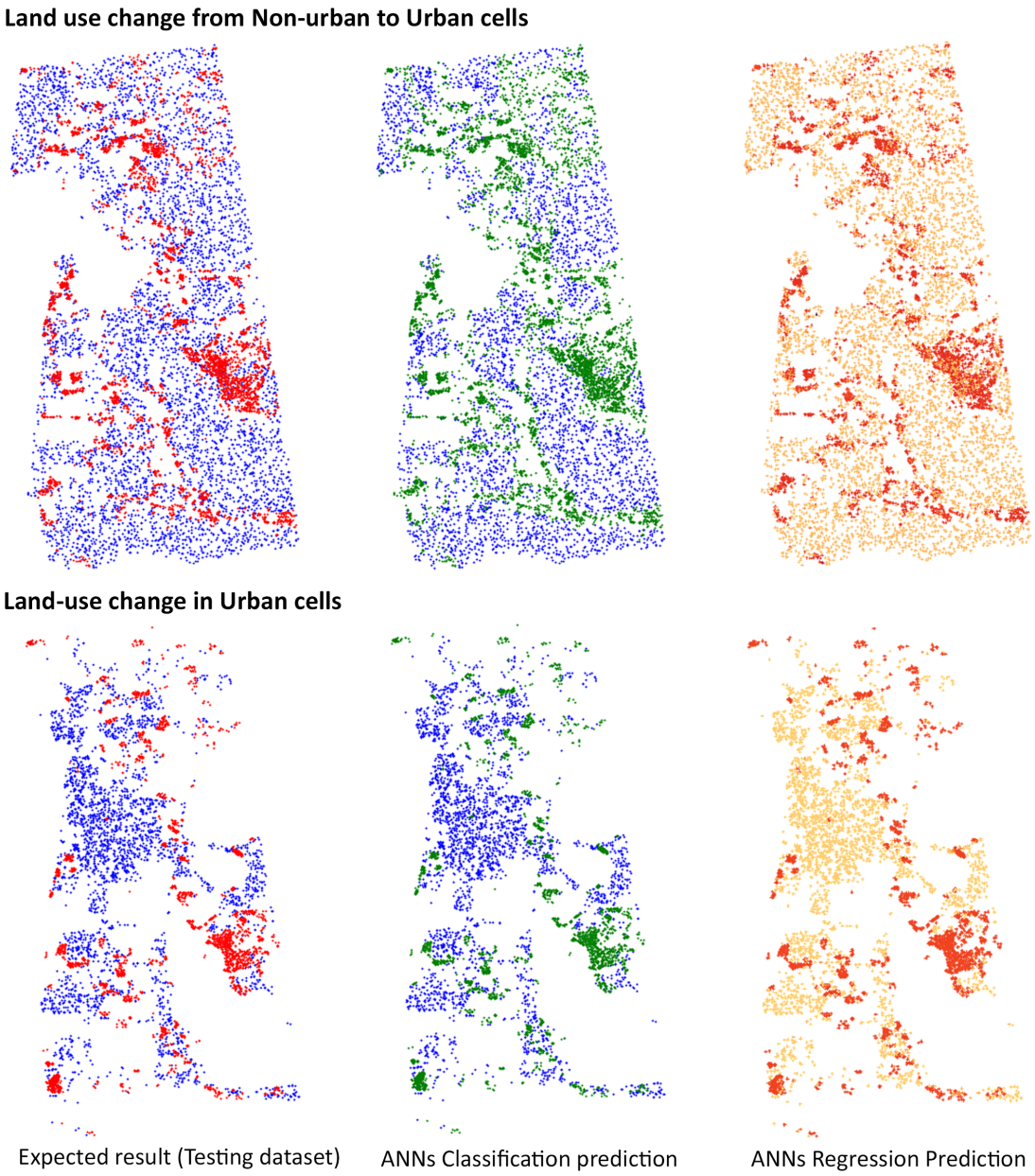

Figure 4.11: Land-use simulation results for the Town of Amherst from 1971 to 2005. Left: Map of the testing dataset that shows the expected value in urban and non-urban cells; red presents cells with a transition and blue shows stable cells. Center: Map of ANNs-Cl predicted values; green represents areas with changes and blue shows areas without any changes. Left: Thematic map of ANNs-Rg predicted values ranging from zero to one (yellow to red) that represent land-use change probability.

4.5 Conclusions and Future Development

In this Chapter, we described how the IUMAT-LUM framework applies Remote Sensing, GIS, and Artificial Neural Networks to simulate urban growth patterns. In IUMAT-LUM, the Building Form Generator integrates vector GIS routines and LIDAR data to building variables in five steps. We outlined a method for extracting building geometry variables by implementing Density-Based Spatial Clustering, Mean Shift, and Fuzzy clustering algorithms for detecting geometric clusters. We fit three predefined normal equation models (using a model-driven approach) to identify the form of each component in the Geometry Detector. In addition to physical, environmental, cultural, and institutional parameters commonly explored in land-use modeling, we introduced building form indices as a new determinant factor in simulating land-use change. We applied the IUMAT-LUM framework to the town of Amherst, Massachusetts. Outcomes suggested where land-use transition will be more likely. IUMAT-LUM distinguishes urban regions (residential, commercial, educational, and industrial areas) from non-urban lands (forest, water bodies, agriculture, conservation), and predicts transition probabilities in each group. Our results indicate that building form indices in combination with other spatial explanatory variables improve the predictive power of land-use modeling. In the town of Amherst, building form indices improve model predictions by 11% in non-urban and 19% in urban datasets. Regions with higher building geometry index have higher probabilities of land-use transitions, in other words, more built-up urban areas will have more land-use change compared less built-up areas. As such, the effects of building form index are more noticeable in urban zones than non-urban areas.

In future, our focus will be on predicting the type of new development. Impacts of explanatory variables might alter from one type to another land-use type (Basse et al., 2014);

for example, greater walkability index promotes residential developments rather than industrial ones, or distance to major roads have similar impacts on residential and commercial type. Like Carrero et al. (2014) and Tayyebi & Pijanowski (2014), we believe that single ANNs modeling methods cannot solely provide a robust approach for simulating different land-use types. In the next stage of this research, multiple ANNs will be integrated into IUMAT-LUM for modeling different types of land-use change. Although the predefined geometry models used in this study can recognize common building forms, in the next stage, we will develop a comprehensive archive of predefined models for detecting more complex geometries. This unsupervised method for parameterizing building geometry can also be automated and integrated into other urban metabolism analytical tools similar to the IUMAT framework (Mostafavi et al., 2014).

Decision makers and city planners can use IUMAT-LUM model for determining roles of explanatory parameters on land-use changes and studying future patterns. They can prioritize the planning resources for future scenarios. The IUMAT-LUM approach to predicting future growth pattern within cities borders is based on historical trends. Comparing simulation results with observed outcomes after implementing a policy could provide new insights into impacts of a particular planning policy. Planners can predict possible developments in environmentally sensitive regions, and regulate non-urban conservation policies accordingly. As an analytical tool for land-use modeling, it is hoped that IUMAT-LUM can be integrated with urban metabolism analyses for developing sustainable land-use policies that account for the complex spatial relationships of dependent parameters.

CHAPTER 5

CONCLUSION

5.1 IUMAT for Planning and Design

Rapid and unplanned urbanization creates social disparities, loss of habitat, resource consumption, and waste production (Lehmann 2011). In response, different sustainable policies, climate action plans, and energy conservation mandates are widely developed to minimize environmental impacts and offset greenhouse gas emissions. It is unknown whether a set of sustainable strategies will have the desired aggregate effects on the overall urban systems or the counterproductive effects. There is a critical need for a modeling framework to analyze the impacts of sustainable policies on the urbanscape. Over the past decades, a number of modeling tools have been developed for simulating urban metabolism and analyzing sustainability within urban systems.

Many of the existing models, instead of considering the urban systems as a cohesive and interrelated structure, broke down the complex urban systems into separate sections and developed individual models for one or multiple aspects of the urban metabolism such as modeling energy consumption (Howard et al. 2012), land-use change and material flows (Douglas et al., 2002), relation between urban economics and ecological systems (Huang, 1998; Huang & Hsu, 2003), and water-related issues (Sahely and Kennedy, 2007). IUMAT has a holistic modeling structure that integrates and quantifies the overall aspects of urban systems. In this comprehensive approach, each phenomenon and the interactions between these features are simulated while the framework provides a quantitative result for an overall sustainability performance.

Different tools have been developed for simulating urban metabolism; some such as iTEAM (Integrated Transportation and Energy Activity-Based Model) are for evaluating policies by implementing micro-simulation agent-based modeling approach and predicts future energy consumption by converting agents' decisions to energy demands (Almeida et al., 2009). Others like Citysim (Robinson et al., 2009) work as an optimization tool and do not have the capacity to project the resource consumption. The goal of CitySim is to establish a complement model by incorporating flows of materials, water, and waste for optimizing urban resource flows (Robinson et al., 2009). SynCity, an agent activity micro-simulation model, monitors citizens' daily activities for calculating resource demands (Keirstead et al., 2010). UrbanSim, another micro-simulation discrete choice model, investigates the association between land-use, transportation, and the environment by employing a dynamic equilibrium approach (Vanegas et al., 2009). This open source urban simulation tool replicates the behaviors of urban agents like households, businesses, developers, and markets in separate models (Waddell, 2011).

IUMAT's main focus is capturing the land-use, energy consumption, water and resources and air quality features categorized as five major indicators of urban metabolism. In IUMAT framework, socio-economic indices are associated with buildings as a basic unit in calculations; each unit is classified together with a matrix of these indices. By simulating flows between recipients or transmitters, IUMAT analyzes the interaction between units to address energy use, material and water consumption, waste and sewage production, and emission to the atmosphere under an alternative scenario in compared to observed data. Unlike the existing simulation tools, Integrated Urban Metabolism Analysis Tool (IUMAT) is a modeling framework that takes existing data of the urban subsystems without directly dividing into different sectors. IUMAT framework simulates the future state based on the

past trend data while suggesting recommendations for the optimization by comparing different design scenarios.

IUMAT has a similar bottom-up modeling structure like ILUTE (Chingcuanco and Miller, 2011) and simulates the behavior of urban agents. In contrast to ILUTE, IUMAT includes resource flows in analytical framework in addition to land-use, transportation, and environment systems. Socio-economic structure of the city plays a significant role in simulating the behavior of agents in urbanscapes. Some tools like SynCity integrate the social and economic features in investigating an optimal urban design based on energy consumption, cost, and carbon emission. Complex ones like Urbansim (Waddell, 2002) use agents' characteristics in finding relationships between land-use, transportation, and the environment. IUMAT associates buildings, the smallest unit of analysis, with socioeconomic features to capture the behavior of agents in relation with other aspects of urban systems.

Existing analytical tools such as Urbansim (Waddell, 2002), ILUTE (Chingcuanco and Miller, 2011), and Citysim (Robinson et al., 2009) simulate urbanscapes in a single scale. While IUMAT employs a range of different scales in modeling and depends on the essence of the phenomenon, simulating occurs at a different range. For example, for capturing the overall urban environmental impacts, analyzing population changes is more meaningful at the scale of a city than building levels. Planners and designers have an opportunity to adapt the complexity level of the model based on a project's needs and purposes. IUMAT can also adapt simulation structure to local political and social conditions alongside providing national comparative results. Depending on modeling purposes, IUMAT Models employs a combination of aggregate (Average) or disaggregate (individual) approached for behavioral resolutions. For defining Units, space, and time, IUMAT models can use different ranges from Macroscopic (Aggregate values for Large Zones), Microscopic (Disaggregate Values)

and Mesoscopic (combination of both) approaches. The IUMAT framework generates data in finer resolution by implementing synthesis methods like Monte Carlo simulation.

Visualization, another key feature in urban modeling, could alter the effectiveness of a modeling tool. Most existing simulation tools are relatively weak in visualizing the mathematical results, which affect the practical implications in planning or design process. In traditional or static visualization techniques, tools use thematic map using GIS or geographically weighted interactive map. In the collaborative approach, with sophisticated computer graphics such as virtual reality visualization technique (Drettakis et al., 2007), and integrated 3D model and data view (Chang et al., 2007, C. A. Vanegas et al., 2010), users have more flexibility and freedom in exploring the data. Lack of in-depth understanding of simulation results, distorted representation, and restricted access are some limitations of static visual representations. On the other hand, lack of real-time visual representation of results can affect the participatory level in the decision-making process (Drettakis et al., 2007). By enhancing visualization techniques, providing real-time visualization representation and integrating with GIS and online web-services, IUMAT can perform as a compelling planning and design tool that assists decision making, participatory, and design process.

IUMAT uses different descriptive statistical methods for capturing general trends of change and relevant parameters. Simple bivariate analyses such as graphical representation and coefficient correlation are employed to investigate the relationship between variables. The algorithm normalizes all explanatory variables between zero and one by subtracting each variable from the minimum value and dividing the product by the maximum value. Descriptive and inferential analyses (including mean, median, standard deviation, etc.) are used for multiple variables to create multi-component variables. In the IUMAT framework, descriptive methods are used within the database for formulating different hypotheses. For

example an association between commercial distribution and household purchasing power, graphical representation and statistical analysis of data will be easier.

Choosing relevant and appropriate variables in modeling complex urban systems is a challenging process since there are several independent variables involved. Instead of common statistical methods, IUMAT-LUM use Artificial Neural Networks (ANNs) that do not make assumptions about the data distribution. ANNs diminish the degree of subjectivity in modeling complex phenomena such as land-use change where there is high nonlinearity between variables (Maithani, 2009). IUMAT recognize patterns in data rather than finding unique relations.

Depending on the modeling purpose, IUMAT employs a combination of aggregate (Average) or disaggregate (individual) approaches for behavioral resolutions. For defining unit, space, and time, IUMAT uses different ranges from Macroscopic (Aggregate values for Large Zones), Microscopic (Disaggregate Values) and Mesoscopic (a mixture of two methods). When the data in microscale is not available, IUMAT generates data in finer resolution by using synthesis methods (Monte Carlo simulation). For quantitative analysis of overall sustainability performance, IUMAT framework also uses a procedural modeling approach to integrate different aspects of urban systems and capture interactions between parameters. Users can adjust the number of variables and alter coefficients in models that exist within the IUMAT framework. Procedural (set of parameters) modeling techniques developed by Müller et al. (2006) mostly used models that try to capture the physical environment of urbanscape like CityEngine (Vanegas et al., 2010). This approach is helpful in dealing with complex systems with a high level of uncertainty.

5.2 Limitations of the Research

The accuracy of IUMAT to analyze and evaluate the impact of urban metabolism depends on the availability of microscale data. One primary challenge for this project was to develop methodologies to generate data for missing microscale databases. Gathering and organizing an appropriate microscale data for IUMAT was beyond the scope of this study. But, simple techniques sometimes were implemented for generating the missing and necessary data. For example, IUMAT-LUM simulates the land-use transition from 1971-2005 in the town of Amherst, but LIDAR data was only available for 2005. Since the probability of rebuilding a structure is negligible in Amherst, we assumed that buildings are the same from 1971 to 2005. Therefore, by using land-use data, building information measurements was used to regenerate LIDAR data for 1985 and 1971. For more complex parameters, we use national and regional databases to formulate the general framework, relations, and analytical models. Some coefficients would be altered if IUMAT models were implemented in other locations. By using UMass Amherst and Amherst City as a case study for this research, we demonstrated that the IUMAT holistic framework can be implemented for urban metabolism analysis, but the same framework is not applicable for using in another urbanscape.

Artificial Neural Networks (ANNs) are embedded in the modeling structure of the IUMAT-LUM. ANNs are interconnected networks of simple units similar to human neural systems that apply the mathematical logic capacity to solve sophisticated problems such as land-use changes and urban growth. ANNs do not make any assumption about data distribution and decrease the degree of subjectivity in modeling complex phenomena. One of the main weaknesses of ANNs models is the “black box” behavior. In many cases, users cannot extract specific rules from the modeling process. For simulating complex phenomena

such as land-use change, which requires wide ranges of variables, the model recognizes patterns in data rather than finding unique relations. Researchers cannot derive definite causality between land-use pattern change and an independent variable from IUMAT-LUM results. Also, the effects of independent variables might alter from one land-use type to another class (Basse et al., 2014); therefore, single ANNs model cannot solely be adequate for simulating different land-use types (Carrero et al., 2014; Tayyebi & Pijanowski, 2014). Due to the complexity of ANNs modeling structure and time limitation for this dissertation, IUMAT-LUM employs one ANNs model for predicting the land-use change. This modeling structure limits the capacity of the IUMAT-LUM in formulating and analyzing different planning scenarios. ANNs models have a tendency for overfitting the data. This characteristic could be regarded both as a potential and a weakness. In the current state of IUMAT-LUM, the model cannot be overfitted to one particular land-use type, since it recognizes the overall patterns of change.

The algorithms of IUMAT-LUM are written in Python to generate, process, and analyze data. Python is an object-oriented programming language with a dynamic interpretation. This programming language supports packages and modules, and is very attractive for rapid application development. Since there is no compilation step in the computing process, the edit-test-debug cycle is relatively fast and effective when compared to other programming languages. These characteristics make Python a suitable candidate for developing IUMAT-LUM framework. But Python is a high-level language and allows the programmer to develop algorithms closer to how humans think. This particular character makes Python codes 10 to 100 times slower than other low-level languages such as C++. The IUMAT-LUM requires significant computing power that was not available at the time of this

dissertation; therefore, numbers of validation and testing of the proposed model were limited in this study.

In many cases, changes of involving parameters in land-use modeling are not limited to the boundaries of urbanscape. For example, demographic changes in city-center neighborhoods might bring more housing developments in suburban districts. Some of the existing models appropriately consider this issue in their methodologies. But it is challenging to analyze land-use transition if the microscale data is not available outside city boundaries. Recognizing this obstacle, IUMAT-LUM simulates land-use change only within borders of the town of Amherst.

IUMAT-LUM, at the current stage, should be regarded as a pilot project until other external validation measures are conducted. The town of Amherst was selected as the only case study for testing the IUMAT-LUM framework and the idea of how urban form indices affects land-use transitions. Although the results provide enough evidence for such a causal relationship between building form and land-use change, I cannot draw any general conclusion. The results might be helpful in forming a new hypothesis that can be tested in different locations. Big cities such as Austin, Denver, and Seattle with a higher rate of urban growth and more comprehensive databases compared to Amherst are appropriate future case studies. In doing so, we can also integrate other demographic, employment, and economic parameters in future analysis. Other independent variables such as different public transportation systems, tree canopy, and flood zone restriction clearly influence the outcomes of IUMAT-LUM, but this model did not specifically test them. Besides, impacts of building geometries indices on the land-use modeling can be explored through a variety of building and urban morphologies in metropolitan areas. Since the major part of this study was to develop the modeling framework of IUMAT-LUM, outcomes of the proposed model did not

compare with other existing models for validation. In addition, no public or elected officials have reviewed the IUMAT-LUM framework, so the practicality and usefulness for professional applications were not yet verified.

At this stage of the research, we have focused on urban metabolism in separate models without connecting them. One of the main goals behind this endeavor was to create a framework to analyze an urban area as a single entity and simulate urban metabolism by taking major urban subsystems into the modeling without directly dividing them. Currently, the IUMAT Land-Use and EMW models have been in development. Both models share similar approaches and principles that will be combined in the future of this collaborative research.

5.3 Future Direction

5.3.1 Professional and Public Engagement in the IUMAT Framework

The idea of public engagement has become part of planning theory and practice to assure fairness in the decision-making process (Arnstein, 1969). Now practitioners and theorists promote integrative approaches that offer comprehensive and inclusive solutions for solving social, economic, and environmental problems (Stollman et al., 2000). Decisions made without including all stakeholders in the process cannot result in sustainable urban development. Recent planning approaches, like communicative planning (Innes & Booher, 1999), collaborative planning (Healey, 1997), and participatory planning (Forester, 1999) provides an opportunity for integrative approaches. But collaborative approaches are not enough to manage sophisticated interactions in the complex urban systems with a wide range of variables (Bulmer, 2001; Higgs, 2006; Howard & Gaborit, 2007). Rational and goal-

oriented methods for measuring and setting targets are still employed by planners dealing with urban conflicts and advancing sustainable solutions.

In this context, a combined method that has the advantage of rational (comprehensive planning) and participatory planning process could be an important alternative. One primary purpose of IUMAT is to facilitate the decision-making process for stakeholders. We anticipate building a platform within IUMAT to collect and incorporate public opinion. IUMAT framework will have a feedback system for engaging the public in current and future planning or design scenarios. Experts will combine public input with national and regional coefficients stored in the IUMAT framework to change local parameters within IUMAT models. The stakeholders involved in the operation and management of cities will need to collaborate within the IUMAT environment to find solutions for social and environmental conflicts in the urbanscape.

The participatory platform in IUMAT framework collects feedback while educating the public about different environmental impacts. In future, a web-based spatial application will be integrated into IUMAT framework for capturing public opinion about different scenarios in an active method. The algorithm will combine inputs and synthesize into spatially aggregated data in the simulation process. This platform will provide real-time results for public opinion (like socioeconomic alterations and environmental impacts) and educate citizens about the implications of different policy and programming decisions. The platform will simplify and represent complex urban systems into a visual format to improve the effectiveness of the participatory process.

In its data structure, however, IUMAT remains part of rational planning and is based on data inputs from professionals (city counselors, policymakers, urban designers, and planners) and public imported into the IUMAT framework for different applications such as

public policies, land-use spatial regulation, micro-scale data, and coefficient values. For supporting stakeholders in decision-making, IUMAT models will simulate future status of urban systems and associated impacts based on existing policies. Models can also provide the detailed information about the effects of an individual policy. IUMAT framework will have the capacity to present a real-time visualization of simulation results. This character is an opportunity for understanding the supply and demand and exploring different aspects of an individual policy relatively quick. IUMAT can also raise different sets of suggestions for optimizing environmental impacts based on user preferences. Greater ability to visualize the simulation outcomes of these policies will educate public and enable a fairer, more participatory local process. In the policy-making cycle, IUMAT will support planners in monitoring the implementation phase, evaluating impacts, and deciding on future actions.

In addition to public policies, new urban development projects can be directly introduced into the IUMAT spatial framework. Depending on availability of data, planners can use micro socio-economic data or aggregated databases for the simulation process. A new development project has spatial and socio-economic implications in an urbanscape. The IUMAT-LUM captures the effects of these spatial changes within urbanscape. Effects of these changes on socioeconomic characteristics will alter the simulation results in the IUMAT-EMW and transportation models. For example, a new affordable housing project might increase spatial densities in a neighborhood in addition to altering socioeconomic parameters.

The IUMAT framework provides both descriptive and statistical outcomes. Users input policies, micro-scale data, maps, etc. will be transformed and compiled in the spatial repository. An interactive explorer embedded in the IUMAT framework works as a platform for exploring the current condition in a city. Spatial representation of simulation results such

as land-use change, energy usage, and GHG emissions will also be accessible in the explorer. Descriptive outcomes in multilayers thematic maps assist designers/policy-makers to analyze current urban conditions and find sensitive regions. This resource is helpful for investigating causalities of different phenomena and formulating explanatory hypotheses. Designers can develop alternative scenarios in response to new assumptions, implement into IUMAT framework, run the simulation, and export analysis results for further review.

IUMAT aggregator wizard transforms the simulation results into different statistical and spatial formats. For multiple planning scenarios (comparative analysis), like most analytical and simulation tools, IUMAT wizards also provides comparable tabular data and graphical reports. IUMAT statistical results that usually are too technical and detailed for the general public are converted into simpler formats. These aggregated analyses improve public knowledge about the technical side of the planning process. In doing so, instead of just gathering public opinion at early stages and excluding them from the rest of the process, IUMAT promotes more active engagement in the decision-making process.

By enhancing visualization techniques, providing a real-time representation, and integrating with an online spatial web application, IUMAT performs as a comprehensive planning and design assist tool for policymaking, public engagement, and the design process. Planners and designers adjust the level of complexity in the framework based on a project's needs and purposes, and they can alter the simulation structure by local political and social conditions. Public input is gathered and organized into different scenarios, which are tested in models. Simulation results can be presented in comparative maps to provide an in-depth visual understanding of environmental impacts alongside detailed statistical results. IUMAT exporter and visualizer is capable of creating different spatial file formats such as Shapefile, Spatial Data File, Vector Product Format (VPF) and Geo-JSON depending on user

preferences. These formats are compatible for importing into Arch map or other mapping tools for further analysis or public sharing.

IUMAT-LUM is responsible for simulating future growth based on an understanding of past urban trends that are not limited to the physical and environmental characteristics of an urbanscape. Socioeconomic parameters, new land-use regulations by policymakers, social interactions of citizens also affect urban growth patterns. The influences of these parameters vary from one land-use class to another. Therefore, one simple model cannot capture all changes in an urban region. In future, IUMAT-LUM will have different interconnected ANNs models. For generating these models, various national/regional databases will be spatially analyzed with supervised machine-learning algorithms. In doing so, the IUMAT-LUM framework will be able to implement most urbanscapes as long as similar robust samples exist in IUMAT databases. Such simulation results are not accurate enough for policymaking, and there is still a need for developing localized models. Coefficients in generated models based on national averages are calibrated and validated by local data to be acceptable for implementation in the planning process.

When IUMAT-LUM is implemented in an existing urban district, the general structure of IUMAT models does not change in the process of localization, and coefficients are adjusted based on microscale local database. For new urban development projects, IUMAT uses similar precedents stored in the IUMAT repository. For localization of IUMAT models, we need at least three structurally similar microscale data collected every 5 or 10 years. Supervised computational algorithm updates variables, coefficients, and ANNs models. The algorithm can be adjusted based on data availability and project needs. Validation of analytical methods by case studies at the University of Massachusetts and the town of Amherst prove that this approach is effective in simulating urban metabolism with an

acceptable confidence level. The validation shows the possibility of implementation of this approach in capturing the complexity of urban systems.

After gathering and analyzing public/professional input, and calibrating models by current data, IUMAT models provide the following outcomes: IUMAT-LUM simulates urban heat island effect, current and projected growth patterns, spatial analysis of socio-economic characteristics, sensitive and congestions areas, and current and anticipated urban form patterns. The EMW model applies IUMAT-LUM results to capture current and projected resource consumption (including energy, water, and material), solid waste and sewage production, and associated atmospheric emissions. The transportation model simulates the travel behavior of residences, Vehicle Mileage Traveled (VMT) per household, public transportation, and associated GHG emissions.

5.3.2 IUMAT Land-Use Model

Planners can employ IUMAT Land-Use Model (IUMAT-LUM) as a policy tool, translating policies with spatial implications into maps. More sophisticated strategies can also be broken down into smaller parts and transformed into spatial data and combined with other historical data. Using these spatial databases as inputs, IUMAT-LUM learns from past trends and provides predictions about future land-use change. IUMAT-LUM cross-validates generated outcomes with expected results for calibration of the model. If micro-data for a particular period is available especially when a planning policy is implemented, it may also be applied in IUMAT-LUM to determine the effects on spatial patterns. Once the model is generated, there are several analytical steps in the procedure. First, planners import the same policy with different spatial characteristics into databases and simulate future patterns for the same region. The results are compared with districts that are not affected by this policy.

Another application of this model is sensitivity analysis of future growth patterns. A generated model can simulate land-use transitions with and without environmental conservation regulations. By comparing these results, planners gain insight about the implications of the regulations within the study area. And, by assigning appropriate periods for simulations, both long term and short-term goals for a policy can also be tested.

IUMAT-LUM generates a comprehensive vectorized database of urban and building geometry from LIDAR data. The generated vectorized databases provide information about the architectural characteristics of a building such as a footprint, site coverage, courtyard ratio, number of floors, height, and building orientation. In the next step, IUMAT-LUM could employ statistical methods to associate building form vectorized databases with other databases for generating a distribution of social and economic indicators, using local averages of parameters like household size in two stories single-family detached home. Since individuals share resources, the need of households does not increase proportionally with an increase in the size of a family. Therefore, instead of using a proportional approach, IUMAT-LUM employs equivalence scales to calculate the adjusted parameters per capita (OECD, 2013).

IUMAT-LUM assigns socioeconomic characteristics to each building. For example, for a 1,100 square feet two-story single-family detached home in a particular neighborhood, the algorithm may assign a three for household size, $100K for incomes, a college degree for education, depending on the user-provided averaged data. The IUMAT-EMW model, which is not the subject of this research, also uses these parameters along with architectural characteristics of buildings for measuring water, energy, materials consumption, as well as associated GHG emissions in a district. Planning and design strategies imported into IUMAT-LUM could change future modeled predictions of growth patterns, alter these

adjusted parameters, and change GHG emissions. Results could provide a reference point and measurement unit for comparing design and planning strategies as well as measuring sustainability targets.

The next stage of this research is combining, calibrating, and validating the IUMAT models. The relation between these models is not one-way or linear. For example, outcomes of IUMAT-LUM can be tested in the transportation model to detect inconsistencies in travel data behavior. We will develop a coordinator that governs the relation between models and data distribution. The ultimate goal of this project is to develop a computer-based program, which can be used in both research and practical sustainable urban development projects. Researchers, designers, and planners can use this framework to assess future growth patterns in a city, analyzing design and policy strategies.

For identifying complex geometries in the IUMAT-LUM framework, we will develop a comprehensive archive of predefined models in the next stage of this research. An automated method for generating building geometry from LIDAR measurements, introduced in Chapter 4, produces information about many architectural characteristics in an urbanscape such as geometric prototype, footprints, site coverage, mass to space ratio, number of floors, and building orientation. Many planning agencies do not have comprehensive 3D geospatial databases about geometries of existing buildings. Taking advantage of the image analysis techniques that convert street views to physical attributes such as materiality and facade details, the proposed method could assist planning agencies to develop vectorized building-form databases for future analysis. For example, new methodologies for investigating the relative influence of urban form on travel mode and behavior (Handy, 1996; McMillan, 2007) can be explored by including building geometries into calculations. These types of analysis could be more applicable for local agencies, as the proposed building

parameterization method offers a relatively quick approach for developing local databases. Although the center of the sustainable urban form debate is the relation between urban form (mostly refers to land-use characteristics) and travel energy use, it is important to understand the impacts of urban forms on the operational energy consumption of buildings (Holden & Norland, 2005). In the future, the proposed model can investigate different design strategies and find the sustainable consumption pattern for a case study by combining the building-form database with socioeconomic and environmental parameters.

Land-use change is necessary for social and economic development; it occurs through a series of nonlinear transitions and has different socioeconomic and environmental consequences (Lambin & Meyfroidt, 2010). A completed version of the proposed land-use model can assist the planners and designers in understanding the impacts associated with land-use change. Regarding socioeconomic impacts, the land-use model could be employed in different areas: for example, the model can predict fluctuations in the housing market by modeling the effects of excessive land-use regulations, or it can anticipate availability of public amenities by simulating conversion patterns in open spaces. The IUMAT-LUM will model the future pattern of suburbanization that is associated with intensification of social and economic segregation (Wu, 2006). In terms of environmental consequences, one simple step is to associate land-use transition to different conversion factors and calculate atmospheric emissions. IUMAT-LUM can also be applied to investigate the heat island effects by capturing land cover changes from green to new developments and impermeable surfaces. Results of the model can predict land changes from agricultural and croplands to urban development; such transitions diminish the amount of land for the food industry and create other environmental impacts such as soil erosion and salinization (Lubowski et al. 2006). In all of these cases, the proposed land-use model can potentially be developed to

assist planners in defining different scenarios to change the current trends or to develop new sets of policies.

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