I, Sweta Byahut, hereby submit this original work as part of the requirements for the degree of Doctor of Philosophy in Regional Development Planning.

It is entitled:
Influence of land use characteristics on household travel related emissions: A case of Hamilton County, Ohio

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Influence of Land Use Characteristics on Household Travel Related Emissions

A Case of Hamilton County, Ohio

A dissertation submitted to the Graduate School of the University of Cincinnati in partial fulfillment for the degree of Doctor of Philosophy

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ABSTRACT

In my dissertation research, I explored the influence of land use characteristics on household travel-related emissions in Hamilton County, Ohio. Carbon dioxide (CO$_2$) emissions from household vehicular travel are a major contributor to climate change, generating up to 65 percent of total transportation emissions in the US, which contribute up to one-third of all CO$_2$ emissions in the US. Urban and regional planners have been exploring the feasibility of using denser, diverse and compact urban development patterns to reduce travel demand. There is debate about which specific land use characteristics have the largest influence on household travel. Most planners agree that there is a statistically significant link between specific built environment characteristics and vehicle miles traveled (VMT), but are not sure of the magnitude of this link due to lack of convincing studies and, often conflicting evidence from various studies.

I have analyzed the influence of various land use characteristics on household travel-related CO$_2$ emissions. I used two main data sources - parcel level land use data for Hamilton County available from the Cincinnati Area Geographic Information System (CAGIS), and the recent Greater Cincinnati Household Travel Survey 2009-10, the first large-scale GPS-based household travel survey in the country. As part of the methodology, I developed an entropy-based measure of land use diversity for each survey household in the GIS environment, using parcel level land use data for Hamilton County. I computed VMT using network analysis in GIS and also developed land use variables including building density, street and intersection density, distance to transit, and regional accessibility using advanced GIS tools. Finally, I used regression models to quantify the influence of land use variables on VMT, controlling for socioeconomic effects of demographics, household structure, and income.

The research outcomes provide interesting insights on the influence of different land use variables on household travel. I found that land use diversity within the local neighborhood is the most important land use characteristic that influences travel, followed by transit availability, and household location with respect to the city center. Contrary to expectations, density and design did not appear as statistically significant variables. Land use diversity at the local level is important and has implications for regional development and sustainability planning, as increasing mixed use at the local level even in less dense developed areas may also provide some environmental benefits.
To my daughter Vani and husband Jay
for all their love and support.
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<th>Abbreviation</th>
<th>Full Form</th>
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<tbody>
<tr>
<td>ACT</td>
<td>Area Characterization Toolbox</td>
</tr>
<tr>
<td>BTU</td>
<td>British Thermal Unit</td>
</tr>
<tr>
<td>°C</td>
<td>Degree Centigrade/Celsius</td>
</tr>
<tr>
<td>CAGIS</td>
<td>Cincinnati Area Geographic Information System</td>
</tr>
<tr>
<td>CAP</td>
<td>Climate Action Plan</td>
</tr>
<tr>
<td>cm.</td>
<td>Centimeter</td>
</tr>
<tr>
<td>CBD</td>
<td>Central Business District</td>
</tr>
<tr>
<td>CCP</td>
<td>Cities for Climate Protection</td>
</tr>
<tr>
<td>CO₂</td>
<td>Carbon Dioxide</td>
</tr>
<tr>
<td>FHWA</td>
<td>Federal Highway Administration</td>
</tr>
<tr>
<td>GDP</td>
<td>Gross Domestic Product</td>
</tr>
<tr>
<td>GHG</td>
<td>Greenhouse Gas(es)</td>
</tr>
<tr>
<td>GIS</td>
<td>Geographic Information System</td>
</tr>
<tr>
<td>GPS</td>
<td>Global Positioning System</td>
</tr>
<tr>
<td>GWR</td>
<td>Geographically Weighted Regression</td>
</tr>
<tr>
<td>ICLEI</td>
<td>Local Governments for Sustainability (formerly, International Council for Local Environmental Initiatives)</td>
</tr>
<tr>
<td>IDW</td>
<td>Inverse Distance Weight</td>
</tr>
<tr>
<td>JHB</td>
<td>Jobs-Housing Balance</td>
</tr>
<tr>
<td>lbs.</td>
<td>Pounds (weight)</td>
</tr>
<tr>
<td>NAWQA</td>
<td>National Air and Water Quality Assessment</td>
</tr>
<tr>
<td>NRC</td>
<td>National Research Council</td>
</tr>
<tr>
<td>O-D</td>
<td>Origin–Destination</td>
</tr>
<tr>
<td>ODOT</td>
<td>Ohio Department of Transportation</td>
</tr>
<tr>
<td>OH</td>
<td>Ohio</td>
</tr>
<tr>
<td>OKI</td>
<td>Ohio-Kentucky-Indiana</td>
</tr>
<tr>
<td>OLS</td>
<td>Ordinary Least Square</td>
</tr>
<tr>
<td>SD</td>
<td>Standard Deviation</td>
</tr>
<tr>
<td>Acronym</td>
<td>Description</td>
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<td>---------</td>
<td>-----------------------------------------</td>
</tr>
<tr>
<td>SGI</td>
<td>Smart Growth Index</td>
</tr>
<tr>
<td>SPSS</td>
<td>Statistical Package for Social Sciences</td>
</tr>
<tr>
<td>SUV</td>
<td>Sports Utility Vehicle</td>
</tr>
<tr>
<td>TAZ</td>
<td>Traffic/Transportation Analysis Zone</td>
</tr>
<tr>
<td>tCO₂e</td>
<td>Tons of Carbon Dioxide Equivalent</td>
</tr>
<tr>
<td>TMN</td>
<td>Transnational Municipal Networks</td>
</tr>
<tr>
<td>TND</td>
<td>Traditional Neighborhood Design</td>
</tr>
<tr>
<td>TOD</td>
<td>Transit Oriented Development</td>
</tr>
<tr>
<td>US</td>
<td>United States</td>
</tr>
<tr>
<td>USEPA</td>
<td>United States Environmental Protection Agency</td>
</tr>
<tr>
<td>USDOT</td>
<td>United States Department of Transportation</td>
</tr>
<tr>
<td>USGS</td>
<td>United Stated Geological Survey</td>
</tr>
<tr>
<td>VMT</td>
<td>Vehicle Miles Traveled</td>
</tr>
<tr>
<td>VHT</td>
<td>Vehicle Hours Traveled</td>
</tr>
<tr>
<td>VIF</td>
<td>Variance Inflation Factor</td>
</tr>
<tr>
<td>WLS</td>
<td>Weighted Least Squares</td>
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1. Introduction

The introductory chapter provides a brief context to my research, a statement of problem, and identifies issues that justify undertaking this study on the influence of land use characteristics on household travel-related carbon dioxide emissions (CO$_2$). It lays out the research hypothesis and research questions, followed by a description of the research design and methodological framework. This chapter also provides background information on the study region, which is Hamilton County in the state of Ohio and includes the City of Cincinnati. Finally it presents the organization of chapters in the dissertation.

1.1 Context

Climate change is a global environmental problem that scientists, environmentalists, politicians and policy-makers are dealing with today, and urban planners are increasingly concerned about the connection between urban form and transportation at a local level and climate change (Bestill and Bulkeley 2007, Blakely 2007, Frank et al. 2007, and others). Land development directly impacts travel behavior by determining where we live, and how, or how much we travel for work, school, family, entertainment, personal business, and social activities. Travel is directly related to fossil fuel consumption and hence influences the amount of greenhouse gas (GHG) emissions. Spatial planners are examining the ways in which land use characteristics of density, diversity, neighborhood design, access to transit, local and regional accessibility, centrality of development, and others impact household travel. In the past decade, dozens of studies have been published that explore the inter-relationships between land use or built form characteristics and vehicular travel from the perspectives of environmental sustainability, public health, quality of life, safety, and resource management. Studies from the
perspective of environmental sustainability have been increasingly focusing on the massive CO$_2$ emissions from personal household vehicles that contribute to climate change in a big way. In addition, there are large-scale local and state government efforts to implement carbon reduction strategies. There is a new synergy in spatial planning today that focuses on integrated land use and transportation solutions as important carbon reduction strategies.

The five major fuel consuming sectors contributing to CO$_2$ emissions from fossil fuel combustion are electricity generation, transportation, industrial, residential, and commercial. In the United States, by economic sector, transportation accounted for 26.6 percent of GHG emissions from fossil fuel combustion in 2010, second only to electric power generation at 34 percent. As much as 65 percent of all transportation emissions resulted from gasoline consumption from use of personal vehicles including cars, SUV, pick-up trucks, and other light duty vehicles (USEPA 2012). From 1990-2010, transportation emissions increased 17 percent, mostly due to increased demand for travel and the stagnation of fuel efficiency across the US vehicle fleet. During 2008-2009 CO$_2$ emissions from the transportation end-use sector declined 4 percent. The decrease in emissions can largely be attributed to the decrease in economic activity in 2008-2009 due to the economic recession and an associated decline in travel demand. The emissions showed an increase again during 2009-2010 with the economic recovery.

In my dissertation, I develop seven measures of land use characteristics that include two different measures of land use diversity, street density, intersection density, building density, distance to transit, and distance to CBD using advanced Geographic Information System (GIS) tools. In particular, the two measures of land use diversity developed in this study using parcel level land use data are innovative and represent an improvement over similar measures used in most previous land use and travel studies. I have measured vehicle miles traveled (VMT) using network analysis in GIS from O-D (origin and destination) points and from the global
positioning system (GPS) data from household travel survey. I then analyzed the influence of each of the land use characteristics on household travel, and corresponding CO$_2$ emissions using regression analysis. This research determines whether changes in any of these land use characteristics are correlated with a corresponding, significant, and measurable change in household travel. My research tries to answer the question whether altering any of these land use characteristics significantly changes the quantity of CO$_2$ emissions generated from daily household vehicular travel.

1.2 Statement of the Problem

In recent years, the inter-relationship between land use and transportation and its explicit link to climate change has become more and more apparent at the local level. Sustainability planners therefore have had a renewed interest in the influence that land use characteristics and land development patterns have on travel-related GHG emissions. Many studies have analyzed the relationship between travel and urban form, and increasingly several have also discussed their findings with respect to climate change in terms of CO$_2$ emissions (Boarnet and Crane 2000, Handy 2005, Ewing et al. 2008, Stone et al. 2009 and others). Handy (2005) finds that our ability to predict the impact of various smart growth policies on the environment is limited and needs to be further researched. The relationship between urban form and travel behavior is complex and needs to be better understood in order to inform urban land use policy related to car travel.

The influence of the built environment on travel behavior has been well researched in almost 200 studies to date. The earliest studies in the 1960s started exploring the linkages between density, congestion, and air pollution. Planners generally tend to agree that there is
evidence of a statistically significant link between different aspects of the built environment and vehicle miles traveled (VMT). In spite of this, due to lack of enough number of convincing studies and inconsistent evidence, they are not sure whether this link is large enough to modify the built environment as a feasible tool for reducing VMT. Even though there has been an increasing quantity of research on the influence of the built environment on travel, there are still several gaps in knowledge that justify further research (Frank 2000, Leck 2006, Brownstone 2008, National Research Council 2009, and others). Key issues that have been raised by Brownstone (2008) about several existing studies are: ambiguity about the specific aspects of the built environment that are important determinants of VMT; lack of sound methodological processes and unanswered questions; concerns that the magnitude of the link between the built environment and VMT is so small that any feasible changes in the built environment will have only negligible impact on the VMT; and the presence of residential self-selection influencing household travel, conflicting with the belief that the location and the built environment influence travel choices. All of these argue against the smart growth proponent’s enthusiasm for manipulating the built environment as a feasible policy tool for reducing VMT.

There are also methodological limitations to many studies due to inadequate data; not adequately controlling for the effect of socioeconomic aspects that introduces a self-selection bias in studies; and many studies do not cover a representative sample of households and geographic area, or use common measures of the built environment to support strong quantitative conclusions. Overall, there seems to be ambiguity and inconsistency in the literature about

---

1 Paper commissioned for the National Research Council 2009 Special Report 298: Driving and the built environment: The effects of compact development on motorized travel, energy use, and CO2 emissions

2 Residential self-selection implies that individuals who prefer walking, biking, or using transit choose to live in compact and dense neighborhoods that offer more opportunities for the same, rather than land use characteristic and design of the neighborhood influencing travel choices of people.
exactly which aspects of the built environment are important determinants of VMT and to what extent (Brownstone 2008, National Research Council 2009). Despite an increasing amount of scholarship on the impact of urban land use characteristics on climate change in the past decade, there is a need to develop a deeper understanding of many aspects of land use and travel interaction: What are the most appropriate land use strategies that will bring about significant reductions in CO₂ emissions from vehicular travel? Are climate protection policies based on compact and mixed use urban development effective? Do these policies help significantly decrease CO₂ emissions from vehicular travel?

In this research, I have tried to address several of the methodological concerns discussed above. I have explored the land use characteristics - household travel relationship using random household travel surveys conducted for the 8-county Ohio-Kentucky-Indiana region, and have controlled for the effect of socioeconomic variables such as demographics, household structure, and income in the analysis. My research extends the existing knowledge on the relationship between land use characteristics like density, diversity, design, transit availability, centrality on household, and travel patterns and related CO₂ emissions. It informs city planners and policymakers on the effectiveness of using land use strategies as a long-term climate protection policy.

Currently, land use characteristics measurement techniques are not very refined and can be improved further. The measurements are usually at the scale of the census tract, census block group, or Traffic Analysis Zone. One of the contributions of this research is improving the methodology for measuring land use diversity, which is considered to be one of the key urban form characteristics that influence vehicular travel. I have measured land use diversity using parcel level land use data of Hamilton County, but reported it at the neighborhood level, considering a half-mile neighborhood immediately surrounding the travel survey household locations. In the context of this research, land use diversity is understood to be the composition
or heterogeneity of land uses within a given geographic area (Frank and Pivo 1994). Diverse areas are those that have a variety of offices, shops, restaurants, banks, and other activities intermingled amongst one another and accessible from residential areas.

### 1.3 Background to the Study Area

My study is limited to Hamilton County, Ohio. As seen in Figure 1 (a), Hamilton County is one of the eight counties in the Ohio-Kentucky-Indiana (OKI) region. It is spread over 413 sq. miles and includes the City of Cincinnati, as shown in Figure 1 (b). Cincinnati enjoys a good quality of life, a picturesque setting on the Ohio riverbank, historical neighborhoods, and a thriving downtown. It is a regional hub of a high number of cultural, educational, research, and medical institutions, and is home to several Fortune 500 companies. Cincinnati is a good study region, being a sprawling metropolitan area having experienced massive increases in land consumption in the past few decades. Similar to several other large industrial cities of the north, Cincinnati lost considerable population in recent decades. It lost 9 percent of its population in the 1990’s but the region grew by 9 percent as a whole, much of that growth happening in the suburban townships through substantial land conversions. The Cincinnati metropolitan area added about 157,000 acres of developed land from 1982-97, whereas its density decreased from 4.4 to 3.5 persons per urbanized acre, or about 21 percent (Brookings Institution 2006).

Hamilton County also lost up to 8.5 percent of its population from its peak in 1970 to 2000 (Mallach and Brachman 2010). During the same time, it experienced rapid sprawl, characterized with the hollowing out of its inner core, and displacement of population and jobs to the outer ring suburbs of the metropolitan area. In 1999, the Sierra Club ranked Cincinnati as the fourth most sprawling metropolitan region in the US. All these led to an unsustainable development pattern that is wasteful, energy intensive, and expensive.
Figure 1: (a) top: Map of the 8-county OKI region, and (b) bottom: Map of Hamilton County, Ohio

Source: CAGIS 2010, OKI Regional Council of Governments 2009-10
Hamilton County displays an interesting mix of urban, suburban, and rural areas with a strong city core, neighborhood clusters, and green, lesser dense population areas. The central city is the economic core, with dense, mixed-use, vibrant areas that contain the central functions and most important assets of the city, such as government offices, universities, recreation, cultural, sports, and medical facilities. According to the USEPA, total vehicle miles traveled (VMT) in Hamilton County increased 20.7 percent during 1999 – 2007, and are projected to increase by a total of 65.6 percent during 1996 – 2030. In addition, the amount of time drivers spend sitting in gridlocks in Cincinnati increased 200 percent from 1982 – 1994 (Sierra Club 1999). OKI estimates that the daily VMT in Hamilton County has grown from 21,859,452 miles in 2005 to about 22,426,021 miles in 2011, and is further projected to increase to 24,098,698 miles by the year 2021 (refer Figure 2).

Figure 2: VMT growth in Hamilton County, Ohio

Data Source: OKI Regional Council of Governments 2010

Transportation accounts for 26.6 percent of the GHG emissions in Cincinnati. In 2008, Cincinnati adopted The Green Cincinnati Plan that proposes several land use and transportation strategies to reduce its GHG emissions. The Plan proposes to use three sets of strategies to reduce transportation emissions: decreasing VMT, improving the fuel economy of vehicles, and reducing the carbon content of fuels. Specific measures to reduce VMT in Cincinnati’s Climate
Action Plan include improvements to mass transit, promotion of bicycling, walking, and other modes of non-vehicular travel, relaxing minimum parking requirement, and incorporating land use strategies that bring people closer to their destinations and to transit facilities, including incentives to promote mixed use developments (The City of Cincinnati 2008). The City of Cincinnati has also recently released a draft of the Comprehensive Plan that incorporates many components of The Green Cincinnati Plan, moving toward form-based zoning codes, and also boasts a Bicycle Master Plan that aims to connect its urban neighborhoods.

The last decade has seen many positive transformative changes in Cincinnati with major investments pouring into redevelopment of its inner city and downtown areas, which have turned around the area by bringing in a high quality, vibrant, and walkable urban character. Completed projects include the revitalization of Fountain Square, Findlay Market, and Queen City Square, Washington Park, and the new Smale Riverfront Park; and ongoing projects include revitalization of the Over-the-Rhine and Vine Street neighborhoods, Uptown area infill developments, the introduction of the Cincinnati Streetcar project, and the Banks project on the riverfront which is a large scale mixed use development now entering into its second phase.

Availability of two high quality and advanced datasets made it possible to undertake this research in Hamilton County. The first dataset is the updated land use GIS database at the parcel level maintained by the Cincinnati Area GIS (CAGIS, the nation’s largest municipal GIS system), and the second is the Greater Cincinnati Household Travel Survey 2009-10\(^3\), the nation’s first large-scale (100 percent) GPS-based household travel survey carried out for the 8-county OKI region.

\(^3\) Supported by the Ohio Department of Transportation, Office of Statewide Planning and Research, and the Ohio-Kentucky-Indiana (OKI) Regional Council of Governments
1.4 Research Hypothesis

Land use characteristics directly impact household travel behavior, and spatial planners in many cities in America and internationally are exploring the feasibility of modifying the built environment as a potential climate mitigation tool. My research explores the influence of land use characteristics on household travel related CO$_2$ emissions.

The *hypothesis* of my research is that there is a measurable and significant influence of land use characteristics on household travel. This also has an influence on travel-related CO$_2$ emissions. The following are the two critical research questions:

1. Is there a statistically significant relationship between different land use characteristics of density, land use diversity, neighborhood design, regional accessibility, and transit availability, and household vehicle miles traveled (VMT)?

2. If there is such a relationship, what is the strength of this relationship? Is the influence of land use characteristics on household travel large enough to modify the built environment as a potential climate strategy?

An important objective of this research is also to develop an improved measure of land use diversity, and explore it in a multi-dimensional manner. Local governments are keen to explore the potential to bring about modifications to land use characteristics as desirable climate protection tools. The research outcomes will better inform the case for using land use interventions like compact and more diverse developments as a long term climate protection policy measure.

1.5 Research Design

In my research, I have used two main sources of data: first, the recent parcel level land use data for Hamilton County, available from the Hamilton County Auditor and obtained from
the Cincinnati Area GIS (CAGIS - the largest municipal GIS database in the US); and second, data from the recent Greater Cincinnati Household Travel Survey 2009-10, the first large scale Global Positioning System (GPS) based household travel survey in the United States. This study is probably one of the first such land use and travel research studies that uses the data from the first ever large scale GPS-based household travel survey in the country.

In my dissertation, I have analyzed the impact of various land use characteristics such as residential density, land use diversity, street density, intersection density, regional accessibility, and transit availability on household travel related CO$_2$ emissions. In the process, I have developed an improved entropy-based measure of land use diversity using advanced spatial analysis tools within the GIS environment and parcel level land use data for Hamilton County at the neighborhood of each individual household. Household VMT has been measured using Network Analyst extension within ArcView 10 software. Advanced GIS tools have also been used to compute other land use variables such as building density, street and intersection density, distance to transit, and regional accessibility. Finally, I have used regression analysis to determine the influence of land use characteristic variables on household VMT, controlling for socioeconomic effects of demographics, household size and structure, and income. The findings from regression analysis have then been converted in terms of CO$_2$ emissions using broad guidance provided by the USEPA. Figure 3 on the next page provides the conceptual methodological framework.
Figure 3: Conceptual methodological framework

**Travel Survey Data**
- Network Analysis
- Spatial Analysis

**Land Use Data**
- Network Analysis
- Spatial Analysis

**Dependent Variable**
- Travel Variable:
  - Vehicle Miles Traveled

**Control Variables**
- Socioeconomic Variables:
  - Income
  - Vehicle Ownership
  - Household Size
  - Household Structure

**Test Variables**
- Land Use Variables:
  - Diversity
  - Density
  - Design
  - Distance to Transit
  - Destination Accessibility

**Regression Analysis**
- Impact of Diversity on household travel (VMT)
- USEPA/USDOT Guidance
- Impact measured in CO₂ emissions
The research methodology consists of the following five stages:

Stage 1: Review the Literature

At the onset of the research study, I reviewed representative literature to explore the following: first, linkages between climate change, cities and spatial planning to understand how cities impact the global climate and are in turn impacted by it, and what climate mitigation and adaptation approaches are they taking in order to deal with it; and second, to understand the influence of various land use and socioeconomic characteristics on household travel as measured by VMT. The literature on influence of land use characteristics on travel is vast, covering over 200 studies; therefore, only key and representative literature was selected and reviewed. The purpose of the literature review was to establish the extent of existing knowledge, identify research gaps, develop research questions and a broad research framework, identify appropriate methodologies and modeling techniques, and, identify appropriate land use, neighborhood, and socioeconomic variables for the regression analysis stage.

Stage 2: Collect and Organize a Database

The Greater Cincinnati household travel survey 2009-10 data was obtained from the Ohio-Kentucky-Indiana Regional Council of Governments (OKI) office. Parcel level land use data for Hamilton County was obtained from the Cincinnati Area Geographic Information System (CAGIS) office. The neighborhood data on residential density, median income, housing tenure status, and race at the census block group level was obtained from the US Census Bureau website for 2010. All relevant data were then standardized and organized for the survey households within Hamilton County selected as the sample for this research in a methodologically intensive and time-consuming effort. The purpose of this stage of the work
was to complete the groundwork for delineating the geographic study region and establish the sample size of the survey households for the research.

**Stage 3: Develop Socioeconomic and Travel Variables**

The next stage of work was to develop a set of distinct socioeconomic variables for the survey households including household size and structure, income range, vehicle ownership, and others from the Greater Cincinnati household travel survey 2009-10 dataset. These formed part of a larger dataset developed using spreadsheets to be used for regression analysis in the later stage of the analysis. The dependent variable of vehicle travel miles (VMT) was computed from the GPS-based O-D (origin-destination) trip data using network analyst tools in the GIS environment. VMT was also computed from the travel records from trip data recorded in the GPS. This database incorporates travel, neighborhood, and socioeconomic variables for the survey households located in Hamilton County.

**Stage 4: Develop Land use Variables**

This stage formed the bulk of the data preparation effort. Extensive land use computations using parcel level data were carried out using GIS based spatial analysis and network analysis tools including the Area Characterization Toolbox developed by the USGS. These land use area calculations were then used to develop two entropy-based advanced land use diversity indices, and other land use variables of building density, street density, intersection density, distance to transit, and, distance to the CBD. Land use variables were then incorporated into a single combined and comprehensive dataset including the travel, neighborhood, and socioeconomic variables developed in earlier stages of work.
Stage 5: Specify Appropriate Regression Models

Developing and choosing appropriate regression models was an iterative process. The purpose was to choose the most appropriate regression models that quantify the influence of specific land use characteristics on the dependent travel variable of vehicle miles traveled (VMT), controlling for the influence of other neighborhood and socioeconomic characteristics of the survey households. Three statistical indicators were investigated: the sign of the regression coefficients - whether positive or negative, the strength of the coefficients that indicates the strength of the relationships, and the significance levels. Finally, based on the strength of the relationship between land use characteristics and household travel determined from the regression analysis outcomes, and based on the guidance provided by the USEPA, the potential for CO₂ emissions reduction from land use strategies are discussed.

1.6 Outline of the Dissertation

The following Chapter 2 explores the association between cities and climate change in several ways. It discusses how cities being the centers of production and activity contribute massively to climate change; and, how in turn they are impacted by the changing climate and are vulnerable to it. In particular, it discusses the contribution of the transportation sector as the second largest source of CO₂ emissions in the US, and analyzes the land use and transportation connection at a regional scale from select representative literature. It also discusses the reasons why American cities are taking leadership in climate protection, the key planning strategies they are adopting to reduce transportation emissions, and the challenges they face while doing so.

Chapter 3 discusses in depth the relationship between different land use characteristics including density, diversity, transit availability, neighborhood and street design, regional accessibility, and parking policies that may influence household travel. It also discusses the
socioeconomic conditions of the households and neighborhood characteristics that influence household travel, as well as the different ways that some of these variables have been conceptualized and computed for analysis in previous studies of a similar nature.

Chapter 4 describes the process of data selection for this study, the data sources, the scope of this research, and the process of organizing this vast set of information to match the requirements of this research. It describes the methodology of computing the dependent variable vehicle miles traveled (VMT) and the socioeconomic variables selected from the travel data and the US census. Chapter 5 describes in detail the methodologies adopted for computing various explanatory land use variables such as population density, land use diversity indices, street density, intersection density, transit availability, and distance to CBD, using advanced spatial analysis and network analysis tools in GIS.

Chapter 6 presents the regression model development and the iterative process adopted to choose them, the model specifications and analysis of the results, and their interpretations. Finally, Chapter 7 discusses the research findings in the context of regional and metropolitan development theory and the possible planning applications of the research outcomes. It also briefly discusses the carbon impact of household travel, the scope and limitations of this research, and points out a few directions for future research.
2. Cities, Urban Development, and Climate Change

This chapter discusses the role that cities and urban areas play in contributing to climate change, and how in turn they are affected by the same. It discusses why cities need to be at the forefront of global climate change mitigation and adaptation efforts. There is a large, important, and growing body of literature addressing the issue of how urban activities contribute to climate change. This chapter also examines the interaction between land use, transportation and climate change, and how these interactions are being understood by cities which are using this knowledge to formulate spatial planning strategies for climate protection.

2.1 Cities and Climate Change

It is an urban world. Since 2008, more than half the world or over 3.5 billion people is urban, and by 2050 more than 6 billion of the future 9 billion people are projected to live in cities. Cities are engines of global economic growth, and only 600 urban centers generate over 60 percent of global GDP. Northern America, Latin America, Caribbean, Europe, and Oceania are highly urbanized, with urban population share ranging from 70 – 82 percent. Most urban populations are in small and medium sized cities, with only 54 cities with a population greater than 5 million, and only 21 megacities with a population of more than 10 million (The World Bank, 2010). In contrast, Africa and Asia remain mostly rural, with just 40 percent and 42 percent of their populations living in urban settlements in 2010 respectively. Almost all of the future global population growth will be driven by growth in urban areas of the developing countries - the world population will grow by 1.7 billion between 2005 – 2030, whereas urban populations will increase by 1.8 billion (The World Bank 2010).
2.1.1. **Cities Contribution to Climate Change**

A great deal of understanding has developed regarding the local and urban production and consumption processes and interactions between them that contribute to global climate change. Climate change is inextricably linked to urbanization - urban areas of the richer developed countries contribute the most to it; and urban areas of the poorer developing world are expected to face the worst consequences of climate change. Cities have long been perceived as being largely responsible for climate change as they generate up to 80 percent of all greenhouse gases (GHG) that are responsible for climate change; and, up to 70 percent of total energy consumption happens in cities (Newman et al. 2008). Cities are nodal locations for a majority of industrial activity and high-density habitats, and are characterized by intensive land uses that consume a lot of energy overall, thereby contributing to large scale GHG emissions. However, on a *per capita* basis, cities produce a lot less GHG emissions, since compact development and higher densities in cities allow for greater sharing of the same resources among larger urban populations and enable more efficient mobility and energy consumption behavior. Urban planners are increasingly concerned about the connection between urban form and transportation and climate change at a local level (Bestill and Bulkeley 2007, Blakely 2007, Frank et al. 2007, and others).

There is a strong link between economic growth, urbanization, and GHG emissions. Generally speaking, the impact of cities on the global climate is proportional to the level of economic output measured as GDP. Cities are large economies by themselves, and the 50 largest cities of the world having a population of more than 500 million people together generate up to 2.6 billion tCO₂e annually, more than all countries except the US and China. The combination of energy sources cities use determines their GHG emissions, particularly the way cities produce their energy and use it in their buildings and transit processes. Sprawling and less dense cities,
and cities that depend predominantly on coal as a source to produce their energy usually emit more GHG. However, there are many large, vibrant, and growing cities like New York, London, Hong Kong, Paris, Sao Paulo, and Tokyo, which are efficient cities and have comparatively lower energy intensities per unit of GDP production, and their per capita emissions are much lower than comparable cities (The World Bank 2010). In contrast, poorly managed, land intensive, and sprawling cities like Atlanta and Houston that grow out, and not up, are unsustainable and energy intensive (The World Bank 2010, Ewing et al. 2002).

2.1.2. **Impact of Climate Change on Cities**

The average global temperature has increased by 0.76°C and the sea level has risen by 17 cm since the 19th century. Both of these are expected to increase further over the next few decades, threatening communities, the environment, and the global economy. Direct impacts of climate change include drought, flooding, heat waves, and increased frequency and intensity of extreme weather events such as cyclones and hurricanes. Indirect impacts include reduced food production and freshwater availability as well as ocean acidification, which are likely to impact lifestyles and slow down global economic growth (The World Bank 2010). Developing countries are likely to bear 75 percent of the costs of damages related to climate change. Cities particularly are highly vulnerable to the impacts of climate change, specially the faster growing cities of developing countries in Africa and South Asia.

Historically, cities developed near coasts to take advantage of the natural transportation and trade advantages. This is now turning to their disadvantage. About 20 of the world’s 30 largest cities are located on low-lying coasts, and approximately 400 million urban residents live in coastal areas less than 10 meters above sea level, making them very vulnerable to coastal flooding and storm surges. These coastal cities have the highest vulnerability, and Asia will suffer disproportionately with its many coastal mega-cities such as Dhaka and Kolkata. China
has about 78 million people living in vulnerable low elevation cities on its eastern coast (The World Bank 2010). The urban poor are the most vulnerable to climate change since they have lesser resources and ability to deal with the climate risks and the effects of extreme environmental events. Many cities have large concentrations of urban poor who are most negatively affected during any extreme weather event. This was also the experience with the Katrina in New Orleans.

Adverse climate impacts in urban areas include urban heat island effect in highly built-up areas, severe droughts and in-land flooding, paralyzing life and damaging property. One of the worst examples is the extremely severe heat waves in Europe in the summer of 2005 which led to the deaths of over 70,000 people. Climate change also poses serious threats to urban infrastructure, quality of life, and entire urban systems. Our densely built urban environments consist of massive investments in permanent infrastructure such as highways, flood protection levies, bridges, highways, sewerage systems, subways, and energy plants. This permanent and immobile nature of densely built urban environments of cities adds to their vulnerability to disruption of critical supplies like food and water, and limits their adaptive capacities.

We have discussed how urban processes and production systems are major contributors to climate change and how cities are increasingly vulnerable to climate impacts. Cities are therefore expected to take the lead in reducing their carbon impact as well as build climate mitigation and adaptation mechanisms into their planning frameworks. Spatial planning can not only help mitigate the causes of climate change, but also help communities adapt to climate impacts and build resilience to climate-related impacts of water scarcity, flood risks, and hazards (Blakely 2007). Urban planners believe that densely and smartly built cities present our best opportunities to tackle the global climate challenge. The permanent and fixed nature of the built environment also implies that any climate or environmental gains from changes introduced to the
built environment (such as higher densities and mixed use, improved transit options, and improved neighborhood design) are going to be cumulative in nature over time. For instance, while the reduction in VMT is an expected benefit from land use interventions, these may also lead to reduced energy costs in heating and cooling of residences, offices, and commercial spaces, magnifying the impacts in other sectors.

2.2 CO₂ Emissions from the Transportation Sector

Urban development, land use, transportation, and climate change are intrinsically connected. Land use and transportation are connected in two ways: first, all land use decisions and urban form have an impact on travel patterns; and second, investments in the transportation infrastructure also impacts location decisions, land use patterns, urban densities, and land prices (Handy 2006). Metropolitan urban development patterns are largely guided by our land use and transportation decisions. Land use characteristics influence our choices as to where we live, how we travel (mode), or how much we travel (vehicle miles traveled or VMT) to work, school, and for leisure. Therefore, the way we develop our land and locate our activities, build our transportation systems, and the way we travel, has a direct impact on energy consumption and CO₂ emissions which directly contribute to climate change. Land use characteristics including the density of development, mixing of different land uses, and location of activities are important determinants of how far schools, jobs, shopping, and entertainment destinations are located from residential areas and generate travel demand. Fossil fuel consumption is therefore a factor of many land development characteristics. Location of residential and other uses, mode of transit, and the amount we drive, all determine the vehicle miles traveled (VMT). In America, VMT is a
Large contributor to GHG emissions. Motorized travel is responsible for considerable fossil fuel consumption and GHG generation by this activity increases with increase in VMT.

Transportation sources emit GHG that contribute to climate change. Vehicular travel contributes to climate change by combusting petroleum, a natural fossil fuel, which releases CO₂ into the atmosphere. Transportation is the second largest contributor to the global climate change in the US. If we examine the end-user sectors, transportation is the largest source of CO₂ emissions, about one-third of the total (see Figures 4 and 5). In 2010, the transportation sector accounted for up to 32 percent CO₂ emissions from fossil fuel combustion⁴. Out of these, up to 65 percent emissions came from gasoline consumption for personal vehicle use only. The remaining emissions came from other transportation activities⁵ (USEPA 2012).

Figure 4: CO₂ emissions from fossil fuel combustion by fuel consuming end user sector

![Graph showing CO₂ emissions from fossil fuel combustion by fuel consuming end user sector]

Data Source: USEPA 2012

The US transportation sector does disproportionate damage to the global climate. The US population is only 5 percent of the world’s population, yet it owns one-third of all vehicles

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⁴ By industrial sector classification, electricity generation is the biggest contributor. But when emissions from electricity are distributed among end-user sectors, transportation accounts for the largest share of U.S. greenhouse gas emissions, followed closely by emissions from the industrial sector (USEPA 2012).

⁵ The remaining approximately 35 percent emissions came from other transportation activities, including the combustion of diesel fuel in heavy-duty vehicles, sea travel, jet fuel in aircrafts, etc. (USEPA 2012)
that contribute up to 45 percent of total CO\textsubscript{2} emissions from cars worldwide (USDOT 2009A). Comparatively speaking, American cars are less fuel-efficient, and are driven much more. Every gallon of gasoline combustion produces approximately 20 lbs. of CO\textsubscript{2} emissions (USDOT 2009A). Transportation emissions in the US increased by 17 percent during the 1990 – 2010 period, mainly due to increased travel demand and the stagnation of vehicle fuel efficiency. Emissions from all sectors decreased from 2007 – 09 due to a recession in the US national economy, but increased again during 2009-10 with the economic situation recovering.

Figure 5: US CO\textsubscript{2} emissions from fossil fuel combustion in 2010 by (a) Economic sector and (b) End user sector

Data Source: USEPA 2012

In 2007, the ratio of carbon dioxide emissions to total emissions (including CO\textsubscript{2}, methane, and nitrous oxide, all expressed as carbon dioxide equivalents or CO\textsubscript{2}\textsubscript{e}) for passenger vehicles was 0.977 (USEPA 2009). In addition to CO\textsubscript{2}, there are minor quantities of other GHGs mainly methane and nitrous dioxide emissions from fuel combustion in driving (about 3 percent of total GHG emissions from vehicles). The analysis of these other GHGs is outside the scope of this research, since the USEPA only provides guidance for computation of CO\textsubscript{2} emissions from driving.
2.2.1. **Growth in VMT**

Household travel accounts for over 80 percent of total road travel, measured by vehicle miles traveled (VMT), and it accounts for almost three-quarters of CO\textsubscript{2} emissions from all road travel (USEPA 2012, USEPA 2010, USDOT 2009A). VMT by light duty vehicles consisting of passenger cars and light duty trucks increased phenomenally by nearly 40 percent during the past two decades alone, mainly due to a combination of factors such as increase in population, economic growth, sprawling urban patterns, and generally low fuel prices during most of this period (USEPA 2012). The average American household makes 5.66 trips a day, traveling 54.38 miles a day (USDOT 2011, Handy and Krizek 2009). The average annual VMT per household increased by 50 percent between 1970 and 2005, from 16,400 to 24,300 miles and at the same time, there has been an increase in vehicle ownership per household and a decrease in the average household size. Since 1980, VMT has grown almost three times the population growth rate, and twice the rate of growth in the number of registered vehicles. Growth in VMT has surpassed growth in highway capacity, economy, population, or any other possible explanations (Handy 2005). Land is also being consumed three times the rate of population growth, leading to the development of sprawling and auto-dependent urban patterns that encourage driving. Americans are just driving more and more!

However, according to the 2009 Summary of National Household Travel Trends, per capita growth in VMT experienced over the past four decades seems to be slowing down recently (USDOT 2011). Compared to 2001, average daily person and vehicle miles generated by US households were lower in 2009. Daily household VMT reduced to 54.38 miles in 2009 as compared to 58.05 miles in 2001, daily household vehicle trips reduced to 5.66 from 5.95, and average person trip length reduced to 9.75 miles from 10.04 miles in the same period. The average person miles traveled also declined nearly 10 percent from 2001. In 2009, the average
person (5 years or older) traveled about 36 miles daily, with approximately one-third for family errands, one-third for social and recreational purposes, and one-third for other purposes including work (USDOT 2011). As evident from Figure 6 (a), in 2009, 30 percent of average person miles traveled per household were for social and recreational purpose, and an additional 30 percent were for family and personal errands and shopping. Work commute and work-related travel accounted for only 25 percent of average person miles traveled, and about 19 percent of total trips. Examining the number of household trips in Figure 6 (b), an overwhelming 42 percent of total trips were for shopping, personal, and family purpose, and an additional 27 percent were for social and recreational purposes. This implies that less than 30 percent of the trips are predictable – for work, school, or church, and the rest can all be categorized as unpredictable travel.

Figure 6: (a) left: Proportion of VMT by trip purpose, and (b) right: Proportion of household trips by trip purpose in 2009

Data source: USDOT 2011

2.2.2. **Technology vs. Planning**

This phenomenal increase in the total amount of driving discussed in Section 2.2.1 has effectively cancelled the substantial gains made by technological improvements in vehicle fuel efficiency and reducing the carbon content of fuel (Brown et al. 2008). This has been due to
increased suburbanization and increased driving, and changing consumer preferences for larger, powerful, and high fuel consuming vehicles like SUVs. Technological solutions like hybrid-electric vehicles have been promoted to reduce GHG emissions, but their market penetration is still limited by costs and technology constraints (Stone et al. 2009). Marshall (2008) argues that although there is a lot of attention given to technological solutions like alternative fuels, smarter vehicles, and electricity generation; better urban planning represents an important but undervalued opportunity for climate mitigation. Reducing the total VMT by modifying the built environment to reduce the need to drive is a key climate protection strategy for cities (Ewing et al. 2008, Stone et al. 2009, Wheeler 2008). Cities, planners, and policy-makers are targeting urban transportation as one of the critical sectors for long-term climate mitigation.

Strategies for reducing GHG emissions in the US must therefore include strategies to reduce CO₂ emissions from passenger vehicles used for daily travel. Low carbon content in fuels, newer and improved vehicle technologies, and reducing VMT by modifying the built environment must together form the three key approaches for reducing GHG from the transportation sector (Ewing et al. 2008, Stone et al. 2009). According to the USDOT, the five most common transportation strategies adopted by state level Climate Action Plans include the following: alternative fuels/low carbon fuel standard (27 states), provision/promotion of transit and alternative modes (21 states), new vehicle emissions standards (21 states), smart growth measures (21 states), and clean vehicle purchase incentives (20 states). In combination, several multi-pronged strategies can significantly reduce transportation-related emissions.

Spatial planners are examining in what way land use characteristics like density, diversity, design, access to transit, destination accessibility, and centrality of development impact travel patterns (Ewing et al. 2008). The way cities and regions develop determines their regional energy consumption through transportation by influencing the location of new developments -
either by pushing them out to the edge of the city in green-field areas, or by redirecting them to inner city locations. The urban and regional development patterns influence car travel in many ways. Trip lengths are determined by distances between various activities or origins and destinations, and the numbers of vehicle trips are determined by modal choice; which is in turn a function of the level of provision of public transportation, provision of bicycle infrastructure, and provision of a safe and walkable urban environment.

2.3 Why should Cities be at the Forefront of Climate Protection?

Cities must be the focus for climate mitigation implementation and action. Broader guiding policy for climate protection might be determined at the regional or state level, but it is the cities that control several aspects of urban development that have a major impact on transportation and mobility that are a leading contributor for climate change. These include land use decisions, location of major activities, guiding location of development through infrastructure investments in roads and public transit, and planning and zoning regulations. These infrastructure investments influence location of private land owners and developers. Methods of solid waste disposal that cities employ determine the methane emissions from the waste sector as well. Several of these decisions determine the location and character of residential and commercial developments, and have direct implications on energy consumption and GHG emissions from fossil fuel burning, and consequently on climate change.

2.3.1 Co-benefits for Cities

Urban climate protection measures are often the same as smart growth measures promoted to achieve compact and sustainable urban development, and are linked with other environmental and health benefits. The premise that most urban planners work with is that smart growth and compact development generates less travel, improves feasibility of public transportation, encourages walkable neighborhoods, and improves health and perception of
safety. There are economic benefits of climate protection measures such as massive energy savings in local government operations and reduction in household energy bills for heating and cooling. Environmental benefits include lesser time sitting in traffic, reduced congestion, better air quality, and walkable urban environments. Health benefits are also plentiful as these measures promote a healthier society by promoting a more physically active lifestyle by encouraging walking, biking, and transit use. Social benefits like safe and walkable neighborhoods and livelier downtowns are important for communities for them to buy into the idea and adopt local climate protection measures.

From the public finance perspective, compact urban form with higher densities and mixed land uses is also a desirable planning goal. There are no large upfront costs associated with urban climate protection measures, and they can generate massive savings in power bills due to energy reduction (Kousky and Schneider 2003). There can be significant savings in new road and infrastructure building in the exurbs, as well as improvement in the overall economic performance of the region. Fiscally healthy city cores support the growth of healthy metropolitan regions (Carruthers and Ulfarsson 2003). Investment in healthy city centers/cores benefits the region as a whole and helps improve the financial base of large American cities that have been losing population to suburban growth.

2.3.2. **Center City Redevelopment Trends**

New trends of densification and revitalization of downtowns indicate a resurgence of growth of central cities due to an increasing movement back to the cities from the exurbs due to multiple factors like changing demographics, residential preferences, and lifestyle changes. There is consumer demand for walkable urbanism and vibrant places to live and work in. As baby-boomers retire, they prefer to move back to cities to be close to various destinations, and the younger population also demands the vibrant lifestyle advantages that city centers and
downtowns provide. There is a pent-up demand for walkable, centrally located neighborhoods in cities that are mixed income, mixed use, walkable, and transit-oriented developments, as the demand now exceeds the current supply (Nelson 2004, Leinberger 2005, Stone et al. 2009). Leinberger (2005) finds that in the 1990s, the high-end outer suburbs contained most of the expensive housing in the US, whereas now the most expensive housing is to be found in the high-density, pedestrian-friendly neighborhoods of the center city and inner ring suburbs which demand a premium. Nelson (2006) forecasts resurgence in building, estimating that more than 50 percent of building stock that would exist in 2025 would be redeveloped or built after 2000. In addition, about 20 percent of non-residential space turns over each decade. All this projected real estate development present unprecedented opportunities to urban planners for shaping the future built environment, and reducing VMT related energy consumption and GHG emissions through compact, mixed-use, transit oriented developments in central cities.

2.4 Planning Strategies for Reducing VMT

The cities of the US have been at the forefront on planning for climate protection, and are adopting a range of land use and transportation planning strategies such as smart growth and new urbanism, street design, as well as transportation demand management measures such as traffic calming and parking management. Increased understanding of local causes and contributors of climate change has led local governments to believe that they play an important role in mitigation and adaptation for climate change, and many cities are modifying their land-use, transportation, and waste management policies accordingly. These strategies are primarily aimed at reducing the impact of transportation on the environment. Planners advocate many more smart growth solutions: urban villages, neo-traditional neighborhoods, transit-oriented developments (TODs), access management, job-housing balance (JHB), traditional
neighborhood design (TND), mixed-use activity centers, context-sensitive highway designs, and traffic calming measures. The effectiveness of these strategies increases with complimentary measures such as intelligent transportation systems, and transportation pricing measures such as reducing fuel subsidies, parking pricing, congestion pricing, and pay-as-you-drive insurance.

Land development measures as regional transportation control measures are also of interest for the USEPA. In an interesting USEPA study of 1999, in the Atlantic Station project in Atlanta, travel forecasting methodology was used to illustrate that VMT and emissions would be more than 30 percent reduced with infill development as compared to green field development for site selection (Ewing et al. 2008). The Portland Metropolitan Authority has deliberately contained growth within its growth boundary and defining infrastructure priority areas for decades, and provides transportation options to its residents. Portland reduced per capita vehicle trips by 17 percent and has maintained its GHG emissions at around its 1990 levels despite a 16 percent population increase (Condon et al. 2009). Another example is a mixed-use, walkable, new-urbanist, suburban neighborhood called Fairview Village in Portland. Having interconnected streets and attractive streetscapes, its per adult VMT was found to be up to 20 percent lower than comparable suburban subdivisions in Portland (Ewing et al. 2008).

Residential energy use for heating and cooling also reduces with denser urban pattern. The average household in the 48 major US metropolitan areas generates up to 35 percent less GHG emissions when located in the city than when located in its suburb (The World Bank 2010). Residential energy use varies with house type and size, which in turn vary with degree of urban sprawl. An average household living in a compact county is estimated to consume 17,900 fewer BTUs of primary energy annually than the same household living in a sprawling county (The World Bank 2010). The denser and the more compact the built form, the lesser the per capita emissions - New York City has the world’s highest total GHG emissions, but on a per
capita basis, its emissions are much lower than other large cities, as much as 40 percent less than per capita emissions in Houston (The World Bank 2010). Cities, especially dense city centers, represent immense opportunities to improve quality of life and protect the climate.

2.4.1. **Smart Growth**

Cities are expected to take the lead in reducing their emissions and carbon impact, as well as in climate mitigation and adaptation mechanisms that need to be built in their planning frameworks. Smart growth and climate protection literature overlap, and the recent climate literature that has emerged dealing with land use and transportation basically extends the sustainability and smart growth argument further to climate protection. The key strategies of smart growth are integrated land use and transportation planning, also necessary strategies for climate protection (Heart and Biringer 2000, Handy 2005). As already stated, since modifications to the built environment are permanent in nature, the impacts will be cumulative over time. Critical are land-use, transportation and waste management policies.

Smart growth proponents believe that the long-term solution is to alter development patterns to reduce the need for people to drive through a range of strategies including mixed use and denser development and concentrating jobs in specific locations in a transit-friendly manner. Modifications in the urban form and guiding land use and transportation activity can bring about measurable reductions in the VMT. The *Growing Cooler* report (Ewing et al. 2008) published by the Urban Land Institute gives an exhaustive review of the current literature on compact urban development, mixed use development, strong employment centers, and climate change. Redevelopment and densification around existing schools, parks, and stores can help reduce VMT for non-work travel, coupled with safe and walkable neighborhoods, biking and transit infrastructure. Ewing et al. (2008) claim that relative to sprawl, cumulative impacts of compact development over time have the potential to reduce the need to drive by as much as 20 – 40
percent, or reduce total US transportation CO₂ emissions by 7 – 10 percent. Their conclusions are based on the analysis of various disaggregate land use and travel studies and report cumulative and interaction effects of different land use characteristics. This means that although the effects of one single land use characteristic might be insignificant or small, but when several variables are tested together, they are significant. This can be achieved mainly by shorter trips and modal shifts at higher densities. An additional up to 20 percent approximate reduction in energy and emissions from residential heating/cooling can be achieved in a compact area due to less exterior wall area and floor area.

Land use and transportation planning decisions fall within the domain of local government decision-making, so that they can contribute to long-term GHG emissions reduction. As mentioned, alternate development approaches like Transit Oriented Developments (TOD) and Jobs-Housing Balance (JHB) are popular with communities that aim to reduce the need for people to travel. It is possible to substantially reduce vehicle trips and distances by compact spatial planning, locating different activities within walking distances, and providing alternate transportation choices (Ewing et al. 2008, Condon et al. 2009). Proactive sustained smart growth measures have been adopted in many states and cities. Planners in the US generally believe that climate protection measures are smart growth initiatives that cities should be doing anyway, regardless of climate change (Wheeler 2008). Spatial planning can also help communities adapt to climate impacts and build resilience to water scarcity, flood risks, and hazards.

2.4.2. **Local and Regional Governance**

Many cities in the US rely on technical support and peer-to-peer learning through membership in different national and transnational municipal networks (TMN) for climate protection. There is increased awareness of the importance of local and regional governance in climate protection in today’s globalizing world. Cities in the US, Europe and across the world are
coming together to form coalitions and networks that use their combined synergy for climate protection. Local governments that actively participate in national or Transnational Municipal Networks (TMC) connect with each other and try to increase their influence in the global politics of climate change (Toly 2008). There are several such networks which have increasing and active participation of cities. As of June 2012 mayors of 1,054 US cities have signed on to the US Mayors’ Climate Protection Agreement, which means that they have committed their cities to Kyoto Protocol carbon reduction goals or more. Hundreds more cities and communities are part of ICLEI’s Cities for Climate Protection (CCP) network. Other networks include the C-40 Cities by the Clinton Climate Initiative, the Sierra Club’s Cool Cities program, and the Energie’ Cities in Europe, and other groups that are working to disseminate information, enable peer-to-peer learning, extend technical support and maximize their global influence. It is predicted that the active role being played by cities will influence the future comprehensive US climate policy at the federal level.

2.4.3. Climate Action Plans

The climate protection effort in the US is bottoms-up and community-driven. Cities are actively following a sustainable agenda for climate protection. States and cities are taking leadership in climate policy, and will likely influence any future Federal climate policy (Toly 2008). They are incorporating climate protection in the planning of cities and neighborhoods, buildings, and streets. State legislation for climate protection include the landmark California’s Global Warming Solutions Act of 2008 (SB 375) that mandates regional planning to consider climate impacts. More than 30 states and hundreds of cities have prepared Climate Action Plans (CAP) specifying measures for compact land use planning, mass transportation, energy-efficient building and infrastructure, and policy intervention (Wheeler 2008). These plans set ambitious GHG emission reduction targets, and aim to become carbon neutral. Tang et al. (2010)
examined a sample of 40 specific CAP across the US in 2008 and found significant variation in the content and quality of the local CAPs which contributes to their strengths or weaknesses (refer Figure 7). One of the reasons for the large variation observed in planning goals and achievements is also the lack of a unifying federal policy in the US guiding the process.

Figure 7: Climate Action Plans in American cities, 2008

Source: Tang et al. 2010
2.5 Challenges Cities Face

Countering the arguments in the section above, several arguments are also extended against the efficacy of cities in addressing climate change. Some of these question the capability and resources of cities to deal with global climate change, beyond what they can accomplish through governance, technical, financial, and regulatory impact. Climate protection is seen to be an important global environmental goal that requires international effort and cooperation, and is therefore seen to be beyond the scope of local governments (Bestill 2001). It is widely perceived that climate change, like global poverty, is a challenge too big for spatial planning to handle and not enough to significantly reduce GHG emissions (Campbell 2006).

In the US, due to lack of clear policy support at federal government and at many state government levels, cities are not able to implement ambitious policy measures. The existing governance structure is multi-level, and each level has a role in climate protection; however, action and implementation aspects largely fall under local governments. Climate issues often extend beyond geographical scope or technical and financial capability of local governments and need higher policy support. Climate change is a cross-cutting environmental problem, and internal institutional barriers also make implementation difficult. Cities must also address climate change in a holistic manner – across different sectors horizontally, and across varying scales of governance vertically. City government offices are fragmented into separate departments that make it difficult to undertake effective policy formulation (Bestill and Bulkeley 2007). Cities also perceive climate change as a future problem and place on the policy backburner, as they deal with more immediate issues.

Climate protection is perceived to have little local or individual benefit (Kousky and Schneider 2003). The theory of free-ridership implies that cities should be least concerned about
climate change, or unlikely to take any voluntary action to reduce emissions for the benefit of the global climate. It is usually cheaper to build on new areas as compared to maintaining and enhancing existing areas, as many subsidies prevent from charging developers the full cost of new development in the fringes. Our tax structure, real estate market mechanisms, lending systems, and public investment policies are all geared toward new developments, and do not support redevelopment which prevents local bodies from investing in already developed areas. Also, local climate policy is largely oriented towards mitigation. Much of the effort at the city level is concentrated on long term carbon reduction, and cities are only recently beginning to address adaptation and climate vulnerability concerns (Bestill and Bulkeley 2007).

Despite all the action at the local level, there is inadequate authoritative research that substantiates urban policy in favor of modifying the built environment to reduce the need for people to travel (Stone et al. 2009, Brownstone 2008). Brownstone believes that the evidence of impact of land use characteristics on travel behavior is weak at best; therefore intervention in taxation policies and pricing mechanisms such as increasing parking prices, congestion pricing, and increasing fuel taxes might be more effective tools for reducing VMT and achieving the same environmental results. Therefore, straight-forward and simplistic technological solutions like improving vehicle fuel efficiency and fuel content that can reduce GHG emissions are seen as the quick fix solutions by policy-makers. Cities face challenges in planning for climate protection due to lack of conclusive studies to show that local planning intervention can bring about a significant reduction in GHGs (Bestill 2001). Even though there is an understanding that compact urban development results in lesser vehicle miles traveled (VMT), more research is needed to determine exactly which aspects of the urban environment have this impact, and the magnitude of these relationships. This knowledge is necessary for cities to be able to decide what possible combination of strategies and land use planning interventions would be most
effective. Decision-makers do not have adequate knowledge about the impact that different land use development types can have on GHG emissions or adaptation strategies to deal with and adapt to the effects of climate change. Are land use strategies the best options, or can taxation, fiscal, or technological measures achieve the same objectives, or will a mix of policies work best? Cities also need access to various planning tools that they can adapt to their local situation and use for climate planning.

2.6 Chapter Summary

Cities play a predominant role with respect to global climate change. Urban systems and processes not only overwhelmingly contribute to climate change, but cities are also strongly impacted by it. There is a strong link between transportation and mobility patterns and GHG emissions. In the US vehicle miles traveled (VMT) by household vehicles have increased phenomenally since the 1980s. Cities in the US are taking the lead in climate protection by adopting Climate Action Plans that attempt to mitigate major GHG contributing activities such as household vehicular travel through demand management strategies including smart growth, integrated transportation and land development strategies such as compact and mixed use developments, and transit provision. They work on the premise that there is a strong relationship between land use characteristics and household vehicular travel. However, urban planners lack sufficient knowledge to determine exactly which aspects of the built environment influence household travel the most, and therefore, which is the best set of land use strategies that will enable them to meet their climate protection objectives.
3. Land Use, Socioeconomic Characteristics, and Household Travel

The potential for reducing travel demand by modifying the built environment is currently the most heavily researched topic in urban planning. This literature is vast, and is growing exponentially. To date, there have been almost two hundred studies that have analyzed travel patterns in many ways, most of which have been published in the last decade alone (Ewing and Cervero 2010). This chapter discusses the relationship between each of the various socioeconomic and land use variables and the computation methods employed by land use – transportation studies. Since this literature is vast, here I have discussed only select, representative, and key literature.

3.1 Overview of Built Environment and Travel Studies

The earliest built environment and travel studies date back to the 1960’s and focused on density and travel with respect to traffic congestion and air pollution. Currently, this vast literature spans research on built environment from the public health perspective including mobility, livability, social justice, traffic safety, air quality, energy consumption, climate change, the social and economic costs of automobile use, and international research. Some studies have also focused on residential preferences, or on specific travel groups or case studies (Ewing et al. 2008). In recent times alone, there have been about 50 empirical studies that have researched one or more aspects of the connection between the built environment and travel. Several are comprehensive literature reviews (including Crane 2000, Ewing and Cervero 2001, Stead and Marshall 2001, Handy 2005, Leck 2006, Ewing et al. 2008, Litman 2008, Ewing and Cervero 2010, and many others); still others are meta-analyses of multiple disaggregate studies that

A few studies have extended this land use – travel connection to climate change by estimating GHG emissions from passenger travel influenced by land use (Heart and Biringer 2000, Ewing et al. 2008, Stone et al. 2008, and others). In the Urban Land Institute report *Growing cooler: The evidence on urban development and climate change*, after a thorough analysis of the literature on land use and transportation studies, Ewing et al. (2008) claim that cumulative impacts of compact development over time has the potential to reduce the need to drive by as much as 20 – 40 percent, as compared to sprawling development, mainly brought about by shorter trips and modal shifts at higher densities. Their conclusions are based on the analysis of various other disaggregate land use and travel studies and report cumulative and interaction effects of different land use characteristics. They also determine that although the effects of one single land use characteristic might be insignificant, when several variables are tested together, they have a far more significant impact. This range of VMT reduction will reduce the US total transportation CO\(_2\) emissions\(^6\) by about 7 – 10 percent. By compact development, the authors do not mean only density, but a combination of different land use factors including mixed land uses, strong population and employment centers, pedestrian-friendly built environment, and infill development. Nelson’s future growth projections determine that two-thirds of new growth will happen in outer suburbs and one-third will happen in cities and inner ring suburbs over the next few decades (Nelson 2004).

\(^6\) All transportation related emissions including from rural and urban travel, air, rail, sea travel, and cargo movements
In their earlier 2001 USEPA funded meta-study, Ewing and Cervero had reviewed 14 studies from the period 1996 – 2001 on the impact of four key aspects of the built environment namely density, diversity, design, and regional accessibility on travel demand, the results of which were incorporated into the USEPA’s Smart Growth Index (SGI) model. They had also found that although the magnitude of the link between the individual variables of the built environment is small, collectively their impact is much higher. Surprisingly, they determined that destination accessibility has more impact on VMT as compared to density or mixed use, and regional accessibility is also a very important characteristic influencing household travel, as more accessible central locations may produce lower VMT as compared to mixed use locations in far-out suburbs. In their recent landmark meta-analysis of 50 statistically-sound studies, a comprehensive and stronger update on their previous 2001 study, Ewing and Cervero (2010) reconfirm that travel variables are not very elastic with respect to land use characteristics by themselves, but that their combined effect can be substantial. Interestingly, they also reaffirm that destination accessibility (access to jobs and other destinations in the neighborhood), and regional accessibility (centrality of location, often measured as the distance to the city center or CBD), are the two land use characteristics with the strongest relationships to household VMT, and street design characteristics also showed up significantly. In addition, they find that transit use is also related to location proximity to transit stops and street network design. They did not find VMT to be strongly related to population or job density or even land use diversity that have been discussed at length in the literature, once these other factors are controlled for (Ewing and Cervero 2010).

In contrast to the above study, Leck (2006) had found residential density to be the most important built environment element influencing travel choice, and also determined a strong link between mixed land use or diversity as being a strong predictor of travel mode choice and
negatively related to VMT, as people living in diverse neighborhoods are more likely to commute to work by transit or other non-car means. Identifying 40 relevant studies, and applying meta-analysis to 17 statistically-sound studies from the period 1991 - 2002, Leck (2006) found mixed evidence for the impact of different land use characteristics on travel. However, he found no link between the grid street design configuration and continuous sidewalk design with travel behavior, as claimed by the New Urbanist proponents. As a policy recommendation he suggests using zoning and land use decisions carefully so that they encourage mixed use and compact developments.

3.2 The 5-D’s

The urban form measures that impact travel can be classified as the measures of proximity and the measures of accessibility/connectivity (Frank 2000, Crane 2000). Measures of proximity include density of development and diversity of land uses, jobs-housing balance, and other land development aspects that bring origins and destinations closer to each other. Measures of accessibility and connectivity include the number of blocks and intersections per unit area; building and block sizes and street design; intersection design, sidewalk continuity, and other neighborhood design characteristics that determine the pedestrian environment and transit accessibility. Accessibility to regional transportation systems also influences how much we drive to these locations. The built environment influences travel, but there is a lot of disagreement on the likely impacts that higher densities, mixed use developments and street connectivity have on household travel patterns and related GHG emissions.

The relationship between different land development characteristics were articulated by Cervero and Kockelman (1997) and other studies in terms of the 3-Ds of Density, Design and
Diversity. The land development characteristics that most impact mode choice and travel distance have come to be known as the 5-Ds (Ewing et al. 2008). As listed in Table 1 below, these include Density, Design, Diversity, Destination accessibility, and Distance to transit.

**Table 1: 5-D’s Influencing Travel Demand**

<table>
<thead>
<tr>
<th>Land Use Characteristics (5-D’s)</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Density</strong></td>
<td>Density of people, households, and jobs</td>
</tr>
<tr>
<td><strong>Design</strong></td>
<td>Urban design features like neighborhood and street design configuration, walkability, presence of sidewalks and trees, street and built form pattern, building setbacks, street accessibility features like average block size, intersections and pedestrian crossings, other physical / aesthetic attributes</td>
</tr>
<tr>
<td><strong>Diversity</strong></td>
<td>Land use mixing, or locating many different land uses in a given area or neighborhood</td>
</tr>
<tr>
<td><strong>Destination accessibility</strong></td>
<td>Number of jobs, schools, attractions that are located within a given driving time from residential areas</td>
</tr>
<tr>
<td><strong>Distance to transit</strong></td>
<td>Proximity to bus or train station or park and ride points</td>
</tr>
<tr>
<td><strong>Two more D’s</strong></td>
<td></td>
</tr>
<tr>
<td><strong>Demand Management</strong></td>
<td>Parking supply, pricing, and location</td>
</tr>
<tr>
<td><strong>Demographics</strong></td>
<td>Socioeconomic conditions of the household like household structure, income, vehicle ownership, and other attributes</td>
</tr>
</tbody>
</table>

Source: Ewing et al. (2008) and other sources

Demand management through parking (its availability, pricing and location) can be considered the 6th-D, and Demographics can be considered as the 7th-D as they are additional but important factors having an impact on vehicular travel. The variables and studies identified in this chapter are representative in nature and are by no means exhaustive. The next few sections discusses in depth the different socioeconomic, travel and land use variables used in land use and travel studies. These 5-Ds are broad categories, and each includes a set of different land use/built form variables.
3.3 Density

Almost all built form-travel studies identify the density of development as a key land use characteristics that impacts vehicular travel. It has long been used in land use-transportation research as a powerful predictor of travel behavior. The earliest studies from the 1960s concentrated on analyzing the impact of higher densities on auto use, traffic congestion and air pollution. Density reflects how intensively land is used for housing, employment, and other purposes (Cervero 2002).

In many studies, density has been found to have the strongest and the most significant relationship to travel pattern: it has been found to be negatively related to vehicle ownership and VMT, and positively related to the share of walk or transit commute trips (Ewing et al. 2008, Stead 2001, Frank 2001, Leck 2006). Trip lengths are also shorter in denser urban environments. Residential and employment density are directly correlated to VMT, vehicular ownership, and less auto travel per capita. Theoretically, higher densities decrease travel distances by bringing origins and destinations closer by increasing compactness, and therefore reduce travel distances. It also has an impact on transit usage as higher densities provide a larger pool of transit riders in a location, improving mobility options (Frank 2000, Litman 2008).

It is believed that low density development encourages an automobile reliant lifestyle, which in turn leads to increases in VMT. Cities that are comparatively denser help in reducing trip lengths and conserve energy. On the one hand, traditional, dense, urban neighborhoods built before the 1940s, transit oriented, and neo-traditional neighborhoods show a higher share of walking and transit use (Ewing and Cervero 2001). But, on the other hand, density has also been found to reduce vehicular speeds and increase traffic congestion, therefore reduce automobile accessibility (Litman 2008). Higher residential and employment densities are also shown to reduce single occupancy vehicle (SOV) travel significantly. After analyzing 17 statistical studies
on urban form and travel, Leck (2006) reaffirmed residential density as the most important land
use characteristic influencing travel choice. Galster et al. (2001) conceptually defined density as
the average number of residential units per square mile in the developable area and visually
presented a concept of high and low density developments at the scale of the neighborhood (as
shown in Figure 8).

Figure 8: Conceptual definition of density

High population density is highly correlated with low vehicle ownership. The National
Household Travel Survey 2009 indicates that about 30 percent households in areas with
population density above 10,000 persons per sq. mile did not own a vehicle in 2009, whereas
almost 70 percent households in the least dense areas owned 2 or more vehicles. However, 45
percent the US population live in areas less than 2000 persons per sq. mile (USDOT 2011). Households in very high density areas of 5,000-9,999 households per square mile produced half the CO$_2$ emissions than households in very low density areas of 0-50 households per square mile (USDOT 2009A).

It is still debatable how increasing densities will result in reduced travel. Although density of development has a direct correlation with travel, it is a very simplistic measure to describe the connection between urban form and travel. Dense development is more conducive to alternate travel modes like walking, biking, and transit, and implies that destinations are located closer to homes. It may be argued that this is partly explained by self-selection that implies that people who live in denser traditional neighborhoods might do so because they prefer to walk or use transit more (Kitamura et al. 1997). Some researchers believe that density by itself might actually not contribute directly to this relationship, but is a proxy for many other characteristics associated with higher density such as better transit service, increased mixed use, better regional accessibility, lower automobile ownership rates, and limited parking availability, that have a far greater impact on travel (Ewing et al. 2008, Ewing and Cervero 2001, Crane 2000, Frank 2000, Frank and Pivo 1994, and others). Based on their analysis of the impact of density on travel in 370 US metropolitan areas, Cervero and Murakami (2010) also contend that density might be a proxy for other travel-reducing variables including a denser street network, higher access to retail shopping and services, pedestrian-friendly design, and mixed use. They find a gross elasticity$^7$ for density on VMT to be -0.604, but still find its net effect elasticity to be -0.381. The implications from this are that several smart growth solutions that do not require

$^7$ Elasticity here means the percentage of change in VMT associated with one percent change in a particular land use characteristic.
higher densities may still be applied to already developed suburban areas similar to the urban
village concept, which might also lead to reduced travel (Litman 2008).

Measuring Density

Population, household, or employment density are the most widely used land
development measures used to study impacts of density on travel, because they are the easiest to
quantify. Density is usually measured in terms of number of people, households, or jobs per unit
area and at the various scales of the census block, neighborhood or the city. Frank and Pivo
(1994) define gross population density as the “entire population or number of residents within a
designated geographic area divided by the size of the designated area, which was the census
tract” and the gross employment density as “the number of employees within a designated
geographic area divided by the size of the designated area, the census tract.” Compact
development is also understood to be primarily a measure of density. Cervero and Kockelman
(1997) suggest that accessibility can be treated as a measure of density as well, as it measures a
neighborhood’s relative proximity to activities and reflects relative compactness.

There is debate on the use of gross vs. net density measures. Gross density specifies total
land area, which includes land used up for parking lots, roads, etc. Net density refers to the net
land area, excluding roads, public open space, parking lots, environmentally sensitive areas, and
other undeveloped land. Net density would be measured by dwelling units per residential acre
and is more applicable for site-specific purposes, indicating efficient land utilization on a site. In
land use and travel studies, gross density is preferable when measuring neighborhood
accessibility as the size and amount of roadways and parking lots directly influence the quality of
pedestrian environment (Krizek 2003B).

Gross population density has been one of the most common measures of density in built
form and travel studies. Examples include gross density calculated as population and
employment per developed acre at the census block level (Boarnet and Crane 2001) and gross population density at trip origin and destination Traffic Analysis Zone (Cervero 2002, Cervero & Kockelman 1997, Frank and Pivo 1994). However, this measure includes all areas that might be undeveloped, so it is a good idea to apply weights to differentiate between developed and undeveloped area or compute net density. Residential density in dwelling units per acre at trip origins and destinations Transportation Analysis Zones (TAZ) have also been used (Frank and Pivo 1994) or housing units per square mile (Krizek 2003A). Another measure is the employment density measured as employment per developed acre (Cervero & Kockelman 1997) or gross employment density per acre at trip origin and destination TAZ (Frank and Pivo 1994), Boarnet and Crane (2001) also used a retail and service employment density measure at the census block level.

### 3.4 Diversity

There is considerable debate in the literature about the role that land use diversity plays in urban travel. Land use diversity is an indication of the heterogeneity in land uses, and an indication of the land use mix in an area. It signifies the presence of different land uses in a given area or neighborhood. It is believed that more heterogeneous land use induces transit and non-drive-alone travel (Cervero 2002). Diversity impacts travel in many ways. It allows compatible uses to be located in close proximity to one another (for instance residential, retail, and office uses) and thus reduces travel distances to different activities and promotes walking.

Mixed land uses around transit nodes increases transit use as well. Through his analysis Leck (2006) shows that land use diversity is also a strong predictor of travel mode choice, as people living in diverse neighborhoods are more likely to commute to work by transit or other non-car travel. Effects of land use mix and choices vary as distances between complimentary
land uses increase, for example residents may choose to walk to shop or restaurants if they are available within 5-10 minutes pleasant walking distance and more likely to use a car if these are located more than a 20 minutes’ walk away (Frank 2000). Ewing and Cervero (2001) find that mixed land uses provide more benefit in compact as compared to dispersed settings, which indicates the presence of an interaction effect between density and diversity. Several studies do not isolate the effect of different land use characteristics which makes it difficult to study and identify which land use characteristics are crucial. Frank and Pivo (1994) have also discussed the impact of land use mix on travel behavior and the relationship between non-work travel and urban form, specifically the collective impacts of urban form on travel choices at both the origin and destination ends of travel. Research has shown that locating shops, banks, restaurants, and other services and conveniences near places of work can reduce vehicular travel. Using land use mix as a travel demand management strategy is becoming popular with city planners, as the political resistance to mixed land use is usually less, as compared to political resistance to higher densities.

The data from the National Household Travel Survey 2009 provides interesting travel statistics (USDOT 2011) which indicates that intermingling of different land uses might work as a smart climate protection policy option. Nationally, about 72.2 percent of all VMT is non-commute, as shown in Figure 6 (a), and as much as 81 percent of all trips are non-work-related as shown in Figure 6 (b). This indicates high levels of travel for family and personal travel, shopping, social and recreation purposes. Up to 42 percent of household trips falls under family and personal business and shopping, and close to 27 percent are for social and recreational purposes. Predictable travel consisting of work commutes, work-related trips, and school and church trips together account for only about 29 percent of travel (USDOT 2011). The current travel trends and trip purpose data indicates that non-work trips are increasing at a much faster
rate as compared to work commutes, or daily travel to school (USDOT 2004, USDOT 2011). Transportation and land use research needs to address these changing travel patterns, and move away from focusing on home-to-work commutes. There exist several opportunities to incorporate retail, services and conveniences to be located near places of work and residence. Mixing compatible land uses like residential, retail, offices, and restaurants is probably a more effective strategy for reducing CO$_2$ emissions from household travel than believed till now, and warrants further investigation. Effects of land use mix and choices vary as distances between complimentary land uses increase. For example, residents may choose to walk to shop or to restaurants if they are available within a 10 minute pleasant walking distance and more likely to use a car if these are located more than a 20 minutes’ walk away (Frank 2000). Many researchers failed to find a significant relationship between diversity and travel demand (Stead and Marshall 2001).

Since diversity indicates the various measures of land use mix in the neighborhoods, it is also a measure of micro-accessibility or destination accessibility which indicates the number of specific attractions/destinations within short distances of residences (Ewing and Cervero 2001). Cervero (1996) looked at the impact of mixed land uses and commuting by examining mixed land use within 300 feet of residence as the test variable. He defines land-use mix as the composition of uses within a given geographic area. According to him "mixed-use developments are those with a variety of offices, also shops, restaurants, banks, and other activities intermingled amongst one another." Frank (2000) defines land-use mix as the evenness of distribution of the square footage of development among different land use categories within a census tract, and the intermixing of land uses as the composition of uses within a given geographic area. Galster et al. 2001 conceptually define mixed-use as the degree to which two
different land uses commonly exist within the same small area. He provides the visual representation of the mixed-use concept at neighborhood scale (see Figure 9).

Figure 9: Conceptual definition of diversity

This section summarizes a wide range of measures of land use diversity as used in representative travel and built form studies over the years. Diversity is usually measured by the number of different land uses or activities in an area, as a share in land area, built-up area, or employment (for example for measuring jobs-housing balance a ratio of the number of residents and jobs is estimated). It can also be measured in terms of entropy, index of dissimilarity, mixed use, and job-housing balance.
Index of Dissimilarity

The index of dissimilarity captures spatial complementarity and looks at the dissimilarity of uses within a given geographical area and has been often used in land use and travel studies (Kockelman 1997, Cervero and Kockelman 1997). One of the first comprehensive approaches to measuring diversity was provided by Kockelman (1997) who developed a land use diversity index based on a one hectare grid and relying on land use descriptions provided for each of the grid cells by local governments in the San Francisco Bay Area. Kockelman used a 1 hectare grid and studied the integration of land uses — the degree to which they come into contact with one another (see Figure 10). This was based on hectare level existing land use descriptions provided by local governments of the area. The process assigns a predominant land use to each hectare of land and measures the dissimilarity of each hectare based on uses of adjacent hectares.

Figure 10: Hectare level dissimilarity index

The average of these point accumulations across all active hectares in a census tract is the dissimilarity or land use mix index for that tract. One-eighth of a point is awarded for each of the adjacent hectares whose use differs from that of the center hectare, and the final index varies between 0 and 1. Krizek (2003A) developed a similar 150m grid and analyzed the number of
jobs in each grid cell to arrive at a measure of land use diversity. Krizek points out that this
dissimilarity index is only a measure of whether or not adjoining grid cells are different from the
central square, and is insensitive to the number or type of uses that are different from the central
square (Krizek 2003A, Krizek 2003 B). At the time of many earlier studies, individual parcel
level land use data was not widely available and diversity was computed at a broader scale.

**Entropy**

Entropy measures have been used sometimes to indicate land use mixes of origin and
destination tracts, for instance in Kockelman (1997). Entropy quantifies the balance of land use
categories, within a census tract, a TAZ, or a defined neighborhood, but is not considered the
best indicator for either functional or spatial complementarily (Krizek 2003B). It measures the
presence or absence of land uses, not the type or intensity of mixing. A main drawback of
entropy based land use index is that all land uses are viewed to be equally important in
computation, whereas they might not all be of equal importance to households from their travel
perspective. Cervero and Kockelman (1997) and Kockelman (1997) used the entropy concept to
measure diversity. They determined mean entropy of land use categories among hectare grid of
cells within half-mile radius of each hectare grid cell, and mean entropy their mean entropy
ranged from 0 (homogeneity, all land uses are of single type) to 1 (developed area is evenly
distributed among all land uses)

\[
\text{Mean entropy} = - \sum_{j,k} \left[ P_{jk} \times \ln(P_{jk}) \right] \\
\text{ln}(J) / K
\]

where K is the number of actively developed hectares in the tract and Pjk is the
proportion of use type j within a 0.8-km radius of developed area surrounding the kth hectare.

Using census track level data Frank and Pivo (1994) applied the entropy method in the
Puget Sound Regional Council area and developed the entropy index based on seven land uses as
follows: Level of land use mix (entropy value) = - [single family • log10 (single family)] + [multifamily • log10 (multifamily)] + [retail and services • log10 (retail and services)] + [office • log10 (office)] + [entertainment • log10 (entertainment)] + [institutional • log10 (institutional)] + [industrial/manufacturing • log10 (industrial/manufacturing)]. Ryan and Frank (2009) also used a similar but advanced entropy concept in half-mile areas around bus stops to calculate mixed land use in their built form and transit ridership analysis.

**Jobs Housing Balance**

Job-housing balance within origin and destination (O-D) tracts is used to indicate the level of employment in residential tracts. At the scale of the zip code, Bento et al. (2005) measured how evenly jobs are distributed relative to residential population. They ordered ZIP codes in each city from the one having the smallest number of jobs to the one having the largest and plot the cumulative percentage of jobs (y-axis) against the cumulative percentage of population (x-axis) to obtain a Lorenz curve. The 45-degree line represents an even distribution of jobs versus population. Their balance measure (based on Massey and Denton’s Gini coefficient) is the area between the Lorenz curve and the 45-degree line, expressed as a proportion of the area under the 45-degree line. Larger values of this measure imply a less even distribution of jobs versus housing. Boarnet and Crane (2001) examine the retail employment divided by land area and service employment divided by land area near person’s residence (radius 300 ft), whereas Boarnet and Sarmiento (1998) examine the number of retail or service employees in a TAZ as a proxy for land-use mix (especially for commercial land uses) near each person’s residence. Cervero (2002) also used employment and population relative to county ratio at O-D TAZ level.
Mixed Land Use

Several measurements of mixed land use are present in literature, and are very widely used. It has been computed in a variety of ways. Using their 150 m grid, Krizek (2003A) analyzed the number of jobs in each grid cell to measure land use diversity - using existing retail activity in each grid cell. For every business detailed employment data from Washington State provided the two-digit Standard Industrial Classification Code assigned to the business, the number of employees, and the latitude and longitude coordinates. Cervero and Kockelman (1997) determined the vertical mixture by proportion of commercial/retail parcels with more than one land use category on site. They also developed a measure of proximity to commercial use by determining the proportion of developed land within one-fourth of a mile of convenience store, retail service use, and proportion of residential use.

At the scale of the census block, Boarnet and Crane (2001) determined mixed use by percentage residential, percentage commercial, and percentage vacant by applying aerial photography and site visits. In their case, land use mix variables are in proportion to the land in household’s census tract in residential use, commercial use, and vacant land. Cervero (1996) examined various instances of mixed use of residence using AHS data and developed measures like: commercial or non-residential buildings within a radius of 300 ft, grocery and drug store within 300 ft or 1 mile and low rise multi-family building or attached units within 300 feet, and high rise multi-family building or attached units within 300 feet. Krizek (2003B) used a binary mixed use classification to classify whether an area contained mixed uses determined by physical inspections. These may be complemented by asking respondents to estimate the distance to the nearest grocery store, gas station, or park to the nearest tenth of a mile. Ryan and Frank (2009) used a half-mile buffer around bus stops, and defined the land use mix as the proportion of seven land use types (commercial, industrial, institutional, office, parks, residential, vacant) within it.
Song and Knaap (2004) developed several very detailed and sophisticated quantitative measures for mixed land use. They define these based on five types of non-residential uses based on Traffic Analysis Zones (TAZ) such as neighborhood commercial stores, multifamily residential units, light industrial sites, public institutions, and public parks. The following four land use mix measure accessibility to the nearest nonresidential uses: MIX 1 – measures the distance from the house to each of the above-mentioned nearest non-residential use; MIX 2 - five measures based on proportions of each of the above-mentioned non-residential land uses within a TAZ that provide a measure of pattern of surrounding land uses; MIX 3 - two measures based on the concept of entropy variation to capture land use diversity within TAZ one that includes single family residential use to capture overall mix of uses, and another that excludes it and only captures the land use mix of the nonresidential sector; and, MIX 4 - this set of variables is developed to represent relative balance between total jobs and service sector jobs with the population within each TAZ.

Land use mixing happens at a much finer scale than previous research has attempted to measure. Computation of diversity is complicated due to issues of measurement, scale, and limited availability of detailed parcel level land use data. Current methods to measure land use diversity are debatable, but recent research is more sophisticated. One of the objectives of this research is to improve upon the computation of the land use diversity measure as compared to those used in most land use and travel studies.

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Song and Knaap (2004) study is not a travel - land use/built form study, but has been included here as they provide detailed account of computing four comprehensive measures of mixed land use.
3.5 Design

Street and neighborhood design metrics can be widely interpreted, difficult to define, and challenging to measure. These can include various urban design, neighborhood, and street characteristics. Improved street and neighborhood designs are an indication of improved accessibility and connectivity. Street pattern is often used as a proxy measure for the “traditional-ness” of the neighborhood and other urban design amenities including walkability. Traditional urban form and its characteristics are seen to support transit, walking, or cycling, as compared to suburban development characterized with the cul-de-sacs (Krizek 2003A, Krizek 2003B).

Street or network connectivity refers to the degree to which a road system is connected, and is a measure of directness between destinations (Litman 2008). Street network within a neighborhood can vary from a connected, dense, urban grid, to a hierarchical, curving and sparse, loop and lollipop suburban system. However, there is considerable debate on what aspects of street design are said to reduce travel demand. Short blocks and many intersections are found to shorten trip lengths as well as encourage walking. Ewing and Cervero (2010) find street design metrics to be one of the strongest land use factors related to VMT generation. Increased intersection density and increased street connectivity are believed to shorten access distances, and provide more routing options for transit users and transit service providers. Grid road networks also improve walkability by providing many different options to pedestrians to walk. In addition, a grid development pattern improves regional accessibility by distributing vehicular traffic across different roads and thus reduces congestion. Pedestrian-friendly design is believed to contribute to an increase in walking and transit use as opposed to car travel. Street design features such as sidewalks and safe pedestrian crossings help, as do smaller blocks and narrower streets. A pedestrian friendly road network grid with traffic calming measures, narrow
streets and short blocks are found to discourage car use (Ewing and Cervero 2001). However, Leck (2006) in his meta-analysis found no relationship between the grid street layout and continuous sidewalk design aspects and travel behavior, as claimed by the New Urbanists.

Measuring Design

Street accessibility is measured in terms of walkability which may include street and built form pattern, building setbacks, block size, number of 3-way and 4-way intersections, street widths, ease of pedestrian crossings, presence of sidewalks and trees, and other physical attributes that determine a pedestrian and cycling environment. Elements of good design that improve pedestrian and cyclist environments include sidewalks, building scale, streetscape, and landscaping (Krizek 2003B). There are some very specific urban design characteristics that most travel studies have not been able to capture, let alone measure, adequately (Litman 2008, Ewing and Cervero 2001). A pedestrian or walkability index is often used to measure street accessibility and connectivity from the pedestrian perspective in modal choice studies.

Several design variables have been used in built form and travel studies. Neighborhood type or character was described by Khattak and Rodriguez (2005) using case study approach. They described a neo-traditional neighborhood as having a town center as a focal point, accessible within a quarter-mile for most residents, having primarily two or three-story brick structures, combining office or commercial space on the first floor with residential on the others; and the conventional neighborhood having homes deeply set back from the street, no sidewalks or sidewalks on one side only, large garages accessed from the street, and cul-de-sac and dead end streets.

At the regional scale, Bento et al. (2005) measured city wide or metropolitan road network characteristics by city shape as the ratio of major to minor axes. They also computed road density based on road length and widths by the size of urbanized area. Boarnet and Crane
(2001) computed the percentage street grid characterized by 4-street intersections within a quarter mile radius of a person’s residence at the neighborhood scale. Krizek (2003A) used a 150m grid cell to compute the average block area within each grid, as neighborhoods with higher intersection density or lower average block area, more closely resemble gridded street patterns and are more representative of areas with high neighborhood accessibility. Other measures of street grid pattern include proportion of 4-way intersections, predominant street pattern, number of underpasses/overpasses, number of dead end or cul-de-sacs, street widths, and average arterial speed limits (Crane 1996, Cervero and Kockelman 1997). Provision of sidewalks has been considered as a measure of completeness of pedestrian facilities. It has been measured by Cervero (2002) as the ratio of sidewalk miles to road miles, and as the ratio of total length of sidewalk system to the total length of block or street frontage (Mouldon et al. 1997). In this case, the optimum ratio would be 1:1, indicating that both sides of all public roadways have sidewalks. Cervero and Kockelman (1997) also measured the pedestrian and cycling provisions as the proportion of blocks with sidewalk, plants, trees, quadrilateral blocks, bicycle lanes, mid-block crossings, etc. in their one hectare grid. Using GIS applications, Ryan and Frank (2009) developed a composite walkability index as a factor of land use mix, residential density, retail FAR and intersection density. Pedestrian route directedness can be measured as the ratio of actual route distance traveled to a straight-line distance, and can be computed for walking distances between the neighborhood center and the surrounding residential areas within walking residential neighborhoods.
3.6 Destination and Regional Accessibility

Several measures of accessibility and centeredness have been used in analysis of land use patterns on travel. Destination accessibility refers to the availability of jobs, schools, and attractions present within a given driving time or distance, and it is reportedly higher in more central locations as compared to peripheral ones (Ewing et al. 2008). It is believed to have the strongest influence on trip lengths (Ewing and Cervero 2001, Ewing and Cervero 2010). It influences travel pattern in two ways. First, in the case of home-based trips, it influences to what extent daily household needs are met within a specific driving time or distance. Stead (2001) reports significant reduction in travel if there are convenience stores located within a comfortable walk. Second, it influences non-home-based trips significantly through trip-chaining, or linking of trips on a tour, that account for up to 27 percent of all commute trips (USDOT 2004), and up to 25-30 percent of all urban trips (Ewing et al. 2008). Trip chaining is on the rise and indicates that concentrating different activities in proximity of homes even in existing sprawling areas has the potential to reduce travel significantly by combining multiple trips in a single auto trip.

Centeredness refers to the portion of employment, entertainment and other non-residential activity that is concentrated in major centers or the CBD. Comparing Chicago and Los Angeles, Litman (2008) stresses that higher levels of centeredness, even in case of comparable densities, have beneficial effects on the overall regional travel patterns. Centeredness directly relates to a larger share of walk and transit trips (Ewing et al. 2008). There are mixed reports regarding regional accessibility or the distance of the development from the regional urban center. Litman (2008) finds that it impacts the trip lengths, but not the number of trips. Ewing and Cervero (2001) also point out that dense and mixed use developments built far out and not connected to the contiguous built environment may not reduce travel significantly. Stead (2001) did not find any relationship between distance between home and the urban center
and the individual travel distance. Studying shopping behavior in suburban San Francisco, Handy (1993) finds that both regional and local accessibility help in reducing shopping distances but they have no effect on shopping frequency. Studies carried out at a larger scale are not able to capture the variations in the fine grain land use fabric. Krizek (2003) studied the impact of neighborhood accessibility using panel data, and found that over time, the same set of residents modify their travel behavior when exposed to different levels of accessibility at the neighborhood scale. Higher neighborhood and regional accessibility reduces total VMT, but increases the number of trips, as the cost for each trip is comparatively lesser in higher accessibility neighborhoods. It is interesting to note that non-work travel, which forms an overwhelming portion of travel, is most likely to be reduced by improving neighborhood accessibility (Krizek 2003A). Neighborhood accessibility is also sometimes considered a proxy indicator of diversity.

**Measuring Destination Accessibility**

Destination accessibility has also been measured as the distance from home to work in miles. Kockelman (1997) defined an Accessibility Index in one hectare zone as \( \text{Accessibility} = \sum_j \left[ \frac{A_j}{t_{ij}} \right] \), where \( A_j \) is the attractiveness of zone j and \( t_{ij} \) is the travel time from zones i to j. Cervero (1996) measured accessibility as a binary variable (0=No, 1=Yes) with the location of residence in the central city of the MSA or not, and the presence of four-lane highway, railroad, or airport within 300 feet of residence or not. Handy (1993) defined local accessibility on the basis of type and location of activity in the neighborhood, and developed a gravity based model to measure local accessibility as a function of retail, service and other employment. She defined regional accessibility as a measure of access to retail shopping centers. Destination accessibility can probably be best measured by drawing out travel-time maps or isochrones (lines of constant
time), showing the time needed to travel from one location to other areas or possible destinations. However, I did not come across any study that has applied the isochrones methodology to a large enough sample size.

### 3.7 Distance to Transit

Distance to bus stops, train station, or park and ride stations impacts travel patterns. Sprawling development pattern increases auto-dependency as it promotes suburb-to-suburb travel, dispersing origins and destinations widely, that makes transit development unviable technically, financially, and politically. Households close to transit lines are estimated to produce up to a quarter less CO₂ as compared to households not near a transit line (USDOT 2009A). In their recent study, Ewing and Cervero (2010) find that living near a bus stop induces people to ride transit, therefore finding support for the practice standard of providing transit access within a quarter mile of most residents. Examining travel behavior in Britain, Stead (2001) reports that bus frequency also has a significant impact on transit use. People living in areas having higher bus frequency travel more than people living in areas not so well serviced. Increasing transit options increases mobility, and might in some cases, increase the total VMT by individuals. However, it decreases the overall CO₂ emissions by combining trips of several individuals, and reducing the car VMT. Transit Oriented Development (TOD) focuses on clustering retail and residential development in compact, mixed use, and walkable areas near transit centers, with the idea that it will reduce the need to own or use an automobile and increases transit ridership (Litman 2008, Cervero 2006). It is also believed that concentrating housing and other non-residential activities in already developed areas improves the efficiency of the transit system. Transit use also seems to depend on other land use factors, namely the quality
of the pedestrian environment, walkability, mixed use, and density. Ryan and Frank (2009) developed a composite walkability measure as a factor of land use diversity, density, and street pattern and analyzed it in a half-mile buffer around transit stops using GIS. They found a positive relationship of walkability on transit ridership in San Diego metropolitan region. Increasing transit service supply can have one of the largest impacts on reducing VMT, when combined with other car reduction measures.

**Measuring Transit**

Access to transit network has been measured at the metropolitan or city wide scale by Bento et al. (2005) as the number of bus route lines per urban area size (city wide measure), and as a binary measure (0 = no, 1 = yes) of public transit availability by Cervero (1996) at the neighborhood scale. Ryan and Frank (2009) measured transit availability as the numbers of bus routes serving a bus stop divided by the mean wait time of all routes serving the bus stop. They calculated bus ridership as the daily number of passengers getting on and off buses at bus stop. Transit availability has sometimes also been measured as transit route density, or miles of transit lines per sq. mile, or the distance between transit stops, or the number of transit stops per unit area.

### 3.8 Demand Management

Demand management - including policies for parking supply, location, and pricing, can be called the 6th-D. Parking has been identified as a key feature that impacts vehicular travel and mode choice. However, parking characteristics have been neglected in most studies. Both parking location and parking supply affect travel behavior. Large dead expanses of parking lots in-between buildings or in-between the streets and buildings discourage walking, and encourage
car use. Abundant and cheap or free parking and provision of complimentary parking as a perk by employers in downtowns promotes car ownership and use. Minimum parking requirements for every kind of land use zoning increases the demand for cars, which leads to an increased demand for parking (Shoup 2005) and this cycle feeds itself. Free or ridiculously low priced parking availability in city centers leads to an increase in driving, since it induces people to cruise around looking for free or cheap curb-side parking. Shoup (2005) shows how cruising around in a 15-block downtown LA looking for free or cheap parking spots resulted in an excess of 945,000 annual extra VMT, 47,000 gallons fuel wasted, and 730 tons CO$_2$ emissions in a year, not to mention the 100,000 hours of driver’s time wasted doing that!

Many studies suggest that parking pricing and supply can work as effective demand management techniques for controlling car travel and encouraging transit use (Litman 2008, Shoup 2005). Shoup suggests cities must charge fair market price for on-street parking, and relax minimum parking requirements in zoning. Parking has been measured as percentage of retail and commercial and service parcels with off-street parking, on street curbside parking, drive-ins or drive-throughs (Cervero and Kockelman 1997). Unfortunately, it is not very easy to obtain comprehensive data on parking location, quantity, and pricing.

Land use and transportation are connected not just at regional level but also at the scale of the neighborhood. The location and planning, as well as the density and design of development are important considerations, as is regional accessibility. All these variables have to support each other together. A well-designed, diverse suburb built too far from the city center would not help in reducing travel. Concentration of jobs and other non-residential developments around already developed areas in few selected locations also becomes important.
3.9 **Travel Variables**

Generally, the following types of household travel variables are used: trip frequencies; trip lengths (either in distance or time); mode choice or mode split; cumulative person miles traveled, or Vehicle Miles Traveled (VMT), or Vehicular Hours Traveled (VHT) Ewing and Cervero (2001). Travel data at the household level is usually collected using travel diaries, and more recently using the GPS O-D point data, which is considered more reliable than trip diaries. In the trip diary, details for each trip - its purpose, mode, duration, and distance are recorded. Trip information is usually sufficient to compute variables related to total travel distance and trip frequency. However, trip measures alone provide an incomplete accounting of trip complexity that involves trip chaining (Krizek 2003). To measure all complexities, vehicle miles traveled, person miles traveled, trip frequency, and trip complexity is summed over travel survey duration and averaged over persons in each household. In their literature review Ewing and Cervero (2001) conclude that different aspects of travel are affected differently by the land use and socioeconomic characteristics, and that VMT is predictable more by land use as compared to socioeconomic characteristics:

- “Trip frequencies are primarily a function of socioeconomic characteristics and secondarily of the built environment; they seem to be independent of land use characteristics and depend more on the household socioeconomic characteristics.
- Trip lengths are primarily a function of the built environment and secondarily of socioeconomic characteristics. Trip lengths are usually shorter in locations that are more accessible and have higher densities, both residential as well as at activity areas.
- Mode choice depends on both the built environment and the socioeconomic characteristics. Mode choice is heavily dependent on local land use pattern as higher densities and mixed land use increases transit use and walking.
- VMT: built form characteristics are more significant predictors of VMT, which is a combination of trip lengths, trip frequencies and mode split.” (Ewing and Cervero 2001)
Various travel variables have been used in built form and travel studies, depending on the objectives of the study. The most common travel variable is the VMT or Vehicle Miles Traveled which measures the average daily person or household travel from travel surveys. Vehicle Hours Traveled (VHT) has also been used extensively and computed in-vehicle and out-of-vehicle travel times for the origin–destination combination of each trip record (Cervero 2002). Krizek (2003A) used trip length or distances, trip frequency measured as number of work or non-work trips taken by an individual and trip purpose that describes the purpose of trip for work, home, school, entertainment, leisure, social or others. Work and non-work travel is often used to measure impact of mixed land uses. Krizek also used trip chaining or trip complexity to measure multi-destination trips. Frank and Pivo (1994) used a variety of measures for travel mode choice including percentage of trips originating and ending in a census tract by single occupancy vehicle, by transit, by carpool, and by walking. Cervero (2002) computed drive-alone automobile, group-ride automobile, and transit modes (based on minimum path skims across highway and transit networks).

3.10 Socioeconomic Characteristics

People from different socioeconomic backgrounds, locations, and in different stages of life, travel differently. Various socioeconomic aspects like the demographics, income group and type of employment, car ownership, and other socioeconomic characteristics are the primary determinants of travel pattern (USDOT 2004). Stead (2001), Brownstone (2008) and others have raised concerns that most empirical studies have primarily examined land use characteristics, but did not sufficiently consider the socioeconomic variables that influence travel. Income, employment status, location, and availability of car, explain much better the differences in the overall travel pattern.
Household travel is primarily the function of the household socioeconomic characteristics, and secondarily of the built environment or land use characteristics. Therefore, the effects of socioeconomic characteristics like household structure and income need to be controlled in any analysis to determine the effects of land use characteristics. Stead (2001) presents a comprehensive study of individual, household, and land use characteristics that impact travel after examining the national travel survey datasets over several decades in Britain. He contends that although most empirical studies show that higher densities are associated with less travel, these variations are explained much better when we consider variations in income, along with the land use variations. According to him, socioeconomic group of the person explains about half the total variation in travel distance for an individual, whereas land use characteristics are only able to explain only about a third (Stead 2001). Different land-use characteristics identified as having an impact on travel are also associated with different socioeconomic characteristics. For instance, higher densities are generally also associated with poorer neighborhoods, and lower car ownership rates. The National Household Travel Survey 2011 for the US gives important insights to the socioeconomic aspects that impact travel. These include neighborhood characteristics, household income and location, demographic, and individual characteristics. Stead and Marshall (2001) identify eleven types of variables that effect travel demand: income, car ownership and availability, possession of drivers’ license, working status, employment type, gender, age, household size and composition, level of education, attitudes, and personality type. These socioeconomic factors are interconnected, and sometimes highly correlated.

3.10.1. **Demographics**

Demographics such as household size, income, education, car ownership and others are considered important characteristics that determine travel patterns, and can be called the 7th-D
Larger household size is believed to increase the VMT and therefore needs to be accounted for in the analysis to control for its effects. Gender, race and ethnicity also impact travel patterns. Everybody is traveling more, but women are traveling much more now than before. Gender is a more robust predictor of home based trips as compared to race or ethnicity (Mauch and Taylor 1997). Since 1969, the annual VMT increased 34 percent on an average for all, but for working women it increased by 54 percent, and for women not working it increased by 49 percent (USDOT 2004). Several studies have indicated that generally women have different work-commute patterns as compared to men and tend to drive shorter distances to work. Women however, take more frequent trips as compared to men, since they are more likely to undertake various household-serving and child-rearing trips. Women are also more likely to use transit, although that is declining. In 2001, women took about the same number of trips as men, but in 2009, women made significantly more trips overall than men, taking more number of trips for family errands and shopping, whereas men took significantly more trips for work and work-related business. Both took about the same number of social and recreational trips. However, men still traveled about 10 more miles daily compared to women. (USDOT 2011).

Six percent of people in the US are considered to have a transportation disability that limits their ability to drive (could be due to old age, physical or mental disability). An aging society indicates that a higher percentage of the US population in the future will have mobility issues, which will also influence their housing location choices and travel. The characteristic of the household is changing, with a distinct demographic shift toward single-person households. In 2000, the proportion of single-person household (25.8 percent) was greater than that of nuclear families (24.3 percent). This group is more diverse, and is more likely to travel more, eat out more, and travel individually to work, shop, relax, and for errands (USDOT 2004).
Location and level of urbanization impacts travel, as people living in rural areas tend to drive more than those living in urban areas, and have vehicles that consume more fuel (for example, pick-up trucks and SUVs). Urban households spend less on travel overall than rural households because they travel fewer miles for everyday trips and generally own smaller and more fuel-efficient cars (USDOT 2011). Within the 3-cars or more households, rural households spent $6,516 per year on fuel, as compared to urban households that spent $5,403 a year on fuel (USDOT 2011). Compared to location, income has a more direct and larger impact on travel.

The socioeconomic variables commonly incorporated as control variables in travel-built form studies are gender, age, race, education, employment, household structure, income, and vehicle ownership. Household structure can be incorporated as the number of children under 16 years of age (Boarnet and Sarmiento 1998), household size, number of school going children under 5, number of students, and number of workers in the household (Boarnet and Crane 2001). For gender, a dummy variable is generally used (Boarnet and Sarmiento 1998, Boarnet and Crane 2001, Cervero and Kockelman 1997). Age is usually the age of the survey respondent (Boarnet and Sarmiento 1998, Boarnet and Crane 2001) or the mean age of survey participants ending trips in each census tract (Frank and Pivo 1994). The latter study also incorporated various measures like the proportion of survey households per census tract with one adult less than 35 years old, between 35 and 64 years old, and over 65 years or older. Race is also incorporated as a dummy variable that equals one if the respondent is non-white (black, Hispanic, or Asian) zero otherwise (Boarnet and Sarmiento 1998, Boarnet and Crane 2001) or as Caucasian status, racial ethnic category (Cervero and Kockelman 1997). Education may be incorporated as a dummy variable for high school graduation or college graduation of the survey respondent (Boarnet and Sarmiento 1998, Boarnet and Crane 2001). Employment may be a
dummy variable for a full time or part time status, or by professional occupation, or industry type (Cervero and Kockelman 1997).

3.10.2. Income

Income is one of the most important socioeconomic variables. Travel and car ownership increase in direct proportion to the household income. It is believed that trip frequency is linked to household income and car ownership. People in higher income households make more journeys than in lower income households. Cervero (1996) shows that commuting distance also increases with increasing income.

In 2009, the average American household spent about $3,300 per year for gasoline for all the vehicles in the household in 2009, as compared to $1,275 in 2001, largely due to increase in gasoline prices in the US which have more than doubled since 2001. Households in the income range $10,000- $20,000 made only 2,435 average annual person trips, which is about half the 4,815 total annual person trips made by households in the highest income group of $80,000 or more. The average number of annual person trips overall was 3,466 (USDOT 2011). In 2001, richer households with incomes more than $75,000 spent about two and a half times on fuel ($1,749) as compared to poorer households (less than $25,000) who spent only $662 per year. Poorer households get more mileage by driving fuel efficient cars (USDOT 2004).

Income is incorporated in modeling as the annual household income (Cervero 1996), individual income and housing type – whether single family or not (Boarnet and Crane 2001), and housing tenure status – whether owner or renter (Cervero and Kockelman 1997). Car ownership, discussed below has often been considered as a proxy for household income.

3.10.3. Car Ownership

Increasing numbers of household vehicles translates to increased mobility and travel. A critical requirement to be able to travel independently by car is the possession of a driver’s
license and car ownership. Vehicle ownership may be considered a proxy for income: two-thirds of zero-car households in the US have incomes less than $25,000 a year, and more than half of these are single person households. Most of these zero car households are located in the largest metropolitan areas, and about half of all transit trips are made by households without a car, although they constitute only 8.7 percent of all households. About one-third (32.3 percent) of households have one vehicle and as many as 59 percent of households have 2 or more vehicles (USDOT 2011).

Car ownership impacts travel behavior. In the past four decades, the growth in the number of vehicles has outpaced the growth in workers, drivers, households, persons, and other indicators. Since 1969, the annual rate of increase in the number of personal vehicles was about one and a half times the annual rate of increase in the number of drivers. The household size has declined, but all other indicators have increased. In 2009, there were 2.5 persons per household; 1.86 vehicles per household; 1.88 licensed drivers per household; 0.99 vehicles per licensed driver; 1.34 workers per household; 1.39 vehicles per worker; and 8.7 percent zero-car households, most of them urban (USDOT 2011). On an average there is now more number of cars in the household than the number of drivers in the US.

Household fleet composition and its vehicle fuel efficiency impact GHG emissions. Share of passenger cars declined from being about 80 percent of all vehicles in 1977 to just under 50 percent in 2009, and the share of Sports Utility Vehicles (SUV) tripled since 1995 (USDOT 2011). SUVs form almost 20 percent of the household vehicle fleet and pick-up trucks another 18 percent. Though SUVs and pick-up trucks are still lesser in numbers as compared to cars, they are driven much more and are less energy-efficient. It is estimated that just by replacing all travel by pick-ups and SUVs with cars, CO₂ emissions from road travel would reduce by 11.6 percent (USDOT 2009B).
Vehicle ownership has been incorporated in studies as the number of automobiles in the household or the number of private automobile per licensed drivers in the household (Cervero 1996, Cervero 2002, Bento et al. 2005). The number of drivers is deduced from the possession of driver’s license (Cervero and Kockelman 1997). Frank and Pivo (1994) developed measures such as proportion of trip ends made by survey participants that have access to less than one vehicle and proportion of survey participants per census tract that have a driver's license.

3.11 Future Travel Trends

The current travel trends and trip purpose data indicate that non-work trips are increasing at a much faster rate as compared to work commutes or daily travel to school. Now, an overwhelming three-fourths of all trips take place for family and personal businesses, shopping, and social and recreational purposes as shown in Figure 6 (b). The proportion of work commutes, work-related trips, and school or church trips only total to about 29 percent (USDOT 2012). Transportation and land use planning research is moving away from focusing primarily on home to work commutes to reflect these changing travel patterns.

Role of Technology

Technology has played a role in reducing daily travel and will continue to do so. Historically, improvements in transportation and communications technology have increased travel, but there has been a slow and steady reversal of this trend. For instance, widespread internet connectivity has provided people with the flexibility to work from home more often. Since 1980, work from home has almost doubled, from 2.2 million workers to 4.2 million workers in 2000 (USDOT 2004). Internet shopping also allows people to shop from home and reduce shopping trips. However, although there is reduction in travel for work and shop, there is
increased travel for errands and recreational purposes. Lifestyle factors like growth of multi-service retail and entertainment malls that provide everything at the same location will also impact travel demand in the future, and therefore travel demand forecasting methods.

**Mobility Management**

Mobility management techniques include flex-work time, bicycle improvements and bike-transit integration, ride-sharing, park and ride facilities, shuttle services, traffic calming measures, financial measures like congestion pricing, fuel taxes, parking pricing, and many other policies, programs and strategies used for transportation demand management (Litman 2008). These trends are likely to impact travel patterns in the future in a significant way.

**Real Estate Trends**

A resurgence of growth of central cities and downtowns is happening due to increasing movement back to the cities from the far out exurbs, which is projected to increase metropolitan growth and urban concentration (Stone et al. 2009, Nelson 2004, Leinberger 2005, Nelson 2006). This is happening due to changing demographics, residential preferences, as well as lifestyle changes. Inner city redevelopment presents many opportunities for smart growth though compact, mixed-use, and transit oriented developments, and for reducing the VMT-related energy consumption and GHG emissions. New thoughts and ideas in sustainable urban transportation and real estate impetus focusing back to city centers will impact future travel patterns. These real estate trends coupled with local and state government efforts to implement carbon reduction strategies together point towards a new synergy in spatial planning that focus on integrated land use and transportation as important carbon-reduction strategies.
3.12 Residential Self-Selection

Some of the most accessible neighborhoods are perceived by the society to have multiple socioeconomic problems. These may be perceived as areas of high crime and unsafe, having high poverty levels and disadvantaged populations, combined with related social and health problems (Litman 2008). On the other hand, sprawling areas may be considered relatively safe, richer and healthier by some people. These strong neighborhood perceptions lead to a clear self-selection or sorting behavior among people that determine to some extent where they choose to reside. People choose their residential locations based on how they want to live, how and where they want to travel, and where they do not want to travel. Behavior, attitudes, and people’s perceptions impact people’s travel behavior and results in a self-selection bias. Self selection suggests that land use might only be a proxy for locational choices and attitudes towards travel by individuals and households. This means that individuals who prefer walking or transit might choose to live in compact and dense neighborhoods that offer more opportunities for the same, rather than the neighborhood design influencing their travel choices. They live in those neighborhoods because they prefer to travel less, rather than the land use characteristics impacting their travel behavior (Brownstone 2008, Stead 2001, Ewing and Cervero 2001, Krizek 2003A and others). This further implies that increasing density and mixed use within the neighborhood, and regional accessibility or transit would not automatically result in lower travel (Litman 2008, Brownstone 2008).

Stead and Marshall (2001) report that people with pro-environment and pro-public transport attitudes make the most non-motorized journeys, whereas people with pro-car attitudes make the fewest non-motorized journeys. To control for self-selection, Kitamura et al. (1997) incorporated data from personal attitudes survey along with land use and socioeconomic variables in analysis, which enabled them to study the impact of attitudes on travel in the San
Francisco Bay Area. They argue that attitudinal variables explained the highest variation in travel, more than the built form variables, suggesting that modifications in the land use factors alone will not be sufficient to alter travel behavior; this requires modifying personal attitudes as well. In contrast, Ewing and Cervero (2010) in their meta-analysis found the presence of both self-selection and built environment factors, but concluded that the built environment seems to play a more important role in determining travel behavior as compared to people’s attitudes and residential preferences.

There are now a few statistically advanced built form and travel studies that have attempted to study the influence of residential self-selection on travel behavior (for example Cao et al. 2009 and Chatman 2009). Controlling for residential self-selection and attitudes on travel, lifestyle, transit, safety, physical activity and other factors through a questionnaire survey, Cao et al. (2009) found a positive relationship between mixed-use and transit availability on modal choice. They suggest that the relationship between attitudes and the built environment is both ways - the built environment shapes people’s perceptions and attitudes as well, implying that the influence of the built environment on travel might actually be underestimated. The behavior of residents might be influenced by new development or addition of new transportation infrastructure that might lead to impacts on the VMT. Chatman (2009) finds that residential self-selection does not much bias the results. While the presence of residential self-selection might reduce the magnitude of the impact of built form characteristics on travel, they are still significant. Findings from different studies are still inconclusive on self-selection and future land use-travel studies need to adequately address the self-selection bias. One way is to build attitudes and preferences into household travel surveys to enable this analysis. Another is to ensure that the data contains detailed measures of household socioeconomics, travel and built environment to reduce self-selection bias. A reliable study must use a large and geographically
spread out sample of random households from different neighborhoods to observe differences in their VMT (Brownstone 2008). Still another method is to use advanced methodologies that internalize residential choice.

3.13 Research Methods and Tools

This section describes the two most commonly used research methods for land use-travel studies. Extensive literature reviews and meta-analyses have helped develop an overall understanding and synthesis of the existing state of knowledge on land use, smart growth, and travel. Transportation and urban planning experts have extensively used multivariate analytical methods and meta-analysis of several disaggregate travel studies. The relationship between urban built form and travel behavior has been a well-researched topic over the years, with almost 200 studies having been conducted (Ewing and Cervero 2010), but not all are methodologically reliable. According to Leck (2006), only 17 of the 40 studies that he chose for meta-analysis were statistically and sound.

Regression Analysis

A predominant number of studies on impacts of urban form on travel apply multivariate statistical analysis and regression analysis. Regression is well suited for research of this nature because there are so many sets of variables involved. As we have discussed in this chapter, there are a host of demographic, socioeconomic, and land use variables that impact household and individual travel patterns. In regression analysis, the land use and socioeconomic variables are usually considered as explanatory variables, and the travel variables as the test or dependent variables. These studies conventionally try to hold the socioeconomic variables constant (as control variables), so that they are better able to observe the effects of land use characteristics
(the test variables) on travel. Factor analysis has been used sometimes to extract the important variables from a large group of explanatory variables (for example, in Cervero and Kockelman 1997 and Kitamura et al. 1997). These land use and socioeconomic variables are identified and regressed against a set of travel variables.

One of the important criticisms of many regression-based studies is that land use characteristics might serve as a proxy for locational choice and individual attitudes toward travel. Regression methods allows the identification of important land use and socioeconomic characteristics that impact travel patterns; however they have limited ability in identifying causal relationships, or individual preferences or attitudes – also known as self-selection bias in sampling (see Section 3.12 for a more detailed discussion on this). This may introduce a bias in regression analysis and makes it difficult to determine whether higher density or diversity or transit availability really reduce travel. Crane (2000) has critiqued regression models as applied in many land use and travel studies, as they tended to treat density in a very simplistic manner, within one or two indices, and have largely ignored socioeconomic factors such as income and household structure that might correlate with it.

There are limitations to many previous regression-based research studies, either in terms of inadequate data or not controlling for socioeconomic aspects that primarily impact travel (Brownstone 2008). In regression analysis, control of socioeconomic characteristics is necessary to avoid self-selection bias. In addition they must cover a representative sample of households and geographic area, and use common measures of built environment to support strong quantitative conclusions. Data used in these studies seem to be a major concern. Brownstone (2008) and Crane (2000) suggest that a reliable study must use good random household samples from different neighborhoods across larger geographical scales to observe differences in the
VMT. The data must also contain detailed information on household socioeconomics, in addition to the usual travel and built environment measures.

**Meta-Analysis**

Since there are such a large number of studies that have addressed land use and transportation inter-relationships, meta-analysis has gained popularity as a way of analyzing impacts of land use on travel patterns in recent years (for example Leck 2006 and Ewing and Cervero 2001). Meta-analysis aggregates and synthesizes the findings from a set of different statistical disaggregate primary travel studies. Leck (2006) summarizes very well why meta-analysis is a useful analytical tool for land use and travel studies: it prevents reliance on the results of one study, increases the sample size, and allows for stronger arguments as even results which may not have proven significant in one study are able to contribute to new aggregated research findings. Ewing and Cervero (2001) conducted a meta-analysis to analyze the effects of density, diversity, design, and destination accessibility from 14 different studies, and their findings were incorporated within EPA’s well known Smart Growth Index (SGI) model, widely applied by cities and communities around the country aiming to be sustainable. In fact, the EPA recently funded a full-blown, comprehensive research with a meta-analysis of all such studies (Ewing and Cervero 2010).

Since meta-analysis relies on a host of other studies and their results, it is critical to choose individual studies that fully controlled socioeconomic and other variables while analyzing impact of land use characteristics on travel patterns (Leck 2006). Also, it is nearly impossible to arrive at common measures for different variables. Almost all studies define land use mix/diversity or measure design differently, even if they did manage to arrive at common or comparative measures for density and travel.
Scenario Planning and Transportation Models

Scenario planning is extensively carried out in practice by transportation engineers and planners. Scenario planning models assume that modifying the built environment and land use characteristics will have a significant impact on travel. They generally tend to develop alternative scenarios to the trend-based land use projections, and study their impacts on travel. This kind of modeling became very popular after one of the first such analyses was completed for Portland, the LUTRAQ (Land Use, Transportation, and Air Quality) study. Traditionally four-step transportation models (an interconnected set of several sub-models) have been used for land use and transportation planning, and to predict the changes on travel of land use policy implementation. These are based on demographic and land use forecasting and incorporate the traditional four-step transportation planning steps of trip generation, trip distribution, mode choice, and route assignment. Then, decision-making criteria like cost benefit analysis is used to finalize projects. These models are widely used, for example, the Integrated Transportation Land Use Package, or Urban Transportation Modeling System (Litman 2008) and tend to be expensive because they are not transferable to other cities due to sensitivity to local conditions. They work best for traditional transportation planning but do not allow analysis of specific effects, or incorporate alternative modes of travel. Often, they are based only on vehicle ownership, household income and household size data and ignore land use characteristics. The large scale, comprehensive, seven-year Atlanta study SMARTRAQ (Strategies for Metro Atlanta’s Transportation and Air Quality) is advancement on such models since it is based on parcel level information on buildings, density, and accessibility measures and also builds in community surveys. Planning authorities and consultants are using post-processing modules additionally which make it possible to determine impacts of transportation demand management policies and smart growth. For example, consultants of the Atlantic Steel redevelopment project used were
able to demonstrate to the USEPA that density, diversity, and pedestrian friendly design would reduce VMT up to 52 percent, and were able to secure project funding (Ewing et al. 2008).

A great many tools are now available that help communities visualize and quantify the impacts of built form on travel, VMT, and GHG emissions. They quantify the impact of land use and transportation decisions on energy consumption, emissions and climate change, and measure sustainability indicators across a range of sectors. A well-known tool is the USEPA’s Smart Growth Index (SGI) Model that can be applied at the neighborhood level to determine how land use management strategies can help achieve various transportation objectives (e.g., lower congestion, emissions, etc). This tool can be applied by communities for simulating alternative land use and transportation scenarios. In this tool, density is measured in terms of residents and jobs per mile, diversity in terms of ratio of jobs to residents as compared to the national average, and design in terms of street network density, sidewalk coverage, and route directness. The Rapid Fire Model for California is a spreadsheet tool to evaluate regional and state land use characteristics and transportation policies and predicts their impacts on VMT, pollution, energy and resource use, as well as public infrastructure costs. Condon et al. (2009) provide a comprehensive inventory of these tools with implementation examples, including Community Energy and Emissions Inventory (CEEI), Athena Impact Estimator for Buildings, Community Viz, The Development Pattern Approach (DPA), Energy Demand Characterization, Envision Tomorrow, INDEX and Cool Spots, I-PLACE3S, MetroQuest, Neighborhood Explorations: This View of Density, Tool for Evaluating Neighborhood Sustainability and UPlan. Although these kinds of modeling techniques are very helpful for city planners, they cannot be applied to develop an understanding of the underlying linkages between urban form and travel behavior. Simulation studies take these for granted, but have been criticized for exaggerating the impact of land use variables, and ignoring important socioeconomic and other relevant factors.
Other Analytical Approaches

A range of other different other modeling approaches have been adopted by researchers while analyzing the land use, socioeconomic and other characteristics that impact travel. Some of these are briefly mentioned here. Case studies based comparisons of different areas are another way of analyzing land use impacts on travel. These studies usually select areas having similar socioeconomic profiles, so as to minimize the impacts of socioeconomic variables on travel. In such studies, it is assumed that variations observed in travel patterns are due to land use characteristics (Stead 2001). Descriptive studies of different areas also present insights into travel patterns in different areas, and are good for explaining travel phenomena at a particular location, but are again difficult to generalize (Crane 2001). There are many behavioral aspects to travel, but land use and travel studies rarely provide insights in to these. Behavioral studies have focused on clarifying how or why travelers choose a certain mode amongst the travel options, based on individual decisions and behavior. These studies usually incorporate urban form measures into a behavioral framework and analyze peoples’ attitudes to travel, lifestyle preferences, and socioeconomic variables (Krizek 2003). Very few studies control for trip purpose, trip lengths, demography, etc. and are not able to explain causal relationships in travel completely. However the literature on behavioral choice in travel tends to ignore the role of land use and urban design (Crane 2001).

3.14 Knowledge Gaps

The relationship between socioeconomic, land use characteristics and travel is complex and needs to be studied further. The built environment influences travel, but there is a lot of disagreement on the likely impacts that higher densities, mixed use, and street connectivity have on household travel patterns and related GHG emissions. Although the relationship between
built environment and travel behavior has been a very well researched topic, there are still several gaps in the existing knowledge:

**Ignoring the Socioeconomic Characteristics**

Much of the research that links compact, dense, and diverse developments to reduced travel has been critiqued for not being reliable or methodologically sound. Most studies tend to ignore the fact that variations in travel patterns are primarily a function of socioeconomic characteristics, rather than land use alone. Most scholars have examined the impact of urban form and land use characteristics on travel patterns, and not sufficiently integrated socioeconomic and behavioral aspects. After an analysis of more than 40 empirical studies on land use and travel, Leck (2006) chose only 17 for meta-analysis that he considered statistically and methodologically sound. Recent and more comprehensive meta-analysis carried out by Ewing and Cervero (2010) initially considered about 200 different land use and travel studies for their meta-analysis, and aggregated results from selecting approximately 50 individual statistically sound studies to provide several reliable insights.

**Quantifying the Magnitude of the Relationships**

Empirical studies often assign different measures to relationships and frame key questions. What is the magnitude of linkage between each individual land use characteristics and VMT? Is it significant and large enough to alter urban development and land use patterns? The NRC paper by Brownstone (2008) suggests that this link is miniscule; it makes more sense to use taxation and pricing mechanisms to achieve the same environmental objectives. According to him, though there is evidence that while there is a statistically significant link between different aspects of the built environment and VMT, few studies provide enough detail to conclusively say whether it is strong enough to make manipulating the built environment a feasible tool for
controlling VMT. He suggests that intervention in the taxation policy and pricing mechanisms (increasing parking prices, congestion pricing, increasing fuel taxes, etc.) maybe more effective in reducing VMT and can achieve similar environmental gains.

Many important assertions of urban planners and smart growth proponents are based on meta-analysis of several disaggregate land use - travel studies, and are therefore required to be studied further to determine the nature and magnitude of these relationships. There is a need for future research in many areas: What is the impact of land use characteristics such as density, land use mix/diversity, neighborhood design, transit availability, local and regional accessibility on travel? What are effective and comparable ways to measure these land use characteristics? What are the impacts of a grid network street configuration on travel? What is the effect of parking supply, location, and pricing on travel? What are the specific elasticities of travel demand for all these different variables? Which set of strategies would be most effective: increasing residential density, locating jobs, retail and entertainment near transit nodes, increasing neighborhood diversity, compact development supported by infill development and stronger city centers, or improving transit service?

The Causation and Self-selection Argument

The causation argument is extended to explain the relationship between compact development and reduced travel. As discussed in Section 3.12, self-selection bias usually creeps in such studies, which implies that the people who live in dense, walkable neighborhoods may do so out of travel-related values, because they want to travel less and use transit and walk more, rather than that compact neighborhood development influences their travel choices. Not adequately controlling for socioeconomic factors also introduces a self-selection bias in studies. (Brownstone 2008, Ewing and Cervero 2006). More research is therefore required in support of the argument that compact development can actually reduce travel demand. There are not
enough reliable studies that control enough socioeconomic characteristics to avoid self-selection bias, cover a representative sample of households and geographic area, and use common measures of built environment to support strong quantitative conclusions (Brownstone 2008). These measures can help improve the reliability of the results.

**Lack of Reliable Quantitative Estimates**

Despite countless studies that have tried to measure impacts of urban form and land use characteristics on travel, there are no consistently agreed upon set of values that describe the magnitude of different land use characteristics on the VMT. Brownstone (2008) raises the issue of reliable quantitative estimates of elasticities of key variables in all these studies. He suggests that the link between the built environment and VMT is so small that feasible changes in the built environment will only have negligible impacts on VMT (Brownstone 2008, Leck 2006). Researchers have come up with a wide range of measured impacts of different land use characteristics on VMT. For example, Ewing and Cervero (2001) report low individual elasticities with respect to local density, land use mix, and design, of -0.05, -0.05, and -0.03, respectively, and with respect to regional accessibility it was -0.20. However, Stone et al. (2009) report higher elasticities for same variables: -0.41 for population density in urban tracts, and -0.19 in suburban tracts. This variation in elasticities reported from different empirical studies also highlights the need for additional quantitative research that can provide reliable and comparable information to city planners and policy makers.

**3.15 Chapter Summary**

The relationship between land use characteristics and household travel has been heavily researched, particularly in the past decade. Socioeconomic characteristics are the primary determinants of household travel, and land use characteristics are secondary. Focus has been on
the various land use characteristics such as residential and employment density, land use
diversity or mixed land use, street and neighborhood design characteristics, accessibility to
possible destinations within a driving range, transit accessibility, and demand management
strategies including provision of parking. There is a wide range of variables that have been used
to compute each of the land use characteristics, travel variables and socioeconomic variables in
research. A range of research approaches used includes multivariate analysis, meta-analysis of
several individual studies, travel demand modeling, case studies and other approaches. Concern
with much of the previous research includes inadequate control of socioeconomic characteristics,
residential self-selection, and not having a set of comparable variables to develop reliable
estimates for the magnitude of built-form and travel relationships.
4. Data and Variables

Chapter 4 presents the data used for research and the sources of that data. The literature review discussed in Chapters 2 and 3 provided guidance in establishing a framework and developing a set of criteria to select the appropriate data for the Hamilton County and the Great Cincinnati 8-county Ohio-Kentucky-Indiana (OKI) region. The literature also helped determine the appropriate dependent variable and control variables necessary to be incorporated into the research model. The data for this research were collected from various agencies. The land use data were collected from CAGIS, the household travel survey data were collected from the OKI Regional Council of Governments, and the census data were obtained from the US Census website. This chapter discusses the process used to select, prepare, and organize the data and the process of selection of the dependent and control variables for regression modeling.

4.1 Data for Research

For the purpose of determining various travel, land development, and socioeconomic variables, I have collected extensive data for the Cincinnati region on demography, density, land use, street network, location of public transit facilities, and socioeconomic characteristics. Most of the data required to compute variables for household travel, land use, and socioeconomic characteristics were obtained from the OKI Regional Council of Governments and the Cincinnati Area Geographic Information System (CAGIS). Additional data were obtained from the US Census Bureau. All data were collected, organized, and collated into a uniform database using spreadsheets in MS Excel 2007 and multiple GIS data layers in ArcVIEW 10 software. The land use and travel survey datasets used in this research are described:
4.1.1. **Travel Survey Data**

I obtained the travel data from the recent Greater Cincinnati Household Travel Survey 2009-10, undertaken for the Ohio-Kentucky-Indiana (OKI) region. This survey was supported by the Office of Statewide Planning and Research, Ohio Department of Transportation (ODOT) and the Ohio-Kentucky-Indiana Regional Council of Governments. The household travel survey was completed using Global Positioning System (GPS) handset tools and covered 1,352 random households distributed across the 8-county Ohio-Kentucky-Indiana metropolitan region. This is the first such large-scale (100 percent) GPS-based household travel survey in the country, and this is one of the first such studies conducted using a large-scale GPS-based household travel survey. As compared to the traditional travel diary method, there are many advantages of using a GPS-based survey. It reduces under-reporting of trip data and increases representative response rates, and most importantly, and it provides detailed geographic information on routes, speeds, and locations, which are not captured by traditional travel diary methods. This makes it possible to improve upon the way travel is spatially modeled (OKI Regional Council of Governments 2011). Since the data are collected using GPS devices, it made it possible for me to accurately locate the survey household locations, and origin and destination points on a map, making fine-grain land use and transportation analysis possible. GPS application also substantially reduces the survey respondent burden associated with traditional travel diary feeds.

The survey was carried out only on weekdays, and each member of surveyed households was surveyed for three consecutive weekdays (from Monday through Wednesday, or Wednesday through Friday). All household members older than 12 years were required to carry a GPS handset device with them for all three survey days, and travel entries for younger household members were recorded in traditional travel diaries by the adults in the household. The household survey included the outcomes of the prompted recall process, which involves
contacting a few of the survey respondents again as a follow-up by internet, phone, or email to fill in gaps and inconsistencies in data reporting and obtain any clarifications needed. Trips by children younger than 6 years are not included in the dataset. Of the 1,352 households surveyed in the 8-county OKI region, 610 survey households are located in Hamilton County\(^9\), which is the sample size for this research. For these households, I have considered their travel pattern in the entire 8-county OKI region and beyond.

The travel survey data provides detailed information in the form of several data tables namely: trip data (origin and destination coordinates, travel mode, number of passengers, purpose, trip distances, trip speeds, travel days and time, and other information), household vehicle ownership (car model and year, beginning and end survey odometer readings), surveyed household location and characteristics, and other information. Socioeconomic data for survey households include information on household size, number of children attending school, number of workers, number of students, number of drivers, household income range, status of household members, and other details. Data on individual survey respondents also includes gender, age, current education status, children, employment details by industrial sectors, and other information. Figure 11 shows trip origin and destination (O-D) points within and outside the OKI region for all trips recorded using GPS handsets. Most destination points for one trip are also origin point for the following trip and are therefore overlapping.

\(^9\) Sample size of survey households located within Hamilton County was determined spatially in GIS using their (X,Y) coordinates.
Figure 11: Origin and destination points from the trip data

Data source: Greater Cincinnati Household Travel Survey 2009-10
4.1.2. **Land Use Data**

Latest parcel level land use data from 2010 for Hamilton County has been compiled by the Hamilton County Auditor Office and was obtained from the Cincinnati Area Geographic Information System, the largest municipal GIS database in the country. It provides detailed parcel level information for approximately 350,000 land parcels (refer Figure 12). Specific land use categories in Hamilton County include: Agriculture (AG), Commercial (C), Congregate Housing (CH), Educational (ED), Heavy Industrial (HI), Institutional (IN), Light Industrial (LI), Multi Family (MI), Mobile Homes (MH), Mixed Use (MU), Office (O), Parks and Recreational (PR), Public Service (PS), Public Utility (PU), Single Family (SF), and Vacant (VA). Each of these land uses is further detailed into several land use codes. These 18 land use categories are further classified into 170 distinct land use codes.

CAGIS has a rich database that includes detailed information on the street network, highways and exits, sidewalks, driveway, parking, pavement, bus routes, and bus stops. Data layers include city, county, census block, block group, census tract, and other administrative boundaries; demographic attributes, parcels, building outlines; natural features such as rivers and streams, contours and spot levels; infrastructure (e.g., highways, highway exits, railroad, dams and levees, bores, towers, and sewer systems), and various other information. However, a major limitation in the land use data is that all publicly owned lands (owned by the federal government, the State of Ohio, Hamilton County, townships, municipalities, and agencies like the Metropolitan Housing Authority, the City of Cincinnati) are classified as Public Service (PS), irrespective of their actual or intended use. To develop a more accurate land use diversity index, and other land use-based measures, this land use data set needs to be updated to provide detailed information on actual land uses on every land parcel in the region.
Figure 12: Example of detailed parcel level land use data for Hamilton County

Data source: CAGIS 2010
4.1.3. **Street Network Data**

Detailed road network data for the entire OKI 8-county region, except for Boone County, KY were obtained from the OKI office. Street centerline data for Boone County were obtained from School of Planning GIS database and incorporated with the rest of the street network. The street network information is detailed and includes minor streets, crucial for mapping small and non-motorized trips. Households located within Hamilton County make trips all across the OKI region and beyond, and all these trips were taken into account while computing the daily household car VMT from GPS records.

4.2 **Scope of the Study**

The land use analysis is limited only to survey households located within Hamilton County, mainly due to unavailability of updated, comparable, and detailed parcel level land use data for all other counties within the 8-county OKI region. The land use characteristics were examined within the Hamilton County at the parcel level. Hamilton County exhibits a wide variety of development patterns, ranging from a densely built downtown with mixed use developments, compact inner ring suburbs, sprawling suburban development, and areas that still maintain their rural character, making it an interesting region to study. The travel activity of people living in Hamilton County was examined all across the Greater Cincinnati 8-county OKI region and beyond.

As mentioned, the household sample for this is research was drawn from the travel survey households located within the Hamilton County. The household travel survey was conducted for the entire 8-county OKI region by the OKI Regional Council of Governments, from which data were extracted for households residing within the Hamilton County after determining their spatial locations in GIS. Household travel patterns were considered for the 8-
county OKI region. The following Table 2 provides information on the household sample for the research.

**Table 2: Households Included in the Travel Survey**

<table>
<thead>
<tr>
<th>Households in travel survey</th>
<th>OKI Region</th>
<th>Hamilton County</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total number of households recruited for travel survey and for which socioeconomic data was collected</td>
<td>5,565</td>
<td>2,697</td>
</tr>
<tr>
<td>Total number of households actually surveyed for travel</td>
<td>1,352</td>
<td>610</td>
</tr>
<tr>
<td>Outliers removed from household sample:</td>
<td></td>
<td>2/545 6/610</td>
</tr>
<tr>
<td>• Models 1 and 2</td>
<td></td>
<td></td>
</tr>
<tr>
<td>• Models 3 and 4</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Households that did not provide income information (included in the sample)</td>
<td></td>
<td>45/610</td>
</tr>
<tr>
<td>Households that traveled outside the 8-county OKI region during the survey period (removed from sample in Models 1 and 2, included in Models 3 and 4)</td>
<td></td>
<td>65/610</td>
</tr>
<tr>
<td>Final household sample size selected for study:</td>
<td></td>
<td>543 604</td>
</tr>
<tr>
<td>• Models 1 and 2</td>
<td></td>
<td></td>
</tr>
<tr>
<td>• Models 3 and 4</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Data source: Greater Cincinnati Household Travel Survey 2009-10

Of the 610 households surveyed within Hamilton County, 45 households did not provide information on household income. In addition, 65 households out of these 610 had traveled outside the 8-county OKI region during the travel survey at least once. Excluding the latter group from the study, the research sample was limited to 545 households. In addition, for Models 1 and 2, two additional households were removed from the sample as they exhibited unusually high travel in the survey period after identifying outliers using Cook’s, Leverage, and Hadi’s measures bringing the sample size for Models 1 and 2 down to 543 households.

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10 The 45 households that did not provide income information were not excluded from the sample but treated as missing data. The assumption made here is that households with missing income data are at random.
Households that traveled outside the OKI region were included in the household sample for Models 3 and 4. In this case, 6 households exhibiting very high travel of over 1000 miles in the three survey days were excluded from sample, bringing it down to 604 households.

4.3 Computing Vehicle Miles Traveled (VMT) in GIS

Daily household car-VMT has been used as the dependent travel variable. Daily household car-VMT was computed from the origin and destination (O-D) points from the trip data in the Greater Cincinnati Household Travel Survey 2009-2010. Travel by non-vehicular modes (walk and bicycle), as well as travel by public transport (bus) were excluded from calculating daily household car VMT. VMT was computed using the Network Analyst extension in ArcView 10 GIS software. The methodology involved measuring the shortest network distances between each pair of origin and destination (O-D) point locations for each trip by each person in the household over three survey days, to obtain daily household car VMT. The methodology is described in the following steps:

Step 1: Build a Network Dataset

The first step was to create a network database from street centerline data for the entire 8-county OKI region. The network dataset consists of a set of street segments called edges which are interconnected with each other at junctions and street end points called nodes (see Figure 13a). The system junctions feature class is created automatically at the intersections of different edges. Street hierarchy is defined while creating network dataset. The next step is to create the new route analysis layer with five network analysis classes - stops, routes, point barriers, line barriers, and polygon barriers.
Step 2: Map Origins and Destinations

Origin points for all trips from the Greater Cincinnati Household Travel Survey 2010 are loaded as one set of stops, and similarly all destination points are loaded on the network dataset as the second set of stops (see Figure 13b). The O-D points are not located directly on the network dataset, but snap to the network by ‘walking’ to the network dataset at the closest point.

Step 3: Route Optimization

The total number of trips in the entire travel data is 38,767 trips for all households. As determined spatially for the 610 households surveyed within Hamilton County, the total number of trips that both originate and terminate in the OKI region was 16,483 trips. Out of these, 14,269 were by a personal vehicle, 571 were by bus, 325 were by bicycle, 1,171 were by walking, and 147 were unknown trips. The most optimal route is the route that has the lowest impedances chosen by the user, and it could be the quickest, the shortest, or the most scenic route. For this analysis, distance was defined as the impedance which provided the shortest network distance. Each dark blue line in Figures 13 (c) and (d) represents the shortest network distance for each trip between a pair of O-D points. Trips originating or ending outside the OKI study region were not solved, as for these Network Analyst was not able to identify the street network dataset, because there does not exist on the network dataset any network path connecting these pairs of O-D points. Any trip that started or ended outside the 8-county OKI region was not solved. Therefore, it was decided to remove those 65 households that traveled

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11 Of the total O-D points, 355 origin points and 346 destination points were located outside OKI, out of which 257 were both origin and destination points. The destination point for 1 trip would frequently be the origin point for another trip.

12 Shortest time will give a more accurate output as people tend to travel by shortest time, not distance. In this case calculation based on shortest time was difficult, as it involves defining road speeds as well as taking into consideration varying travel times for peak and non-peak traffic. Daily household car VMT was also computed from GPS data directly.
outside the 8-county OKI region from the original 610 sample size for Models 1 and 2. By doing this, we removed households whose travel pattern included longer trips as well as those households traveling well beyond the region, which resulted in a much lower mean daily household car VMT for the selected household sample of $n = 545$ households.

**Step 4: Computing Household Daily Car VMT**

To calculate daily household car VMT per household, all trips for each household over three days were consolidated to obtain household VMT for all members of the household. Total miles traveled per household represent all travel undertaken by all persons in each household for the three-day travel survey period using all vehicular modes. Daily car VMT per household gives the network distance traveled daily for each vehicle trip for each individual in the household. The total household car VMT over three days was then converted to household daily car VMT per household, the dependent variable for Models 1 and 2. The daily household car-VMT for the 545 sample households computed in GIS using network analysis with shortest distance measure is 32.43 miles per household per day. The daily household car VMT calculated using the O-D points from GIS using the shortest distance parameter is considerably less than the actual car VMT computed by the GPS units.
Figure 13: Illustration of stepwise methodology for calculating VMT using Network Analyst in GIS

a) Create a Network Dataset consisting of edges and nodes

b) Load origin and destination points as stops

c) Run the RouteSolver tool

d) The output - blue lines represents solved routes between pairs of O-D points

Data source: Greater Cincinnati Household Travel Survey 2009-10, CAGIS 2010
Daily household car VMT is also a factor of modal choice, as a greater proportion of trips by bus, bicycle, or walk would result in lower car miles. For the 545 households in Hamilton County that did not travel outside the OKI region, an average of 87.05 percent of all household trips were made by personal vehicle, 3.74 percent trips were transit, 1.69 percent trips were bicycle trips and 7.52 percent trips were walk trips. Table 3 gives the travel characteristics for all \( n = 610 \) households (including high travel households) located within Hamilton County. These are averaged on a daily basis computed from survey data collected over three days.

**Table 3: Summary of Household Travel Characteristics**

<table>
<thead>
<tr>
<th>Travel characteristics</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Daily GPS trips by household</td>
<td>8.93</td>
<td>6.20</td>
<td>0.33</td>
<td>42.00</td>
</tr>
<tr>
<td>Household daily car VMT (GPS)</td>
<td>54.43</td>
<td>69.78</td>
<td>0.00</td>
<td>834.05</td>
</tr>
<tr>
<td>Household daily car VMT (GIS)</td>
<td>34.91</td>
<td>28.92</td>
<td>0.00</td>
<td>213.31</td>
</tr>
<tr>
<td>Number of daily car trips by household</td>
<td>7.80</td>
<td>5.63</td>
<td>0.00</td>
<td>39.67</td>
</tr>
<tr>
<td>Number of daily bus trips by household</td>
<td>0.31</td>
<td>0.66</td>
<td>0.00</td>
<td>6.33</td>
</tr>
<tr>
<td>Number of daily bicycle trips by household</td>
<td>0.18</td>
<td>0.45</td>
<td>0.00</td>
<td>5.00</td>
</tr>
<tr>
<td>Number of daily walk trips by household</td>
<td>0.64</td>
<td>1.20</td>
<td>0.00</td>
<td>9.33</td>
</tr>
</tbody>
</table>

Data source: Greater Cincinnati Household Travel Survey 2009-10, CAGIS 2010

The daily household car VMT was also computed from GPS records directly, without using GIS. This was the dependent variable for Models 3 and 4. On average, for the same subset of households (removing all households traveling outside OKI region), the VMT obtained directly from GPS records is 22.7 percent higher than the VMT computed from the GIS shortest route calculation. The daily household car VMT from the GPS records calculated for 604 households is 49.59 miles (removing 6 high travel households that traveled over 1,000 miles by car in the three survey days). If we do not remove these 6 outliers, based on the GPS data, for all

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13 This difference is for 545 households only which did not travel outside the 8-county OKI region during the survey period. This difference would be different for all 610 households
610 households within Hamilton County, the total daily household VMT from all modes is as high as 56.61 miles (for all households, including high travel households), and the daily household car VMT increases to 54.43 miles. The travel for school attending children between 6 - 12 years of age was recorded in traditional travel diaries and not using GPS, so their trip distances and trip origins and destinations were not available in a spatial format. Travel and other information on children less than 6 years of age were not included in the survey. Hence, computation of VMT using GIS is an underestimation of the actual household travel.

### 4.4 Socioeconomic Variables

All socioeconomic data used in the analysis were obtained from the Greater Cincinnati Household Travel Survey 2009-10. The data on households within the survey data include information on the household size, household income, number of vehicles owned, number of drivers, number of workers, number of students, and other information. Table 4 below gives socioeconomic characteristics for all $n=610$ households in Hamilton County:

<table>
<thead>
<tr>
<th>Household characteristics</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Household size</td>
<td>2.24</td>
<td>1.26</td>
<td>1.00</td>
<td>6.00</td>
</tr>
<tr>
<td>No of kids in household 13-18yrs of age</td>
<td>0.30</td>
<td>0.74</td>
<td>0.00</td>
<td>4.00</td>
</tr>
<tr>
<td>Total child trips (13-18 years age)</td>
<td>4.54</td>
<td>3.75</td>
<td>0.00</td>
<td>20.00</td>
</tr>
<tr>
<td>Total no. of workers in household</td>
<td>1.14</td>
<td>0.95</td>
<td>0.00</td>
<td>5.00</td>
</tr>
<tr>
<td>Total no. of students in household</td>
<td>0.58</td>
<td>0.95</td>
<td>0.00</td>
<td>5.00</td>
</tr>
<tr>
<td>Total no. of drivers in household</td>
<td>1.67</td>
<td>0.82</td>
<td>0.00</td>
<td>5.00</td>
</tr>
<tr>
<td>Total no. of vehicles in household</td>
<td>1.80</td>
<td>1.10</td>
<td>0.00</td>
<td>8.00</td>
</tr>
<tr>
<td>Total no. of bicycles in household</td>
<td>1.05</td>
<td>1.53</td>
<td>0.00</td>
<td>8.00</td>
</tr>
</tbody>
</table>

Data source: Greater Cincinnati Household Travel Survey 2009-10, US Census 2010
**Household income**

Use of income as a control variable would account of much of the socioeconomic variation that is the primary determinant of household travel. This information was obtained from the travel survey household data. The travel data provides the annual household income group of the survey households in four categories of less than $25K, $25K-$50K, $50K-$75K, and more than 75K for \( n = 610 \) households in Hamilton County. As shown in Table 5 below, categorical variables were created for the four income intervals:

<table>
<thead>
<tr>
<th>Annual Household Income Range</th>
<th>Number of households</th>
<th>Categorical variable</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt; $25,000</td>
<td>107 (17.54%)</td>
<td>1</td>
</tr>
<tr>
<td>$25,000-$50,000</td>
<td>147 (24.10%)</td>
<td>2</td>
</tr>
<tr>
<td>$50,000-$75,000</td>
<td>116 (19.02%)</td>
<td>3</td>
</tr>
<tr>
<td>&gt; $75,000</td>
<td>195 (31.97%)</td>
<td>4</td>
</tr>
<tr>
<td>Do not know or did not tell household income</td>
<td>45 (7.38%)</td>
<td>Treated as missing data</td>
</tr>
</tbody>
</table>

Data source: Greater Cincinnati Household Travel Survey 2009-10

The median income range in the research sample was $50,000-$75,000.

**Car Ownership**

Car ownership represents number of cars owned by each household. This has been incorporated into the analysis as literature suggests that households having more number of vehicles tend to drive more. Literature also suggests that higher vehicle ownership is correlated with higher household incomes and both of these are believed to induce higher travel.

Information on the number of vehicles per household has been extracted from the Greater Cincinnati Household Travel Survey 2009-10. Out of the \( n = 610 \) total survey households in Hamilton County, 34 were (5.57 percent households) zero-car households, 235 (38.52 percent) households were 1-car households, 222 (36.39 percent) households were 2-car households and 119 (19.51 percent) households were 3 or more car households.
**Household Size**

Household size represents number of persons in each household. This has been incorporated in the analysis as literature suggests that larger households tend to drive more. This information has been extracted from the Greater Cincinnati Household Travel Survey 2009-10. Larger household size is believed to increase the VMT so it has been accounted for in all the models. Out of the $n = 610$ total survey households in Hamilton County, 211 (34.59 percent) households were single-person households, 206 (33.77 percent) households were 2-person households, 74 (12.13 percent households were 3-person households and 119 (19.51 percent) households were 4 or more person households.

**Workers**

The number of workers in each of the household has been incorporated in the analysis. Literature suggests that households with more workers tend to drive more. The information on number of workers per household has been extracted from the Greater Cincinnati Household Travel Survey 2009-10. Out of the $n = 610$ total survey households in Hamilton County, 176 (28.85 percent) households were zero worker households, 222 (36.39 percent) households were 1-worker households, 169 (27.70 percent) households were 2-worker households, 43 (7.05 percent) households were 3 or more worker households.

**Students**

This represents the number of students in each of the household. This has been incorporated in the analysis as literature suggests that households with more number of students attending higher education institutions tend to drive less. This information has been extracted from the Greater Cincinnati Household Travel Survey 2009-10. Out of the $n = 610$ total survey households in Hamilton County, 407 (66.72 percent) households were zero-student households,
96 (15.74 percent) households were 1-student households, 73 (11.97 percent) households were 2-student households and 34 (5.57 percent) households were 3 or more student households.

**Drivers**

This represents the number of drivers in each of the household. This has been incorporated in the analysis as literature points out that households with more number of drivers tend to drive more. This information has been extracted from the Greater Cincinnati Household Travel Survey 2009-10. Out of the $n = 610$ total survey households in Hamilton County, 28 (4.59 percent) households were zero-driver households, 234 (38.36 percent) households were 1-driver households, 279 (45.74 percent) households were 2-driver households, and 69 (11.31 percent) households were 3 or more driver households.

**Neighborhood Characteristics**

Neighborhood variables of tenure status as rental housing as a percentage of total occupied housing, median household income at the census block group level, percentage of African-American only households, and gross population density have been incorporated in regression analysis. Several variables including these have often been used in literature as an indication of household income or race, and are therefore necessary to control for their effect in analysis. All these were obtained for 2010 from US census websites. Table 6 provides details on the four neighborhood variables created at the census block group level for the total survey sample $n = 610$ households in Hamilton County.
Table 6: Summary of Neighborhood Characteristics

<table>
<thead>
<tr>
<th>Neighborhood</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Median household income in 2010 in the census block group in dollars</td>
<td>57,795.04</td>
<td>33,599.78</td>
<td>5,250</td>
<td>250,001</td>
</tr>
<tr>
<td>Percentage of African American households in 2010 in the census block group</td>
<td>24.30</td>
<td>28.04</td>
<td>0.00</td>
<td>96.18</td>
</tr>
<tr>
<td>Percentage of rental houses of total occupied houses in 2010 in the census block group</td>
<td>39.40</td>
<td>27.66</td>
<td>1.04</td>
<td>100.00</td>
</tr>
<tr>
<td>Gross population density in 2010 in the census block group</td>
<td>17.19</td>
<td>12.46</td>
<td>0.38</td>
<td>90.71</td>
</tr>
</tbody>
</table>

Data source: US Census Bureau 2010

The travel survey also provides information on the area type – whether surveyed household is located in the CBD, an urban area, a suburban area, or a rural area. These classifications are based on employment and population densities and computed for the transportation modeling requirements of the OKI Regional Council of Governments. According to their classification, out of the total sample $n = 610$ households in Hamilton County, only 5 (0.82 percent) households are located in CBD, 349 (57.21 percent) households are located in an urban area, 245 (40.16 percent) households are located in a suburban area, and 11 (1.80 percent) households are located in a rural area.
5. Methodology for Creating Explanatory Variables

This chapter describes the methodology to calculate and operationalize various land use variables that have been used for developing the regression models for analyzing their impact on daily household car VMT. One of the objectives of this research has been to develop a more precise and accurate method of measuring land use diversity using detailed parcel level land use data for Hamilton County procured from the Cincinnati Area Geographic Information System (CAGIS). I have applied advanced Spatial Analyst and other tools in the Geographic Information System (GIS) environment to compute two measures of land use diversity in the surrounding half-mile neighborhood area for each of the households surveyed within Hamilton County as part of the Greater Cincinnati Household Travel Survey 2009-10. I have also applied Network Analyst and Spatial Statistics tools to compute other land use and travel variables such as building density, street and intersection density, distance to the nearest bus stop, and distance to the CBD.

5.1 Spatial Unit for Computing Land Use Variables

The concept of “unit of analysis” and “scale of analysis” in land use-travel studies have usually been defined at the neighborhood level. Researchers have defined the neighborhood in many different ways ranging from a Traffic Analysis Zone (for example in Boarnet and Sarmiento 1998), grid-based neighborhood (for example in Krizek 2003A), to the immediate neighborhood surrounding the household locations (for example in Cervero 1996). Several studies that encompass many cities in a comparative analysis have been conducted at the metropolitan or regional scale. In many cases where individual or household surveys were conducted, the concept of neighborhood assumes an individualized meaning. Very few studies
defined neighborhood using a buffer distance around each household, and a majority of studies defined neighborhoods by aggregating data over census tracts, block groups, zip codes, or Traffic Analysis Zones (TAZ).

Land development and land use processes are spatial in nature, and each parcel of land has unique characteristics and unique relationships to its surroundings. Each household is situated on its unique location, and is surrounded by its unique set of neighborhood characteristics in its immediate vicinity. I have developed an advanced measurement of land use diversity that captures this locational uniqueness into the computation of land use characteristics through a disaggregate approach. Figure 14 (a) shows multiple households located within a census block group. This illustrates that if the census block group were applied as the unit of analysis, all survey households located within each census block group would generate same the values for all land use characteristics calculated at the scale of the census block group, even if they have different surroundings. In this research, the spatial unit of analysis for computation of land use diversity and other land use variables is the individually defined neighborhood around each individual survey household. As shown in Figure 14 (b), I demarcated a half-mile area neighborhood around each survey household location using buffers. Although debatable, half-mile can be considered as a comfortable walking distance, equivalent to a 10-minute walk.

The purpose of creating half-mile area neighborhoods is to capture the uniqueness of each survey household location. This half-mile area neighborhood was considered for computation of various explanatory variables including land use diversity index, building density, street density, and intersection density. The sections below provide the detailed methodology for computing each of the seven explanatory land use variables used in the analysis.
Figure 14: (a) top: Example of several survey households located within a census block group, (b) bottom: Example of half-mile radius neighborhood area around each survey household location for computing LUMix1, building density, street density, and intersection density.

Data source: Greater Cincinnati Household Travel Survey 2009-10, CAGIS 2010
5.2 Computing Land Use Diversity

This section describes the methodology to operationalize the test variable of land use diversity for its application in the regression models and its specifications for analyzing the impact of land use diversity on household VMT. I have developed an improved and precise method of measuring land use diversity using parcel level land use data for Hamilton County procured from CAGIS, applying spatial analysis tools in GIS and using the ArcVIEW 10 software. The land use diversity index was developed for the surrounding half-mile neighborhood area for the surveyed households located within Hamilton County. A fine-grain land use composition analysis helped compute an entropy-based land use diversity index more accurately and helped analyze its impact on household vehicle travel. Two measures of mixed land use were created:

**LUMix1** was computed using only the surrounding land uses. It measures the presence and composition of all different land use (for example residential, retail, office, industrial, parks, and others) in an area buffer of half-mile radius around each of the survey household locations using parcel level land use data. The process included demarcation of an individual half-mile radius circular neighborhood around each surveyed household location. LUMix1 is based on the Shannon-Entropy Index and all 18 land use categories were included in its computation.

**LUMix2** was computed using both the surrounding land uses and the surrounding street network. It can also be considered as a measure of local accessibility to the non-residential land uses in the neighborhood. It is conceptually similar to LUMix1 because it is also based on the Shannon-Entropy Index. However, unlike LUMix1, it measures the presence and composition of only 9 non-residential uses (Public Service, Institutional, Parks and Recreation, Education, Commercial, Office, Light industrial, Heavy Industrial, and Mixed Use) that can be considered
as possible destinations within the half-mile network irregular-shaped polygons created around each survey household location.

The step-wise methodology for creating land use diversity variables is described:

**Step 1: Creating Neighborhood Areas**

Existing land use data at the parcel level obtained from CAGIS was loaded onto ArcGIS 10 software. To compute LUMix1, a uniform circular buffer area neighborhood zone of half-mile (2,640 ft.) around each of the 610 household locations was constructed by using the buffer Geo-processing tool, as shown in Figure 15 (a). Similarly, LUMix2 was computed based on a half-mile network distance to generate irregular shaped service area polygons around the survey household locations using the Service Area tool in Network Analyst.

**Step 2: Land Use Composition**

I attempted to measure land use composition using several methods, including the Zonal tool within Spatial Analyst extension in ArcVIEW 10. The output was unsuitable for land use diversity calculations. The reason is that the circular buffer neighborhoods and the irregular shaped polygon areas created in Step 1 overlap considerably, as shown in Figures 15 (b) and (d). Spatial Analyst extension is suitable for area calculations where individual areas do not overlap (for example if the spatial unit of analysis were the census tracts, block group, or TAZ) since it computes each parcel of land only once and at the same time resulting in a loss of information. For this analysis, I therefore chose to use the National Water Quality Assessment (NAWQA) Area-Characterization Toolbox (ACT)\(^{14}\) developed by United States Geological Survey (USGS)

which allows a similar land use computation and analysis for overlapping areas on a one-by-one basis.

Land uses within half-mile area neighborhood for each of the 610 surveyed households in Hamilton County was computed on an individual basis as shown in Figure 15 (c). The output provided the land use area compositions for each land use category within each half-mile area and was used to calculate the land use diversity index. The summary of main land use areas in the half-mile circular area neighborhoods was created for calculating LUMix1 surrounding 545 survey households:\footnote{One limitation in Cincinnati’s land use dataset (based on the Hamilton County Auditor Office and available from CAGIS) is that all publicly-owned lands owned by the federal government, the State of Ohio, the Hamilton County, townships, municipalities, and agencies like the Metropolitan Housing Authority, are classified as Public Service (PS), irrespective of their actual or intended use. This implies that the areas for Public Service are over-reported, whereas those of other uses like Parks and Recreation, Education, Institutional, and others are under-reported. The City of Cincinnati has completed an exercise to create the existing land use dataset for the City of Cincinnati based on actual uses, but no such database exists for entire Hamilton County.}: single family (37.53 percent), public service (14.61 percent), vacant (7.65 percent), institutional (4.43 percent), parks and recreation (2.47 percent), heavy industrial (1.83 percent), multi-family (5.74 percent), agriculture (1.18 percent), education (3.14 percent), commercial (5.65 percent), light industrial (2.17 percent), congregation housing (0.45 percent), office (1.64 percent), public utilities (1.29 percent), two-family (2.81 percent), mobile home (0.15 percent), and mixed use (0.34 percent).
Figure 15: Illustration of stepwise methodology for computing LUMix1 using Spatial Analysis in GIS

(a) Delineating half-mile radius neighborhoods around survey households

(b) Clipping the land use raster image for the half-mile neighborhood areas

(c) Running the ACT to obtain land use compositions

Data source: Greater Cincinnati Household Travel Survey 2009-10, CAGIS 2010
Step 3: Computing Land Use Diversity Index

Two measures of diversity were created: LUMix1 and LUMix2. The following Shannon-Entropy Index was to calculate both the land use diversity indices:

$$\text{Land Use Diversity Index} = - \frac{\sum k (p_k \ln p_k)}{\ln N}$$

Where, $k$ is the category of land-use, $p$ is the proportion of the developed land area devoted to a specific land-use, and $N$ is the number of land-use categories in each defined half-mile neighborhood around each household survey locations in Hamilton County. The computed value of the entropy calculation or land use diversity index range from 0 to 1, with 0 representing a completely homogeneous area (the neighborhood is covered by one single land-use type) and 1 representing complete heterogeneity (all possible land-use categories are present the neighborhood area, and are equally distributed). Land use diversity index was converted to a 0-100 scale from 0-1 to enable measuring the effect of a unit change in land use diversity on VMT.

**LUMix1** measures the presence and composition of all different land use in a buffer of half-mile radius neighborhood area around each of the survey household location with in Hamilton County from parcel level land use data. As described, the methodology included demarcation of an individual half-mile radius circular neighborhood around each surveyed household location. LUMix1 ranges between 0-1 and has been converted to a 0-100 scale for regression analysis. As shown in Figures 17 (a) and (b) for the total sample of $n=610$ households within Hamilton County, the minimum LUMix1 computed was 37.39 and the maximum was 91.85, the mean LUMix1 was 68.94, and the standard deviation was 14.08.

**LUMix2** measures the presence and composition of nine non-residential land uses computed on a half-mile network distance based irregular shaped polygons around each of the survey household locations using the Service Area tool in Network Analyst (see Figure 16). The
shape and areas of these polygons depends on the street network surrounding the survey household locations and the connectivity pattern. LUMix2 ranges between 0-1 and has been converted to a 0-100 scale for regression analysis. As shown in Figures 18 (a) and (b), for the total sample of \( n = 610 \) households within Hamilton County, the minimum LUMix2 computed was 0, and the maximum was 31.43, the mean was 11.54, and the standard deviation was 5.04.

Land use composition and extent in each of the service area polygons formed the basis for LUMix2. The half-mile circular buffer used for LUMix1 around the survey household location ignores the actual pedestrian or vehicular access, whereas LUMix2 considers the actual network access in the half-mile neighborhood area as shown in Figure 16. As with the overlapping circular half-mile radius circular buffer areas used to calculate LUMix1, these irregular shaped polygons also overlap considerably. Land uses and their areas within each irregular shaped polygon neighborhood were also calculated by applying the NAWQA ACT toolset which allowed land use calculations for overlapping polygons in a disaggregated manner.

Figure 16: Example of land use area computation for determining LUMix2

Data source: Greater Cincinnati Household Travel Survey 2009-10, CAGIS 2010
Figure 17: (a) left: Half-mile radius neighborhood with minimum LUMix1, and (b) right: Neighborhood with maximum LUMix1

Data source: Greater Cincinnati Household Travel Survey 2009-10, CAGIS 2010

Figure 18: (a) left: Half mile network distance neighborhood with minimum LUMix2, (b) right: Neighborhood with maximum LUMix2

Data source: Greater Cincinnati Household Travel Survey 2009-10, CAGIS 2010
Figure 19: (a) top: Example of LUMix1 within half-mile radius circular neighborhood areas, and (b) bottom: Example of LUMix2 within half-mile network distance irregular shaped polygons

Data source: Greater Cincinnati Household Travel Survey 2009-10, CAGIS 2010
As seen in Figures 19 (a) and (b), the neighborhood areas on which the land use diversity index LUMix1 (based on half-mile radius) is calculated can be much larger than the neighborhood areas on which the land use diversity index LUMix2 (based on half-mile network distance) is calculated.

5.3 Computing Explanatory Variables

Several other land use or explanatory variables were created using various GIS tools. These include population and building densities, distance to transit, regional accessibility, and street and intersection densities. These are described below:

5.3.1. Population Density

Gross residential density variable is measured as number of persons living in a unit area. The population data was obtained at the census block group level for each of the survey household location for 2010 from the US census website. This was used to compute gross residential density per unit area. Only the land area was used for density calculation and the area covered with water was removed from the gross area. For the total sample \( n = 610 \) households located within Hamilton County, the maximum population density was 90.71 persons per ha, the minimum was 0.38, the standard deviation was 12.46, and the mean was 17.19 persons per ha.

5.3.2. Building Density

Building density or percentage of built up land or ground coverage was determined as one of the proxy design measures. Higher percentage of built up can be considered a proxy for a more walkable, grid pattern, and denser development. Building footprint information from CAGIS land use data was used to compute the building density after converting it to high resolution raster image as shown in Figure 20 (a). Building density was computed using NAWQA ACT tool developed by the USGS.
Figure 20: (a) top: Example of building density computed for the half-mile radius surrounding neighborhood around each survey household locations, (b) bottom, left: Neighborhood with minimum building density, (c) bottom, right: Neighborhood with maximum building density

Data source: Greater Cincinnati Household Travel Survey 2009-10, CAGIS 2010
As shown in Figure 20 (b) and (c), for the total sample $n = 610$ households located within Hamilton County, the minimum built-up density was 2.0 percent, the maximum was 70.94 percent, the mean was 39.40 percent, and the standard deviation was 13.11 percent.

5.3.3. **Distance to Transit**

This variable measured the shortest street network distance to the nearest Metro bus stop. The information on the bus routes and bus stops is available from CAGIS for the Hamilton County. Closest Facility tool in the Network Analyst extension for ArcVIEW 10 was used to calculate the shortest network distance to a transit stop as shown in Figure 21. The households are shown as small red circles on the map, and the bus stops as the green squares. The closest bus stop from a survey household location was at a distance of close to 0 mile, and the farthest bus stop from a survey household location was as much as 4.8 miles away. For the total sample $n = 610$ households within Hamilton County, on an average households are located at about half mile distance from the nearest bus stop. The mean distance of a survey household from the closest bus stop is 0.52 miles, the standard deviation is 0.81 miles, the minimum distance from the nearest bus stop is 0 miles, and the maximum is as much as 6.76 miles.

5.3.4. **Distance to CBD**

Distance to the CBD is a measure of centrality of development, or a measure of how far the development is from the city center or the Central Business District (CBD), considered to still be the largest concentration of jobs and services in the metropolitan region. I measured the shortest network distance between each survey household location and the CBD of the City of Cincinnati in Network Analyst using ArcView 10 software as shown in Figure 22. The households are shown as small green circles on the map, and the large red circle is the city center location derived as the geographic center of the CBD/Riverfront neighborhood in Cincinnati, obtained using the neighborhood layer from CAGIS database.
Figure 21: Example of network distance to the nearest bus stop from survey household locations

Data source: Greater Cincinnati Household Travel Survey 2009-10, CAGIS 2010
Figure 22: Regional accessibility measured as the shortest network distance to the CBD from survey household location.

Data source: Greater Cincinnati Household Travel Survey 2009-10, CAGIS 2010.
5.3.5. **Street Density**

Street density has been often used as a measure of street design metrics. A higher street density is considered to be an indicator of a denser, more walkable, grid-based, compact development pattern. It has been calculated by delineating the total length of streets or edges from the network dataset developed in Network Analyst. As shown in Figure 23, street density is calculated for the half mile radius around the household survey locations as a floating point raster for the entire Hamilton County. The street density was then extracted for the specific household survey locations using the extract values at points tool in Spatial Analyst extension in ArcVIEW 10, measured in miles per square mile area. For the total sample of \( n = 610 \) households located within Hamilton County, the minimum street density was 1.80 miles/sq. mile and the maximum was 41.49 miles/sq. mile, the mean street density was 14.75 miles/sq. mile, and the standard deviation was 6.36 miles/sq. mile.

5.3.6. **Intersection Density**

This variable measures the number of 3-way and 4-way intersections per square mile in the half-mile radius around each survey household. Intersection density is also a widely used measure of neighborhood design in planning and urban design research. A higher intersection density is considered a proxy for a smaller block size, a denser street network, and a more walkable urban development pattern by providing increased walking choices to pedestrians, as well as increasing routing options for public transit provision. It has been calculated by delineating the number of street intersections from the network dataset consisting of nodes and edges developed in Network Analyst extension. All street dead-ends and cul-de-sacs were excluded from intersection density computation as these reduce the walking and biking options instead of enhancing them.
Similar to the computation of street density, intersection density was also calculated as a floating point raster for the half-mile radius for the Hamilton County as shown in Figure 24. The intersection density was then extracted for the household survey locations using the extract values at points tool in Spatial Analyst in ArcVIEW 10 software. A large range was observed between the minimum and maximum intersection densities. For the total sample of \( n = 610 \) households located within Hamilton County, the minimum intersection density was as low as 6.37 intersections/sq. mile and the maximum was as high as 2028.27 intersections/sq. mile, the mean intersection density being 322.19 intersections/sq. mile, and the standard deviation was 316.64 intersections/sq. mile.
Figure 23: An example of street density

Data source: Greater Cincinnati Household Travel Survey 2009-10, CAGIS 2010
Figure 24: An example of intersection density

Data source: CAGIS 2010
5.4 Chapter Summary

The spatial unit of analysis was specified as the half mile radius neighborhood areas or the half mile network distance neighborhood area around each of the $n = 610$ survey household locations within Hamilton County. Seven measures of land use characteristics were developed using advanced GIS tools such as Spatial Analyst, Network Analyst and the NAWQA ACT. Land use variables include two measures of land use diversity index LUMix1 and LUMix2, building density, intersection density, street density, distance to nearest bus stop, and distance to the CBD. Table 7 below provides the descriptive statistics of land use characteristics for all $n = 610$ survey households within Hamilton County:

**Table 7: Descriptive Statistics for Land Use Variables**

<table>
<thead>
<tr>
<th>Land use characteristics</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Land use diversity index LUMix1</td>
<td>69.94</td>
<td>14.08</td>
<td>37.39</td>
<td>91.85</td>
</tr>
<tr>
<td>Land use diversity index LUMix2</td>
<td>11.54</td>
<td>5.04</td>
<td>0.00</td>
<td>31.43</td>
</tr>
<tr>
<td>Building Density</td>
<td>39.40</td>
<td>13.11</td>
<td>2.00</td>
<td>70.94</td>
</tr>
<tr>
<td>Intersection density</td>
<td>322.19</td>
<td>316.64</td>
<td>6.37</td>
<td>2028.27</td>
</tr>
<tr>
<td>Street density</td>
<td>14.75</td>
<td>6.36</td>
<td>1.80</td>
<td>41.49</td>
</tr>
<tr>
<td>Distance to nearest bus stop</td>
<td>0.52</td>
<td>0.81</td>
<td>0.00</td>
<td>6.76</td>
</tr>
<tr>
<td>Distance to CBD</td>
<td>8.56</td>
<td>4.52</td>
<td>0.26</td>
<td>22.49</td>
</tr>
</tbody>
</table>

Data source: Greater Cincinnati Household Travel Survey 2009-10, CAGIS 2010
6. Model Specification and Analysis

This chapter presents the models that were conceptualized and developed to quantify the influence of land use characteristics on household vehicular travel. It includes a descriptive summary of the data and variables used in the models, followed by the functional form of the conceptual model. After an extensive iterative process to arrive at the solutions that best describe the influence of various land use variables on household travel, four multivariate Ordinary Least Square (OLS) regression models were prepared using the Statistical Package for Social Scientists (SPSS version 15.0). These models are proposed to explain the relationships between the several land use characteristics and household car travel.

6.1 Model Preparation

A model is an abstraction of reality, and a statistical model is basically a formalization of relationships among different variables. A model can therefore be represented in many forms using many approaches. Regression analysis is a popular statistical tool to determine the strength and significance\(^{16}\) of relationships between variables. OLS regression method was chosen for analysis, as it is the most widely used quantitative multivariate research method in social sciences.

Model preparation involves developing the specifications of the OLS regression model to determine and isolate the impact of land use characteristics on travel patterns. A large set of explanatory variables was used in the regression iteration process. As discussed in the review of literature in Section 3.10, vehicular miles traveled (VMT) is primarily a function of

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\(^{16}\) Significance is the degree of confidence to which the true relationship is close to the estimated relationship
socioeconomic characteristics, and secondarily a function of land use characteristics. Several earlier studies that have analyzed the influence of various land use and built form characteristics on household travel have been critiqued for their inadequate consideration of socioeconomic characteristics. Therefore, I have chosen to control for the effects of socioeconomic variables by incorporating these more fully within the regression models developed in this research. The selection and computation of all variables are described in detail in the previous two chapters.

The following general form of the regression model is used:

\[ Y_i = \beta_0 + \beta_i (\text{Socioeconomic})_i + \beta_i (\text{Neighborhood})_i + \beta_i (\text{Land Use})_i + \epsilon_i \]

It can also be expressed as:

\[ Y_i = \beta_0 + \beta_1 S_i + \beta_2 N_i + \beta_3 L_i + \epsilon_i \]

where, \( Y_i \) is the dependent variable vehicle miles traveled (VMT); \( \beta_0 \) is a constant term to be estimated; \( S_i \) is a set of socioeconomic variables for the survey households; \( L_i \) is a set of land use variables in the surrounding neighborhood of the households, \( N_i \) is the set of neighborhood characteristics in the census block group where the survey households are located, and \( \epsilon_i \) is the error term. The socioeconomic variables include household income, vehicle ownership, household size, number of students, and number of drivers in the survey household.

Neighborhood variables are computed at the census block group level and include rental housing as a percentage of total occupied housing, percentage of African-American only households, and median household income. Land use variables include neighborhood gross residential density, building density, street density, intersection density, two land use diversity indices as a measure of the heterogeneity of land uses; transit accessibility as measured by the network distance to nearest bus stop, and the shortest network distance to the CBD. Table 8 gives the descriptive summary of the sample data used in the regression models.
### Table 8: Travel, Socioeconomic, Neighborhood, and Land use Variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Notes</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min.</th>
<th>Max.</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Travel variables</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>GIS_daily_carVMT (Models 1 and 2)</td>
<td>Daily car Vehicle Miles Traveled computed using GIS for n = 543 households</td>
<td>32.43</td>
<td>26.11</td>
<td>0</td>
<td>171.41</td>
</tr>
<tr>
<td>GPS_daily_carVMT (Models 3 and 4)</td>
<td>Daily car Vehicle Miles Traveled computed from GPS for n = 604 households</td>
<td>49.56</td>
<td>48.16</td>
<td>0</td>
<td>317.60</td>
</tr>
<tr>
<td><strong>Socioeconomic variables</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HH_size</td>
<td>No. of people in household</td>
<td>2.17</td>
<td>1.24</td>
<td>1</td>
<td>6</td>
</tr>
<tr>
<td>Workers</td>
<td>No. of workers in household</td>
<td>1.09</td>
<td>0.90</td>
<td>0</td>
<td>4</td>
</tr>
<tr>
<td>Students</td>
<td>No. of students in household</td>
<td>0.55</td>
<td>0.95</td>
<td>0</td>
<td>5</td>
</tr>
<tr>
<td>Drivers</td>
<td>No. of drivers in household</td>
<td>1.62</td>
<td>0.80</td>
<td>0</td>
<td>5</td>
</tr>
<tr>
<td>Vehicles</td>
<td>No. of vehicles in household</td>
<td>1.69</td>
<td>0.99</td>
<td>0</td>
<td>7</td>
</tr>
<tr>
<td><strong>Neighborhood variables</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Nhood_black</td>
<td>Percentage of African-American only households in census block group</td>
<td>24.51</td>
<td>28.20</td>
<td>0</td>
<td>96.18</td>
</tr>
<tr>
<td>Nhood_rental</td>
<td>Percentage of rental housing in census block group</td>
<td>40.32</td>
<td>27.63</td>
<td>1.04</td>
<td>100</td>
</tr>
<tr>
<td>Nhood_inc</td>
<td>Median annual household income in census block group in dollars</td>
<td>5,7168.02</td>
<td>33,750.39</td>
<td>5,250</td>
<td>25,0001</td>
</tr>
<tr>
<td>Nhood_density</td>
<td>Gross residential density in census block group in persons per hectare</td>
<td>17.57</td>
<td>12.68</td>
<td>0.67</td>
<td>90.71</td>
</tr>
<tr>
<td><strong>Land use variables</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bldg_den</td>
<td>Percentage built up area in half-mile radius around household</td>
<td>39.72</td>
<td>12.82</td>
<td>4.37</td>
<td>70.94</td>
</tr>
<tr>
<td>Transit_dist</td>
<td>Distance from household to closest bus stop in miles</td>
<td>0.49</td>
<td>0.75</td>
<td>0</td>
<td>4.8</td>
</tr>
<tr>
<td>LUMix_1</td>
<td>Land use diversity in half-mile radius around household</td>
<td>69.02</td>
<td>10.86</td>
<td>37.39</td>
<td>91.85</td>
</tr>
<tr>
<td>LUMix_2</td>
<td>Land use diversity in half-mile network distance around household</td>
<td>11.71</td>
<td>5.07</td>
<td>0.00</td>
<td>31.43</td>
</tr>
<tr>
<td>Street_den</td>
<td>Street density in half-mile radius around household in miles/sq. mile</td>
<td>14.86</td>
<td>6.19</td>
<td>2.37</td>
<td>40.86</td>
</tr>
<tr>
<td>Intersec_den</td>
<td>Intersection density in half-mile radius around household in number of intersections/sq. mile</td>
<td>323.64</td>
<td>307.13</td>
<td>8.91</td>
<td>2028.27</td>
</tr>
<tr>
<td>Dist_CBD</td>
<td>Distance of household from the CBD in miles</td>
<td>8.41</td>
<td>4.40</td>
<td>0.26</td>
<td>22.28</td>
</tr>
</tbody>
</table>

Data source: Greater Cincinnati Household Travel Survey 2009-10, CAGIS 2010, US Census 2010

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17 All descriptive statistics in Table 8 are based on the sample size of n = 543 households used in Model 1 and Model 2, except for GPS daily car VMT used in Model 3 and Model 4. Descriptive statistics for GPS daily car VMT are based on a sample size of n = 604 households.
For Model 1 and Model 2, the sample size was \( n = 543 \) households, after removing the 65 households that traveled outside OKI region during the survey period and also removing two additional outliers from the original sample of 610 households in Hamilton County. These 543 households traveled on average 32.43 miles by car per day (calculated from O-D points from travel survey data using Network Analyst in GIS as described in Section 4.3). For both Model 3 and Model 4, the sample size is \( n = 604 \) households, determined after removing from the original sample of 610 households those 6 households that traveled over 1000 miles during the 3 survey days.

6.2 Model Development

The objective of the model development process was to determine a set of regression models that best explain the variation in household vehicular travel as measured by the daily household car VMT with respect to differences in the set of explanatory land use variables. This process involved:

1. Completing initial regression models to arrive at the different models,
2. Determining the parameters and their coefficients and significance levels,
3. Investigating violations of model assumptions and identifying outliers,
4. Modifying the basic model through an iterative process to remove model violations and ensure that assumptions hold, and
5. Developing solutions in the form of Model 1, Model 2, Model 3, and Model 4.

Three indicators were investigated: 1) the level of significance of land use characteristic variables to understand which of these have a statistically significant effect on the amount of vehicular travel as measured by VMT; 2) the sign of the estimated regression coefficients (whether positive or negative) showing whether the land use characteristics positively or
negatively influence the amount of household car VMT; and, 3) the magnitude of the regression coefficient of the land use characteristics to show the quantum of their influence on VMT. The Statistical Package for Social Sciences version 15.0 (SPSS) was used for the regression analysis and to estimate the constant term and unknown parameters. I developed several models in an iterative process to select the ones that best explain the influence of various land use characteristics on VMT ($Y_i$).

Multicollinearity implies that two or more independent variables are highly correlated. Multicollinearity was detected through a scatter plot analysis of all independent variables and by examining the Variance Inflation Factor\(^\text{18}\) (VIF) during regression model iterations. A VIF of 1 is considered perfect, indicating total absence of multicollinearity among independent variables. VIF values higher than 10 need to be addressed, as they indicate high multicollinearity and instability of the $\beta$ coefficients (Chatterjee and Hadi 2006). In the initial regression iterations, all land use, socioeconomic and neighborhood variables as described in Table 8 were considered for analysis. The correlation coefficient\(^\text{19}\) was also examined between different explanatory variables in order to determine the degree of correlation between them. A correlation coefficient of less than 0.5 is weak, so it was considered as the threshold for selecting or removing the explanatory variables to be included in the regression. Based on the VIF, the tolerance value, $18$ Tolerance is a measure of multicollinearity and is the inverse of VIF. Tolerance value lower than 0.1 are considered an indication of collinearity (Hadi and Chatterjee 2006).

\(^\text{19}\) Correlation coefficients between two variables $X_1$ and $X_2$ represent the covariance between the them and is computed as follows:

$$Corr(X_1, X_2) = \frac{1}{n-1} \sum_{i=1}^{n} \left( \frac{x_{1i} - \bar{x}_1}{s_{x_1}} \frac{x_{2i} - \bar{x}_2}{s_{x_2}} \right),$$

where $n$ is the number of observations; $x_{1i}$ and $x_{2i}$ are the values of the variables $X_1$ and $X_2$ for the $i$th observation; $\bar{x}_1$ and $\bar{x}_2$ are the mean values of the variables $X_1$ and $X_2$; $s_{x_1}$ and $s_{x_2}$ are the standard deviations for the variables $X_1$ and $X_2$.

Correlation coefficient of zero indicates total absence of collinearity, however that is usually not possible to obtain in analysis.
and the correlation coefficient, for each pair of explanatory variables with high multicollinearity, one of the variables was removed from the regression analysis. For instance, it was found that the independent variables of street density and intersection density showed very high multicollinearity with a VIF of over 17 and 12 respectively, and had a correlation coefficient of 0.94, so intersection density was removed from the regression analysis. Similarly, LUMix1 and LUMix2 were also highly correlated so LUMix1 was removed from the models, and number of students in the household correlated highly with household size, so number of students was removed from the models to maintain parsimony.

Four regression models were developed and finalized. All four models are based on the generic form of the model described in Section 6.1. In Model 1 and Model 2, GIS computed VMT was used as the dependent Y variable. In this case, the origin and destination points from the data were used to reconstruct the travel distances in GIS using Network Analyst, and all high travel households that traveled outside the OKI region were removed. Model 2 is similar to Model 1, but it has an additional land use variable of distance to CBD added to the model. In Model 3 and Model 4, GPS based VMT was used as the dependent variable. Daily car VMT of each household was computed from the GPS records directly into a spreadsheet without using network analysis. Model 4 is similar to Model 3, but it has an additional land use variable of distance to CBD added to the model. OLS assumptions were verified in the iteration process to arrive at these four models. Models 2 and 4 were specifically developed to determine whether distance to CBD has a significant impact on household travel, or whether it was masking the effect of other more important land use variables. Each of these four models is discussed here.

6.2.1. Model 1

In Model 1, the dependent variable is daily car VMT of the household, as calculated in GIS using Network Analyst extension. To arrive at the household travel survey sample of
$n=543$ households, first, 64 households that recorded any travel outside the OKI region during the 3-day survey period, as detected spatially from mapping the trip O-D points, were removed from the original sample of $n=610$ households. Then, outliers in the household travel data were checked for any households that exhibited unusually high travel. Applying the Cook’s distance, Leverage value and Hadi’s statistic for outlier analysis (Chatterjee and Hadi 2006), 3 outliers were identified and removed from the sample household size in stages, resulting in an analytical sample of $n=543$ households.

**Interpretation**

With an R-square\(^{20}\) obtained for this model of 0.321 and the adjusted R-square\(^{21}\) of 0.305, the independent variables in Model 1 explain about 30 percent of the variation in daily car household VMT. The R-square statistic tends to provide a slightly higher, but false indication of the model fit, since it increases with the addition of any variable. The adjusted R-square is a downward adjustment on the R-square as it takes into account the number of variables and the sample size, and as compared to R-square is considered a better indicator of the model fit or strength of the model. The F-value was significant at $F=19.259$ at $\alpha=0.000$. The Durbin-Watson\(^{22}\) statistic is 1.96, very close to 2.0, which indicates that the model has no autocorrelation. Table 9 gives the summary of the regression outcome:

\(^{20}\) In OLS regression, R-square is the coefficient of determination, and can also be considered as the goodness of fit for the overall model. It is basically the fraction of variation explained by the model.

\(^{21}\) Adjusted R-square is a more conservative measure of the model’s R2, or the goodness of fit, as it takes into account the number of variables applied.

\(^{22}\) The Durbin Watson statistic in regression analysis is an indicator of presence of autocorrelation between values of the residuals, which is often present when values are separated from each other by a time lag. Durbin Watson Statistic ranges from 0 – 4, and a value of 2 indicates zero autocorrelation.
Table 9: Model 1: Model Summary

<table>
<thead>
<tr>
<th>Model</th>
<th>R</th>
<th>R Square</th>
<th>Adjusted R Square</th>
<th>Std. Error of the Estimate</th>
<th>Durbin-Watson</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>.567(a)</td>
<td>.321</td>
<td>.305</td>
<td>21.77086</td>
<td>1.959</td>
</tr>
</tbody>
</table>

a Predictors: (Constant), LUMix_2, transit_dist, workers, Nhood_black, Nhood_density, HH_size, income, vehicles, street_den, Nhood_inc, bldg_den, drivers, Nhood_rental
b Dependent Variable: GIS_daily_carVMT

Table 10: Model 1: Coefficients

<table>
<thead>
<tr>
<th>Model</th>
<th>Unstandardized Coefficients</th>
<th>Standardized Coefficients</th>
<th>Collinearity Statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>B</td>
<td>Std. Error</td>
<td>Beta</td>
</tr>
<tr>
<td>1</td>
<td>(Constant)</td>
<td>8.033</td>
<td>8.728</td>
</tr>
<tr>
<td></td>
<td>HH_size</td>
<td>3.701</td>
<td>1.021</td>
</tr>
<tr>
<td></td>
<td>Workers</td>
<td>5.827</td>
<td>1.401</td>
</tr>
<tr>
<td></td>
<td>Drivers</td>
<td>2.942</td>
<td>2.051</td>
</tr>
<tr>
<td></td>
<td>Vehicles</td>
<td>3.190</td>
<td>1.464</td>
</tr>
<tr>
<td></td>
<td>Income</td>
<td>.103</td>
<td>1.135</td>
</tr>
<tr>
<td></td>
<td>Nhood_black</td>
<td>.048</td>
<td>.042</td>
</tr>
<tr>
<td></td>
<td>Nhood_rental</td>
<td>-0.117</td>
<td>.060</td>
</tr>
<tr>
<td></td>
<td>Nhood_inc</td>
<td>1.13E-005</td>
<td>.000</td>
</tr>
<tr>
<td></td>
<td>Nhood_density</td>
<td>.014</td>
<td>.106</td>
</tr>
<tr>
<td></td>
<td>Bldg_den</td>
<td>.127</td>
<td>.121</td>
</tr>
<tr>
<td></td>
<td>Transit_dist</td>
<td>2.933</td>
<td>1.598</td>
</tr>
<tr>
<td></td>
<td>Street_den</td>
<td>-.349</td>
<td>.249</td>
</tr>
<tr>
<td></td>
<td>LUMix_2</td>
<td>.015</td>
<td>.088</td>
</tr>
</tbody>
</table>

a Dependent Variable: GIS_daily_carVMT

Table 10 provides the beta weights, t values, and the significance levels of variables for Model 1, including the VIF values. There are several socioeconomic variables used in the research including household size, the number of workers in the household, the number of drivers in the household, the number of vehicles in the household, and household income range. Household size, number of workers in the household, and number of vehicles in the household are highly significant and influence the number of miles that people drive their cars every day. For the household socioeconomic variables that are found to be significant, the signs of the values of \( \beta \) are as expected. Household size is highly significant at \( p<0.000 \). For every additional person in the household, its household daily car VMT increases by 3.7 miles. Number of workers
in the household is highly significant at p < 0.000. For every additional worker in the household, its household daily *car VMT* increases by 5.83 miles. *Number of vehicles* in the households is highly significant at p < 0.03. For every additional vehicle owned by the household, its household daily *car VMT* increases by 3.2 miles. Among the neighborhood characteristics, it was found that the *amount of rental housing* in the neighborhood is negatively related to the household daily *car VMT*. Rental housing is significant at p=0.051, which means that for every 1 percent increase in rental housing as a percentage of total occupied housing in the census block group, the household daily *car VMT reduces* by 0.12 miles.

In Model 1, among all land use variables only *distance to transit*, a measure of transit availability, is found to be significant at p<0.067, with $\beta = 2.933$ within $\alpha=0.05$. For every extra mile that a household lives farther away from the nearest bus stop, it travels almost 3 additional miles every day by car. In Model 1, with a sample size of $n=543$ households, the *distance to transit* (nearest bus stop) has a mean value of 0.49 miles, standard deviation is 0.75 miles, and the maximum value is 4.8 miles. The mean household daily *car VMT* is 32.43 miles for this dataset. The implication is that on an average, based only on the mean household location with respect to the nearest bus stop, each household drives an additional 1.47 miles every day, or 536.56 extra miles a year. The household living the farthest distance from the nearest bus stop at 4.8 miles, drives up to 14.11 additional miles by car every day, predicting over 5,150 extra miles in a year. Other land use variables are insignificant at $\alpha<0.05$ level (5 percent confidence level).

There are many assumptions in OLS regression. The important ones are: there is a linear relationship between the dependent (Y) variable with each of the independent (X) variables; the independent variables are measured without errors; the residuals are statistically independent; and the residuals are normally distributed with a mean of zero and have a constant variance. Model 1 was tested for some of these assumptions and possible violations. It was found that
there is no serious multicollinearity since the VIF values for all the variables are within or just over 3.0. This means that the model is stable, and all explanatory variables are independently contributing to the model prediction. Normality of data was tested from the frequency chart of the standardized residuals in Figure 25. It was found to be near normal, but slightly skewed to the right. Normality of error terms was checked through the Normal Probability Plot of the residuals, as shown in Figure 26. The distribution of errors is normal as the points on this plot fall close to the diagonal line. Independence of error terms was checked using a plot of standardized residual vs. index number. Figure 27 shows that this plot has random points without any pattern, indicating that this assumption holds.

Figure 25: Model 1: Histogram showing normally distributed data

![Histogram showing normally distributed data](image1.png)

Figure 26: Model 1: Normal Probability Plot

![Normal Probability Plot](image2.png)
6.2.2. **Model 2**

Model 2 is similar to Model 1, except that it has an additional land use variable of distance to CBD. The dependent variable is also the same as Model 1, *household daily car VMT* calculated in GIS using Network Analyst. After removing from the original sample of $n=610$ the 65 households that traveled outside the OKI region and 3 households that were outlier households in Hamilton County (as described in Model 1 in Section 6.2.1), the end household travel survey sample was $n=543$ households.

**Interpretation**

The R-square obtained for Model 2 is 0.327 and the adjusted R-square is 0.309. The independent variables in Model 2 explain about 31 percent of the variation in *daily car household VMT*. The addition of the *distance to CBD* variable resulted in only a marginal increase in the adjusted R-square value, from 0.305 in Model 1 to 0.309 in Model 2. The F-value was significant at $F=18.316$ at $\alpha=0.000$. The Durbin-Watson statistic was 1.96, very close to 2.0 which indicates that the model has no autocorrelation. Table 11 below gives the regression model summary:
Table 11: Model 2: Model Summary

<table>
<thead>
<tr>
<th>Model</th>
<th>R</th>
<th>R Square</th>
<th>Adjusted R Square</th>
<th>Std. Error of the Estimate</th>
<th>Durbin-Watson</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>.572(^{(a)})</td>
<td>.327</td>
<td>.309</td>
<td>21.70062</td>
<td>1.961</td>
</tr>
</tbody>
</table>

\(^{a}\) Predictors: (Constant), Dist_CBD, workers, LUMix_2, Nhood_black, bldg_den, HH_size, income, vehicles, transit_dist, Nhood_density, Nhood_inc, street_den, drivers, Nhood_rental

\(^{b}\) Dependent Variable: GIS_daily_carVMT

Table 12: Model 2: Coefficients

<table>
<thead>
<tr>
<th>Model</th>
<th>Unstandardized Coefficients</th>
<th>Standardized Coefficients</th>
<th>t</th>
<th>Sig.</th>
<th>Collinearity Statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Tolerance</td>
</tr>
<tr>
<td>1</td>
<td>(Constant)</td>
<td>1.468</td>
<td>9.242</td>
<td>.159</td>
<td>.874</td>
</tr>
<tr>
<td>HH_size</td>
<td>3.682</td>
<td>1.017</td>
<td>.175</td>
<td>3.619</td>
<td>.000</td>
</tr>
<tr>
<td>Workers</td>
<td>5.830</td>
<td>1.397</td>
<td>.201</td>
<td>4.174</td>
<td>.000</td>
</tr>
<tr>
<td>Drivers</td>
<td>2.815</td>
<td>2.045</td>
<td>.086</td>
<td>1.376</td>
<td>.169</td>
</tr>
<tr>
<td>Vehicles</td>
<td>3.127</td>
<td>1.460</td>
<td>.119</td>
<td>2.142</td>
<td>.033</td>
</tr>
<tr>
<td>Income</td>
<td>.360</td>
<td>1.138</td>
<td>.015</td>
<td>.316</td>
<td>.752</td>
</tr>
<tr>
<td>Nhood_black</td>
<td>.044</td>
<td>.042</td>
<td>.047</td>
<td>1.038</td>
<td>.300</td>
</tr>
<tr>
<td>Nhood_rental</td>
<td>-.084</td>
<td>.062</td>
<td>-.088</td>
<td>-1.354</td>
<td>.176</td>
</tr>
<tr>
<td>Nhood_inc</td>
<td>-3.53E-006</td>
<td>.000</td>
<td>-.005</td>
<td>-.080</td>
<td>.936</td>
</tr>
<tr>
<td>Nhood_density</td>
<td>.049</td>
<td>.107</td>
<td>.024</td>
<td>.460</td>
<td>.646</td>
</tr>
<tr>
<td>Bldg_den</td>
<td>.100</td>
<td>.121</td>
<td>.049</td>
<td>.828</td>
<td>.408</td>
</tr>
<tr>
<td>Transit_dist</td>
<td>1.579</td>
<td>1.718</td>
<td>.046</td>
<td>.919</td>
<td>.358</td>
</tr>
<tr>
<td>Street_den</td>
<td>-.191</td>
<td>.259</td>
<td>-.045</td>
<td>-.736</td>
<td>.462</td>
</tr>
<tr>
<td>LUMix_2</td>
<td>-.009</td>
<td>.088</td>
<td>-.005</td>
<td>-.105</td>
<td>.917</td>
</tr>
<tr>
<td>Dist_CBD</td>
<td>.727</td>
<td>.346</td>
<td>.123</td>
<td>2.105</td>
<td>.036</td>
</tr>
</tbody>
</table>

\(^{a}\) Dependent Variable: GIS_daily_carVMT

Table 12 gives the beta weights, \(t\) values, and significance levels of variables for Model 2, including the VIF values. Socioeconomic variables of household size, number of workers in the household, and number of vehicles in the household are highly significant and impact the number of miles that people drive their cars every day. All significant socioeconomic variables have the expected signs for the \(\beta\) coefficients. *Household size* is highly significant at \(p<0.000\). For every additional person in the household, their household daily car VMT increases by 3.7 miles. *Number of workers* in the household is highly significant at \(p < 0.000\). For every additional worker in the household, its household daily car VMT increases by 5.83 miles. *Number of vehicles* in the households is highly significant at \(p<0.03\). For every additional
vehicle owned by the household, its household daily car VMT increases by 3.13 miles. None of the neighborhood characteristics were found to be significant within $\alpha=0.05$.

In Model 2, among all land use variables, only distance to CBD, a measure of centeredness, was found to be significant at $p<0.036$, with $\beta=.727$. For every extra mile that a household lives farther away from the CBD, it travels 0.73 additional miles every day by car. In Model 4, the sample size is $n=543$ households. The distance to the CBD has a mean value of 8.41 miles, standard deviation of 4.4 miles, and a maximum value of 22.28 miles. The mean daily car VMT is 32.43 miles for this dataset. The implication is that on an average, based only on the mean household location with respect to the CBD, each household drives an additional 6.11 miles every day, or as much as 2,232 miles a year. The one household living the farthest distance from the CBD at 22.28 miles drives up to 16.2 additional miles by car every day, which would predict as many as 5,912 extra miles in a year. Other land use variables are insignificant within $\alpha<0.05$.

Model 2 was tested for OLS assumptions and possible violations. The model does not have any serious multicollinearity since the VIF values for all variables are within or just over 3.0. This means that the model is stable, and all explanatory variables are independently contributing to the model’s predictive power. The normality of data was tested as shown in the frequency chart of the standardized residuals in Figure 28. It was found to be near normal, but slightly skewed to the right. Normality of error terms was checked through the Normal Probability Plot of the residuals, as shown in Figure 29. The distribution of errors is normal, as the points on this plot fall close to the diagonal line. Independence of error terms was checked using a plot of standardized residual vs. index number. Figure 30 shows that this plot has random points without any pattern, indicating that this assumption holds.
Figure 28: Model 2: Frequency chart for standardized residuals

![Frequency chart for standardized residuals](image)

Figure 29: Model 2: Normal Probability Plot

![Normal Probability Plot](image)

Figure 30: Model 2: Residual vs. Index no. plot

![Residual vs. Index no. plot](image)
6.2.3. **Model 3**

Model 3 has the same set of variables as Model 1, but in this model the dependent variable household daily car VMT is calculated differently and the sample size is also different. *Household daily car VMT* is computed from the GPS travel data (and not in GIS) which measures the actual distance traveled by the households within and outside the OKI region. The sample size is \( n = 604 \) households after removing 6 households from the original sample that exhibited unusually high daily car travel of over 1,000 miles in 3 survey days. These 604 households traveled on average 49.56 miles by car each day, with a standard deviation of 48.16. The minimum miles traveled was 0 miles, with the maximum household travel being 317.6 miles a day (see Table 8).

**Interpretation**

The R-square obtained for Model 3 was 0.25 and the adjusted R-square was 0.233, so variables in Model 3 explain about 23.3 percent of variance in the household daily car VMT (see Table 13 below). The adjusted R-square for this model at 0.233 is much lower than that obtained for Model 1 at 0.305 and Model 2 at 0.309. The F-value is significant at \( F= 15.072 \) at \( \alpha=0.000 \). The Durbin-Watson statistic is 1.928, very close to 2, so there is no autocorrelation in Model 3.

**Table 13: Model 3: Model Summary**

<table>
<thead>
<tr>
<th>Model</th>
<th>R</th>
<th>R Square</th>
<th>Adjusted R Square</th>
<th>Std. Error of the Estimate</th>
<th>Durbin-Watson</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>.499(a)</td>
<td>.249</td>
<td><strong>.233</strong></td>
<td>42.18676</td>
<td>1.928</td>
</tr>
</tbody>
</table>

a Predictors: (Constant), Street_den, HH_worker, LUMix_2, Nhood_black, Transit_dist, HH_vehicle, HH_size, HH_income, Nhood_med_Inc, Pop_density, Bldg_density, HH_driver, Nhood_rental

Table 14 presents the \( t \)-values, the beta values and the significance levels of the variables used in Model 3 and the VIF values. The VIF values for all variables are under 3.0, indicating that there is no serious multicollinearity among the variables with all the variables independently contributing to the model’s predictive power.
Looking at the significance levels, it is clear that several household socioeconomic characteristics are significant contributors to household daily car VMT. Household size is significant at p<0.03. For every additional person in the household, the household drives and additional 4.1 miles every day. Number of workers in the household is highly significant at p < 0.000. For every additional worker in the household, the daily car VMT increases by approximately 10 miles. Number of vehicles in the households is highly significant at p < 0.002. For every additional vehicle that is owned by the household, its daily car VMT increases by 6.74 miles. Among the neighborhood characteristics, rental housing as a percentage of total occupied housing came out significant at p=0.055. For every 1 percent increase in rental housing in the census block group, the daily car VMT of the households located within that census block group decreases by 0.20 miles.

Five land use characteristics were used in Model 3 as test variables: neighborhood residential density, building density, street density, land use diversity as measured by LUMix2, and distance to CBD. Out of these, the four variables including neighborhood residential

<table>
<thead>
<tr>
<th>Model</th>
<th>Unstandardized Coefficients</th>
<th>Standardized Coefficients</th>
<th>Collinearity Statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>B</td>
<td>Std. Error</td>
<td>Beta</td>
</tr>
<tr>
<td>1</td>
<td>(Constant)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>34.586</td>
<td>13.534</td>
</tr>
<tr>
<td>HH_size</td>
<td>4.101</td>
<td>1.874</td>
<td>.106</td>
</tr>
<tr>
<td>HH_worker</td>
<td>10.016</td>
<td>2.510</td>
<td>.194</td>
</tr>
<tr>
<td>HH_driver</td>
<td>4.855</td>
<td>3.577</td>
<td>.081</td>
</tr>
<tr>
<td>HH_vehicle</td>
<td>6.743</td>
<td>2.214</td>
<td>.152</td>
</tr>
<tr>
<td>HH_income</td>
<td>-.318</td>
<td>2.064</td>
<td>-.007</td>
</tr>
<tr>
<td>Nhood_black</td>
<td>.107</td>
<td>.077</td>
<td>.062</td>
</tr>
<tr>
<td>Nhood_rental</td>
<td>-.202</td>
<td>.105</td>
<td>-.116</td>
</tr>
<tr>
<td>Nhood_med_Inc</td>
<td>-7.18E-005</td>
<td>.000</td>
<td>-.050</td>
</tr>
<tr>
<td>Pop_density</td>
<td>-.093</td>
<td>.198</td>
<td>-.024</td>
</tr>
<tr>
<td>Bldg_density</td>
<td>-.153</td>
<td>.221</td>
<td>-.042</td>
</tr>
<tr>
<td>Transit_dist</td>
<td>2.658</td>
<td>2.770</td>
<td>.044</td>
</tr>
<tr>
<td>LUMix_2</td>
<td>-.712</td>
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<td>-.075</td>
</tr>
<tr>
<td>Street_den</td>
<td>-.037</td>
<td>.438</td>
<td>-.005</td>
</tr>
</tbody>
</table>

a Dependent Variable: OKI_dailyCarVMT
density, building density, street density, and distance to CBD were found to be insignificant within $\alpha<0.05$. In Model 3 land use diversity index $LUMix2$ was found to be the only significant land use variable that influences household travel. $LUMix2$ has a negative sign which indicates that the dependent variable daily car VMT decreases with increase in land use diversity. $LUMix2$ has $\beta = -.712$ at $p = 0.051$, which means that for every unit increase in the land use diversity index of the household, its daily car travel decreases by 0.71 miles. Model 3 was tested to check stability, reliability and non-biasness. Least square assumption for linear relationship between $Y$ and each $X$ were checked through partial regression plots for each dependent variable and were found to be linear. The frequency distribution chart for the standardized residuals shows a near-normal distribution, slightly skewed to the right (see Figure 31). The Normal Probability Plot of the residuals shows normality of error terms as the points on this plot fall close to the diagonal line (see Figure 32). The standardized residual vs. index number plot shows a random spread of points without a pattern and indicates independence of error terms (see Figure 33).

Figure 31: Model 3: Frequency chart for standardized residuals
6.2.4. **Model 4**

Model 4 is similar to Model 3, except that an additional land use variable *distance to CBD* is introduced here. The dependent variable is household daily car VMT computed from the GPS travel data and measures the actual distance traveled within and outside the OKI region. Model 4 has the same household sample size as Model 3 of *n* = 604, after removing 6 outliers from the sample as described in Section 6.2.3. These 604 households traveled on average 49.56 miles each day by car, with a standard deviation of 48.16. The minimum miles traveled was 0 miles, and the maximum household daily car VMT was 317.6 miles a day (see Table 8).
Interpretation

For Model 4, the R-square obtained is 0.252 and the adjusted R-square obtained is 0.234 (see Table 15), very close to the adjusted R-square obtained in Model 3 which is 0.233, but much lower than Model 1 at 0.305 and Model 2 at 0.309. Model 4 explains 23.4 percent of variation in the dependent variable daily car VMT. The F-value was significant at $F=14.152$ at $\alpha=0.000$. The Durbin-Watson statistic is 1.94, indicating absence of any autocorrelation.

Table 15: Model 4: Model Summary

<table>
<thead>
<tr>
<th>Model</th>
<th>R</th>
<th>R Square</th>
<th>Adjusted R Square</th>
<th>Std. Error of the Estimate</th>
<th>Durbin-Watson</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>.502(a)</td>
<td>.252</td>
<td>.234</td>
<td>42.15486</td>
<td>1.939</td>
</tr>
</tbody>
</table>

a Predictors: (Constant), CBD_distance, HH_worker, LUMix_2, Nhood_black, Bldg_density, HH_vehicle, HH_size, HH_income, Pop_density, Nhood_med_Inc, Transit_dist, HH_driver, Street_den, Nhood_rental

Table 16: Model 4: Coefficients

<table>
<thead>
<tr>
<th>Model</th>
<th>Unstandardized Coefficients</th>
<th>Standardized Coefficients</th>
<th>t</th>
<th>Sig.</th>
<th>Collinearity Statistics</th>
<th>Tolerance</th>
<th>VIF</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>B</td>
<td>Std. Error</td>
<td>Beta</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>(Constant)</td>
<td>25.791</td>
<td>14.958</td>
<td>1.724</td>
<td>.085</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>HH_size</td>
<td>4.058</td>
<td>1.873</td>
<td>.105</td>
<td>2.167</td>
<td>.031</td>
<td>.543</td>
</tr>
<tr>
<td></td>
<td>HH_worker</td>
<td>10.047</td>
<td>2.508</td>
<td>.194</td>
<td>4.005</td>
<td>.000</td>
<td>.540</td>
</tr>
<tr>
<td></td>
<td>HH_driver</td>
<td>4.820</td>
<td>3.575</td>
<td>.081</td>
<td>1.348</td>
<td>.178</td>
<td>.356</td>
</tr>
<tr>
<td></td>
<td>HH_vehicle</td>
<td>6.603</td>
<td>2.215</td>
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<td>.003</td>
<td>.509</td>
</tr>
<tr>
<td></td>
<td>HH_income</td>
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<td>2.074</td>
<td>.000</td>
<td>-.003</td>
<td>.998</td>
<td>.577</td>
</tr>
<tr>
<td></td>
<td>Nhood_black</td>
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<td>.077</td>
<td>.059</td>
<td>1.310</td>
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<td>.633</td>
</tr>
<tr>
<td></td>
<td>Nhood_rental</td>
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<td>.109</td>
<td>-.094</td>
<td>-1.499</td>
<td>.135</td>
<td>.325</td>
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<tr>
<td></td>
<td>Nhood_med_Inc</td>
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<td>.000</td>
<td>-.061</td>
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<td>.277</td>
<td>.401</td>
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<tr>
<td></td>
<td>Pop_density</td>
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<td>.200</td>
<td>-.013</td>
<td>-2.255</td>
<td>.798</td>
<td>.473</td>
</tr>
<tr>
<td></td>
<td>Bldg_density</td>
<td>-.186</td>
<td>.222</td>
<td>-.050</td>
<td>-2.038</td>
<td>.402</td>
<td>.351</td>
</tr>
<tr>
<td></td>
<td>Transit_dist</td>
<td>.957</td>
<td>3.031</td>
<td>.016</td>
<td>3.16</td>
<td>.752</td>
<td>.501</td>
</tr>
<tr>
<td></td>
<td>LUMix_2</td>
<td>-.798</td>
<td>.370</td>
<td>-.084</td>
<td>-2.158</td>
<td>.031</td>
<td>.841</td>
</tr>
<tr>
<td></td>
<td>Street_den</td>
<td>.152</td>
<td>.459</td>
<td>.020</td>
<td>.331</td>
<td>.741</td>
<td>.342</td>
</tr>
<tr>
<td></td>
<td>CBD_distance</td>
<td>.877</td>
<td>.637</td>
<td>.082</td>
<td>1.376</td>
<td>.169</td>
<td>.361</td>
</tr>
</tbody>
</table>

Table 16 provides beta values, t values, and the significance levels of variables in the model, including the VIF. The VIF values for all variables used in this model are less than 3.
which implies that the model is stable, there is no serious multicollinearity among the variables, and all variables contribute independently to the model.

The socioeconomic variables of household size, number of workers, number of vehicles, and number of drivers in the household are statistically significant within $\alpha<0.05$ and have positive signs as expected. Household daily car VMT increases with increase in the household size, the number of workers, and the number of vehicles in the household. Household size is significant with $\beta = 4.058$. For every 1 additional member in the household, the household travels an additional 4.06 miles every day by car. The number of workers in the household has the largest and most significant impact on household car travel with $\beta = 10.047$. For every additional worker in the household, the household travels an additional 10 miles every day by car. For every additional vehicle in the household, the household travels an additional 6.6 miles every day by car. For all variables that were found to be statistically significant, the signs of the $\beta$ were as expected. The three neighborhood characteristics that are used as control variables in the model were found to be insignificant within $\alpha<0.05$.

Land use variables of neighborhood residential density, building density, street density, and distance to CBD were found to be insignificant at $\alpha<0.05$ level. Similar to the outcome of Model 3, in Model 4, land use diversity $LUMix2$ was found to be the only significant land development characteristic that impacts household travel. Land use diversity was significant at $p=0.03$ level, and has a negative sign which indicates that household daily car VMT decreases with increase in land use diversity, and that it has a role in determining the daily household VMT. For every unit increase in land use diversity index $LUMix2$, there is a corresponding decrease of 0.798 miles in daily household car VMT. This is higher than the value obtained for the land use diversity variable in Model 3, which was 0.712 miles. The outcome of Model 4 therefore
reinforces that LUMix2 is a significant predictor of household car travel. The findings are discussed in detail in Section 7.1.

Model 4 was also tested to check stability, reliability and non-biasness. Least square assumption for linear relationship between Y and each X were checked through partial regression plots for each dependent variable and were found to be linear. The frequency distribution chart for the standardized residuals shows a near-normal distribution, slightly skewed to the right (see Figure 34). The Normal Probability Plot of the residuals shows normality of error terms as the points on this plot fall close to the diagonal line (see Figure 35). The standardized residual vs. index number plot shows a random spread of points without a pattern and indicates independence of error terms (see Figure 36).

Figure 34: Model 4: Frequency chart for standardized residuals
Figure 35: Model 4: Normal Probability Plot of the residuals

![Normal Probability Plot](image)

Dependent Variable: OKI_dailyCarVMT

Figure 36: Model 4: Standardized Residuals vs. Index number plot

![Residuals vs. Index Number Plot](image)
7. Findings and Conclusions

The concluding chapter presents the research findings from the regression models developed and described in the previous chapter. The discussions focus on the influence of specific land use characteristics of *land use diversity, distance to transit, and distance to the CBD* on daily household travel as inferred from the four OLS regression models developed in Section 6.2. It discusses the significance of this research for climate change issues and measurement, and explores the magnitude of the relationship between land use characteristics, household travel and CO₂ emissions in the context of climate policy. Finally, it discusses the research contributions and limitations, extensions of this research to the fields of land use and transportation research, and points out a few directions for future research.

7.1 Research Findings

As discussed in Section 1.4, the first research question was to determine whether there exists a significant relationship between specific land use characteristics of density, land use diversity, street density, intersection density, regional accessibility, transit availability and household travel. The second question was to explore if there are any such relationships, what is the extent or strength of these relationships, and estimate how much they contribute to daily household car travel. The answer to both of these research questions is that there is indeed a statistically significant and strong relationship between the land use variables of *land use diversity index LUMix2, distance to travel, and distance to CBD* with household *Vehicle Miles Traveled* (VMT) in the four models developed and discussed in Section 6.2.
Table 17 shows all variables tested and details the regression model coefficients and summarizes the significance levels for the socioeconomic, neighborhood, and land use variables that emerged as significant in each of the four models.

**Table 17: Summary of Regression Models**

<table>
<thead>
<tr>
<th>Variables</th>
<th>Model 1</th>
<th></th>
<th>Model 2</th>
<th></th>
<th>Model 3</th>
<th></th>
<th>Model 4</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>adj. R²=0.305</td>
<td>adj. R²=0.309</td>
<td>adj. R²=0.233</td>
<td>adj. R²=0.234</td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>GIS calculated VMT</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>GPS calculated VMT</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Socioeconomic variables</strong></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Household size</td>
<td>3.701</td>
<td>(0.000)</td>
<td>3.682</td>
<td>(0.000)</td>
<td>4.101</td>
<td>(0.029)</td>
<td>4.058</td>
<td>(0.031)</td>
</tr>
<tr>
<td>Number of workers</td>
<td>5.827</td>
<td>(0.000)</td>
<td>5.830</td>
<td>(0.000)</td>
<td>10.016</td>
<td>(0.000)</td>
<td>10.047</td>
<td>(0.000)</td>
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<td><strong>Neighborhood variables</strong></td>
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<tr>
<td>Percentage African-American only</td>
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<td></td>
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<td>households</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Percentage rental housing</td>
<td>-1.17</td>
<td>(0.051)</td>
<td></td>
<td></td>
<td>-0.202</td>
<td>(0.055)</td>
<td></td>
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</tr>
<tr>
<td>Median neighborhood income</td>
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<td></td>
<td></td>
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<td></td>
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<tr>
<td>Neighborhood residential density</td>
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<td></td>
<td></td>
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<tr>
<td><strong>Land use variables</strong></td>
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<td>Building density</td>
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<td></td>
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<td></td>
</tr>
<tr>
<td>Distance to transit</td>
<td>2.933</td>
<td>(0.067)</td>
<td></td>
<td></td>
<td>-0.712</td>
<td>(0.051)</td>
<td>-0.798</td>
<td>(0.031)</td>
</tr>
<tr>
<td>Land use diversity index LUMix2</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>Street density</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Distance to CBD</td>
<td>Not included</td>
<td></td>
<td>.727</td>
<td>(0.036)</td>
<td>Not included</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Figures in parentheses indicate significance levels.
The following are the key research findings:

1. **Household socioeconomic characteristics are the most important determinants of VMT**

   In all the four models, exactly the same socioeconomic characteristics emerged as significant in predicting household travel. As argued in much of the land use and travel research that is considered statistically sound, household socioeconomic characteristics are the strongest and the largest determinants of household travel. Number of people in the household, number of workers, and number of vehicles owned by the household consistently emerged as the most significant variables that determine daily household car VMT in all four models.

   *Household size* is a clear predictor of household travel, and it was highly correlated with the number of students and the number of children. It is reasonable to assume that a household with higher numbers of members would travel more, as there would be more people who would need to get to work or school, shop, attend to family businesses, eat out, be dropped off at school or daycare, or engage in a range of other activities that require travel.

   *Number of workers* is the most important variable and has the largest impact on total household travel. Commuting to work is a non-negotiable activity and represents predictable travel. More workers in the household suggest that there are more people who might have a need to commute to work every day.

   Similarly, a *higher number of vehicles* owned by the household means that there are more vehicles available to be used, which could generate higher number of household miles traveled.

   While *number of vehicles* correlates with the household income, annual household income did not by itself emerge as significant. This may be due to the fact that groupings of income data ranges were provided in the data set (i.e., < 25K, 25K-50K, 50K-75K, and >75K) instead of ratio level actual income data which would have been more suitable for regression modeling. In addition, over 7 percent of households could not or did not provide information on
their household income resulting in missing data. The only income-related variable which emerged as significant in two of the four models was percentage of rental housing in the census block group, where the models predicted lower household vehicle travel as the proportion of rental housing increased.

2. Land use diversity is a significant determinant of household travel

Models 3 and 4 both establish a clear relationship between land use diversity LUMix2 and household daily car VMT. The outcomes of Models 3 and 4 are almost the same, and consistent with each other. In Model 3, the adjusted R-square obtained was 0.233, almost exactly the same as that for Model 4 at 0.234, so both models fit equally well. Although an additional variable of distance to CBD was introduced in Model 4, it did not contribute additional explanatory power, and the model outcomes did not change.

Land use diversity LUMix2 was found to be significant in both Model 3 and Model 4 as discussed in Section 6.2.3 and 6.2.4 with $\beta = 0.712$ and 0.798 respectively. LUMix2 has a mean of 11.71, standard deviation of 5.07, the minimum LUMix2 is 0 and a maximum LUMix2 is 31.43. Figures 18 (a) and 18 (b) visually indicate what these minimum and maximum values of LUMix2 mean in terms of actual land use diversities. We can interpret the effects of change in X on Y taking several values of land use diversity LUMix2 within this range, and see its proportional change in the household VMT as determined from regression Models 3 and 4. From the outcome of Models 3 and 4, we determine that keeping other things constant, for the variable land use diversity LUMix2, we have the following two partial regression equations:

\[
Y^ = 34.586 - 0.712X \quad \text{..................Model 3}
\]

\[
Y^ = 25.791 - 0.798X \quad \text{..................Model 4}
\]
Using these two partial regression equations, in Table 18 we construct the following interpretation by taking hypothetical changes in the value of X, assuming that survey households live in a range of neighborhoods with varying land use diversity index LUMix2.

Table 18: Interpretation of Partial Regression Equations

<table>
<thead>
<tr>
<th>Land use diversity index LUMix2</th>
<th>0 (min)</th>
<th>5</th>
<th>11.71 (mean)</th>
<th>15</th>
<th>20</th>
<th>25</th>
<th>31.43 (max)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Daily household VMT (Model 3)</td>
<td>34.57</td>
<td>31.01</td>
<td>26.23</td>
<td>23.89</td>
<td>20.33</td>
<td>16.77</td>
<td>12.19</td>
</tr>
<tr>
<td>Daily household VMT (Model 4)</td>
<td>25.79</td>
<td>21.80</td>
<td>16.45</td>
<td>13.82</td>
<td>9.83</td>
<td>5.84</td>
<td>0.71</td>
</tr>
</tbody>
</table>

Table 18 shows that as there is an increase in land use diversity index LUMix2, there is a corresponding decrease in household daily car VMT. From Model 3 we can infer that for the mean value of LUMix2 of 11.71, there is a total reduction of 8.34 miles in household daily car VMT (it reduces from 34.57 miles to 26.23 miles). Since the mean daily household car VMT for Model 3 is 32.43, this is equivalent to a 25.72 percent reduction in daily household car VMT. Similarly, from Model 4 we can infer that for the mean value of LUMix2 of 11.71, there is a reduction of up to 9.34 miles in household daily car VMT (reduces from 25.79 miles to 16.45 miles). Since the mean daily car VMT for Model 4 is 49.46, this is equivalent to 18.89 percent reduction in daily household car VMT. Models 3 and 4 suggest that on an average, the potential for VMT reduction from land use diversity LUMix2 is in the range of 18.89 percent to 25.72 percent.

From Models 3 and 4, we can infer that land use diversity is an important land use determinant of household travel. Both models clearly suggest that higher land use diversity induces less daily household car VMT. This is probably due to the fact that higher diversity allows for more destinations to be located near the places of residence, effectively reducing the distances between origins and destinations. A heterogeneous mix of compatible land use such as
residential, retail and office, allows several possible destinations or activities such as offices, retail shops, restaurants, schools, parks, libraries, banks, grocery stores, and industries to be located closer to each other and to residences.

LUMix1 that takes into account all the surrounding land uses, but not the street network was not significant in any of the model iterations. LUMix2, a measure of both the surrounding mix of non-residential land uses as well as the street network, was significant in two of the four models. This implies that simply having a higher mix of land uses around the households is not enough - these land uses should be possible destinations and be accessible through a street network. The way land use diversity index LUMix2 is conceptualized and measured in this research, it is not only a measure of proximity bringing origins and destinations closer to each other spatially, but it is also a measure of accessibility and connectivity since it considers the extent of the street network in the neighborhood of the sample households. It measures not only the presence and extent of surrounding land uses around the household locations, but also access to them from the location of survey households.

To visually illustrate the influence of land use diversity index LUMix2 on the household daily car VMT, I developed two interpolation raster images using the IDW tool (Inverse Distance Weighted) in ArcVIEW 10 using the actual values of LUMix2 and household daily car VMT for the sample survey household locations. Comparing Figures 37 (a) and (b) visually (darker shades indicate higher values) it can be said that generally, the two appear to be correlated spatially in a negative manner. Figure 37 (a) shows households located in areas with higher land use diversity LUMix2 in the central areas of the study region are also the ones that appear to have a lower VMT as shown in Figure 37 (b).
Figure 37: Interpolation images of (a) top: Land Use Diversity Index LUMix2, and (b) bottom: Household daily car VMT (measured by GPS)

Data source: CAGIS 2010, Greater Cincinnati Household Travel Survey 2009-10
In both of these maps, interpolation technique is used to predict values of cells at locations that lack sample points. IDW is a deterministic method of raster interpolation and creates an interpolation raster based on the assumption that things closer to one another are more alike than things farther apart. The weight given to the points closer to prediction location is higher than those farther away. To generate these maps, I specified a fixed distance search radius that limits the input sample points used to perform the interpolation, and specified $p = 2$ (called the inverse distance squared weighted interpolation), as in this case the distance decay is more rapid.

**Transit accessibility is significant**

*Transit accessibility*, measured as the shortest network distance from the survey household location to the nearest bus stop, was found to be significant in several model iterations including Model 1 (refer Section 6.2.1). From Model 1, we can infer that for every additional mile that a household is located away from the nearest bus stop, it travels 2.93 miles more every day, or over 1,000 miles extra in a year. However, beyond a certain accessible distance, the distance to the nearest bus stop would cease to matter. This is likely to happen at the half-mile network distance, equivalent to a comfortable 10-minute walk.

This builds the case for provision of public transit within walkable distance as an important urban transportation infrastructure which can lead to a reduction in car travel. This is mostly due to a modal shift due to provision of alternative transportation options and providing increased travel choices to people. The industry practice of providing transit stops within a 20 minute walk of most neighborhoods is well-supported in this argument. The literature suggests

---

$^23$ $p$ controls the significance of surrounding points on the interpolated value. A higher power results in less influence from distant points. As $p$ increases, the weights for distant points decreases. $p = 2$ is the default value in ArcVIEW 10.
that integration of bike mode travel with public transit might help expand the threshold distance to a mile or more. Beyond that, it does not matter much if the nearest bus stop is located 2 miles or 10 miles away, because beyond 2 miles would not be considered “accessible”. There is much potential for reducing household daily VMT though greater transit availability. However, a necessary pre-condition for transit provision is presence of high population density to support a threshold transit ridership.

**Distance to CBD is also significant**

In Model 2 the distance to the CBD is a significant land use variable, and has a measurable influence on household travel. Distance to CBD is a measure of centeredness or an indication of how spread out the development is from the center of a metropolitan region. Although used frequently in research, the effects and importance of distance to CBD are highly debatable. From Model 2, we can infer that for every additional mile farther away from the CBD a household is located, household members drive 0.727 miles more every day. This variable was not significant in Model 4, and when the same models are run without the distance to CBD variable (as in Models 1 and 3), other land use variables such as land use diversity and distance to transit emerged as significant.

The distance to CBD is a crude measure of centeredness and is possibly masking the influence of other more important land use characteristics that are more refined in measurement. This argument also seems to be in agreement with a recent large scale meta-study of about 50 studies by Ewing and Cervero (2010). In their earlier 2001 study, they had found the distance to downtown to be one of the strongest predictors of vehicle travel and state that “…equally strongly, though negatively, related to VMT is the distance to downtown. This variable is a proxy for many Ds (land use variables), as living in the city core typically means higher densities in mixed-use settings with good regional accessibility….” (Ewing and Cervero 2010, p 275).
Areas developed farther away from the city center are also generally less diverse and less dense in character and have lower transit availability, which in combination is influencing peoples’ driving behavior, rather than only a simplistic measure of distance to CBD. Perhaps there is higher VMT observed among households living farther away from the CBD because they are traveling to more spread out destinations involving longer trip lengths. Many more jobs, retail, businesses, entertainment, parks, and facilities are being located in more spread out areas in the suburbs. As a result, more and more travel is now happening from suburb-to-suburb, as compared to suburb-to-center city.

The research outcomes provide interesting insights on the impact of various land use variables on household travel. From the outcomes of this research, we can infer that land use diversity is the most important land use characteristic, followed by transit availability and distance to the CBD. Contrary to expectations, and in conformity with more recent research, density did not emerge as a significant characteristic in predicting household Vehicle Miles Traveled. Land use diversity LUMix2 is the most important land use characteristic, implying that the idea of diversity as propagated by smart growth enthusiasts does have merit, and there are far ranging implications for long-range regional development planning. It also implies that increasing diversity in suburban development away from the central core might also have beneficial environmental impacts, even though these areas may be comparatively less dense.

7.2 Significance for Climate Change Issues and Measurement

7.2.1. Determining the Carbon Footprint of Household Travel

So what is the best way to measure or convert the potential VMT savings from land use modifications into CO₂ emissions? In this section, the findings of the OLS analysis in the previous chapter are presented in terms of contribution to the GHG emissions from vehicular
travel and its implications. It is important to recognize that each gallon of gasoline weighing only 6.3 lbs., when burnt, produces as much as 20 lbs. of CO\textsubscript{2} emissions\textsuperscript{24}, and for every mile we drive, we emit about 1 lb. of CO\textsubscript{2} into the atmosphere!

The methodology for estimating CO\textsubscript{2} emissions from household travel is complex, and it is difficult to determine accurately the carbon footprint from travel. It depends on several factors including vehicular fleet composition (number of different personal vehicles such as light duty trucks, SUVs, pick-ups, and passenger cars), carbon content of fuel, vehicular fuel efficiency (gasoline consumption and mileage, age of vehicles), total VMT, and even the local climate (as colder conditions result in more cold starts). USEPA provides broad guidance with assumptions to guide the computation of CO\textsubscript{2} emissions from VMT. The USEPA guidance and the Department of Transportation (USDOT fuel economy information) can be adopted for broadly computing GHG emissions from household travel. This would help us determine the impact of land use characteristics on VMT and on GHG emissions.

According to the information on the USEPA website\textsuperscript{25}, passenger vehicles are those classified as 2-axle, 4-tyre vehicles including passenger cars, vans, pickup trucks, and sport utility vehicles (SUV). USEPA estimates that the amount of CO\textsubscript{2} emitted per gallon of gasoline combustion is $8.92 \times 10^{-3}$ metric tons or 19.67 lbs., very close to the previous estimate of 20 lbs. based on the atomic weights of carbon, hydrogen, and oxygen. Combined with the fact that the combined average fuel economy for cars and light duty trucks in 2007 was 20.4 miles per gallon,

\textsuperscript{24} There is a scientific explanation of this based on the atomic weights. During combustion of fuel, carbon and hydrogen separate and individually combine with oxygen. Hydrogen combines with oxygen to form water ($H_2O$), and carbon combines with oxygen to form carbon dioxide (CO\textsubscript{2}). Carbon has atomic weight of 12, and oxygen has atomic weight of 16, giving each molecule of CO\textsubscript{2} an atomic weight of 44 (12 from carbon and 32 from two oxygen). Now to get the amount of CO\textsubscript{2} produced from a gallon of gasoline, the weight of carbon in gasoline is multiplied by 44/12 or 3.7. Gasoline is 87 percent carbon and 13 percent hydrogen by weight, so the carbon in 1 gallon gasoline weighs 5.5 lbs. (6.3 lbs. x 0.87). Multiplying the weight of carbon (5.5 lbs.) by 3.7 gives 20 lbs. CO\textsubscript{2}.

\textsuperscript{25} http://www.epa.gov/cleanenergy/energy-resources/refs.html#vehicles
we can say that on an average, every vehicle mile traveled (VMT) by household vehicles consisting of cars and light duty trucks, produces 1.037 lbs. CO$_2$. And indeed, close approximations of the same have been used in Climate Action Planning by communities in the US. For instance, the City of San Carlos, CA adopted a conversion rate of 1.077 lbs. of CO$_2$e$^{26}$ emissions per VMT while computing its GHG inventory as part of its Climate Action Plan preparation process (Bosewell et al. 2012).

From the OLS Models 3 and 4 in Sections 6.2.3 and 6.2.4, we determined that there is a decrease of 0.712 or 0.798 miles traveled per household per day respectively if there is a 1 percent point increase in the land use diversity index LUMix2. Taking these values, we can construct Table 19 to demonstrate CO$_2$ emission reduction for varying levels of land use diversity index LUMix2.

<table>
<thead>
<tr>
<th>Land use diversity index LUMix2</th>
<th>0 (min)</th>
<th>5</th>
<th>11.71 (mean)</th>
<th>15</th>
<th>20</th>
<th>25</th>
<th>31.43 (max)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Corresponding VMT (Model 3)</td>
<td>34.57</td>
<td>31.01</td>
<td>26.23</td>
<td>23.89</td>
<td>20.33</td>
<td>16.77</td>
<td>12.19</td>
</tr>
<tr>
<td>Corresponding CO$_2$ (Model 3)</td>
<td>35.85</td>
<td>32.16</td>
<td>27.20</td>
<td>24.77</td>
<td>21.08</td>
<td>17.39</td>
<td>12.64</td>
</tr>
<tr>
<td>Corresponding VMT (Model 4)</td>
<td>25.79</td>
<td>21.80</td>
<td>16.45</td>
<td>13.82</td>
<td>9.83</td>
<td>5.84</td>
<td>0.71</td>
</tr>
<tr>
<td>Corresponding CO$_2$ (Model 4)</td>
<td>26.74</td>
<td>22.61</td>
<td>17.06</td>
<td>14.33</td>
<td>10.19</td>
<td>6.06</td>
<td>0.74</td>
</tr>
</tbody>
</table>

We can say from this analysis that for the mean value of LUMix2 of 11.71, there is up to 24 percent less CO$_2$ emissions from household travel from Model 3 (it reduces from 35.85 to 27.20 lbs.), and up to 36 percent less CO$_2$ emissions from household travel from Model 4 (it

---

$^{26}$ Average estimate that calculated by dividing total carbon dioxide equivalent (CO$_2$e) by total VMT. Individual calculations may vary from this average coefficient based on model year and vehicle class.
reduces from 26.74 to 17.06 lbs.), as compared to CO₂ emissions for the *minimum* value of LUMix2 which is 0. This range of 24 percent to 36 percent is quite large, and indicates a potential to significantly reduce CO₂ emissions from household travel through application of smart planning and zoning strategies that increase land use diversity through intermingling of non-residential land uses with residential land uses.

7.2.2. *Applications to Climate Planning*

There are possibilities for direct applications of this research in the field of climate action planning. Climate Action Plans across the US are applying a range of land use and transportation measures as climate mitigation strategies. Many of these strategies are targeted at reducing the CO₂ emissions through reducing travel demand. Land use interventions are being examined as possible demand management strategies. Sustainable urban development models and ideas of smart growth, New Urbanism, TOD, infill development, and similar alternative developments are all meant to reduce vehicular travel demand. This type of land use and travel research has the potential to contribute to determining the ability and usefulness of various smart growth strategies that rely on land use and transportation strategies to reduce VMT, energy, and emissions. To make informed policy decisions and adopt strategies as part of their climate action planning process, city planners estimate projected VMT based on projected alternative land development patterns. Hundreds of cities and regions are already making projections on reducing VMT based on their land use interventions as part of their GHG reduction targets – and indeed, many are mandated to do so by state legislations such as the SB 375 in California. Many other states have also adopted GHG reduction targets and strategies that engage metropolitan planning organizations to examine mobility and reduce VMT through smart growth. For example, many cities use land use tools to encourage diversity either through site-specific standards or regulations that may result in shorter and fewer car trips, as higher diversity
provides more land uses within close proximity or residences or offices. From the outcomes of Model 3 and Model 4, we can say that for each 1 percent increase in the land use diversity index $LUMix2$ for a household, it travels 0.712 or 0.798 miles less respectively. The elasticity values obtained from research like this one has the potential to guide cities to make projections about reductions in VMT and related CO$_2$ emissions from different mixed use and local accessibility scenarios.

The findings of this research supports the argument for higher mixed use developments, better transit availability, and more compact urban development. As literature suggests, in addition to VMT reduction and related CO$_2$ emissions reduction, a more diverse urban development pattern is estimated to result in additional and considerable GHG reductions associated with up to 20 percent reduction in energy bills to heat and cool residential space (Ewing et al. 2008). Any modifications to built environment are slow to materialize, but are cumulative, permanent, and fixed in nature – environmental benefits arising due to modifications to the built environment are expected to accrue over the long term.

As discussed in Section 3.11, 20 percent of non-residential space is expected to turn over every decade, and more than half of the built environment that will exist in 2025 did not exist in 2000 (Nelson 2004, Nelson 2006). This scale of projected rebuilding provides an unprecedented opportunity for planners to reshape and guide future urban development to achieve a more compact, sustainable, and energy-efficient urban form. There is a perceptible shift in residential preference fueled by new trends in densification, infill development, and revitalization of downtowns, as well as by changing demographics and lifestyle changes of the retiring Baby Boomers and young adults (Nelson 2004, Leinberger 2005, Nelson 2006). Real estate studies show a surging and unmet consumer demand for walkable, dense, livable, accessible, and transit-oriented urban environments.
7.3 Research Contribution, Applications, and Future Research

This research contributes to regional development planning in several ways. It is probably the first land use and transportation research study to incorporate data from the first large-scale household travel survey data in the country. This allowed me to spatially map the origin – destination (O-D) coordinates and determine the network travel distance to compute the VMT in the GIS environment. I was able to compare the VMT obtained using GIS using shortest distance specifications with the VMT obtained from the survey records using GIS. Examining the travel information from the same set of households, this exercise found that, people actually traveled almost 23 percent more than the shortest distance!

This research has attempted to improve upon the existing methodology for the way land use diversity is conceptualized and computed both in terms defining disaggregated units of analysis by using individually defined half-mile neighborhoods around each of the survey households, using parcel level land use data, and applying advanced spatial analysis tools in the GIS environment. This approach allowed this research to capture the uniqueness of each household location, which would otherwise have been aggregated within an administrative boundary such as a census tract or TAZ. The approach taken in this study assigned each household its individual diversity index derived on the basis of its own specific location. Several other land use characteristics were also computed using this strategy including building density, intersection density, and street density.

Four separate models were developed in this research – two each based on two different method of VMT computation, and together give interesting insights on the influence of specific land use characteristics such as land use diversity, transit accessibility, and distance to CBD. The research contributes to the vast and exponentially growing knowledge in recent years on the relationship between land use characteristics and travel. It provides additional insights on the
potential for travel demand management through compact and mixed use development, and on the possibilities for household travel demand management from land use policy intervention. Since this is a detailed, disaggregate, and quantitative analysis at the county level examining several land use variables at the same time, it contributes to the existing knowledge, and to the convincing literature on the influence of land uses characteristics on VMT that is shaping the policy response to climate and sustainable transportation.

Applications to Transportation Research

Research of this nature also has applications for transportation research field which is moving towards more advanced activity-based and disaggregate travel demand modeling, and away from the traditional four-step transportation model. These models rely on detailed household socioeconomic and land use characteristics for travel demand analysis. Disaggregate modeling takes into account trip activity/chaining behavior, and not just travel volumes based on total trips from one TAZ to another from aggregated O-D points. As discussed in Section 3.13, though the four-step travel demand models might have the potential to take into account VMT reductions due to mixed-use, it is usually in an aggregated format and not applied at the detail it is desired, which leads to a masking effect of mixed use development impacts. A detailed land use diversity index computed using a finer grain land use analysis has the potential to improve land use and transportation models that take into account VMT reductions from scenario building with different land use characteristics. Elasticities obtained from this type of research has the potential to be built into transportation models by more accurately predicting trip generation rates from areas with varying land use characteristics such as inner city/infill development and suburban development. Detailed land use analysis can feed into transportation modeling, improving their capacity to predict future travel demand. This may also shift the focus from meeting travel demand to managing travel demand, a more sustainable approach.
7.3.1. **Research Limitations**

The research study has several limitations in terms of geographical and research scope and methodologies used. This research was conducted using a subset of the Greater Cincinnati Household Travel Survey 2009-10. It is limited to households located only within the Hamilton County, which does not allow the results to be truly regional in scale. A disaggregate level land use and travel study covering all 8 counties of the OKI or Greater Cincinnati region would provide in-depth insights into household travel behavior at a regional level. Several predictors of household travel such as trip generation depend on local factors, demographics, and analytical methods applied. It is better to be on the conservative side while considering the impact of any of the land use factors on travel or emissions. It is not advisable to rely on the results on one or few studies in formulating implementation policy.

In addition, the research design only considers the locations and neighborhoods of residences of survey households, and not their places of work. This is a limitation since household travel actually happens as a series or chain of activities that are either home-based or work-based, and there is considerable trip chaining happening. The research was therefore not able to capture many aspects of household travel activity between different destinations that are related to each other.

The study also does not adequately address the larger issue of residential self-selection, although the regression models do control for the effects of household socioeconomic and neighborhood characteristics. Some portion of the impact credited to land use characteristics might actually be attributed to residential self-selection. Therefore, application of the findings of this research to other areas should be done carefully and conservatively.
7.3.2. **Possibilities and Opportunities for Future Research**

The discussions in this section point towards several possible directions for taking this research forward.

**Improving Urban Metrics**

Developing improved measurement of urban land use characteristics was one of the most exciting aspects of this research, and also the most extensive and time consuming stage of work in the research methodology. This research has attempted to improve upon the way land use diversity has been computed as a variable using GIS as computed in most land use and transportation studies. Several land use characteristics need to be incorporated in a more comprehensive manner in land use and travel impact studies including such factors as parking, sidewalks, bike lanes, and other urban design characteristics. It would be valuable to have region-wide detailed information on the extent of sidewalks and bike lanes in the city, whether those sidewalks have shady trees and interesting *urban design* features that contribute to a making walking and biking a pleasant, enjoyable, and safe experience (e.g., interesting retail store front character, human walkable scale as a result of a build-to-line regulations, and safe pedestrian crossings at intervals). Even though CAGIS has one of the most advanced land use databases, it is based on the County Auditors’ requirements and is not a true reflection of actual land use on publicly owned lands. Another example of study limitations is the challenge of computing *transit availability*, which could be more sophisticated than the simple measure of shortest distance from the closest bus stop, and could incorporate additional factors such as frequency of bus services to a given location, number of routes serviced at that location, and the level of regional connectivity it provides. Using the modern tools and technologies and the detailed data currently available, there are many such possibilities for improving and standardizing urban metrics for comparative research and analysis.
Exploring Key Relationships

This study also is limited to using only the vehicle miles traveled (VMT) in the analysis, and does not analyze other travel aspects of modal choice or travel time which represent important travel costs. For this research, household VMT was the most appropriate test variable since emissions are directly proportional to the miles traveled. It would be interesting to find out how modal choice varies with the surrounding urban environments, and how residents perceive travel costs. Analysis of vehicle hours traveled (VHT) would be interesting, since most travel decisions are made with the purpose to minimize travel time, which after the actual costs of the gas and vehicle, is generally seen as an important travel cost. Urban environments have the potential to influence modal choice. Whether households choose to travel by car, use the transit, walk or bike to a destination is determined to some extent by their surrounding built environment. These need to be explored further by more focused studies, and could be undertaken with this existing travel survey data for the Greater Cincinnati region.

More studies also need to be undertaken with focus on land use diversity near places of work, to fully ascertain the influence of diversity on household travel. Modeling land use characteristics near the location of residence, as well as near the location of work would help analyze trip-chaining behavior which is on the rise. This is a critical and interesting area of research as households are increasingly trip-chaining, or interlinking various tasks in a chain of travel events that may be based from home or work. The trip-chaining phenomenon is particularly influenced by measures of proximity, accessibility, and connectivity, and has many implications for transportation planning that will impact future modeling techniques.

Addressing Residential Self-selection

To a limited extent, self-selection has been addressed in this study by incorporating a range of household socioeconomic characteristics as control variables. Without the
incorporation of a residential and travel preference information or behavioral attitudes of the
survey respondents, this research study has limited control for self-selection which may have
introduced some bias into the study (refer Section 3.11 for detailed discussion). There is a need
to address this type of bias in future research through improved modeling approaches. Advanced
methodologies that attempt to control for self-selection bias are being increasingly applied in
land use and travel research.

These approaches range from basic approaches like incorporating attitudinal and
behavioral variables into regression models, as in Kitamura et al. 1997, to more recent and
advanced methodologies that jointly estimate residential choice and travel behavior through
models that treat residential choice as an endogenous variable (Ewing and Cervero 2010). In
personal attitudes surveys, respondents are asked questions on their attitudes and preferences
regarding travel, public transit, walking and biking, and their perception of city living and
urbanism. Modifying travel behavior implies not just modifying the built environment but also
modifying people’s personal attitudes (Kitimura et al. 1997). However, it must be pointed out
here that even self selection reflects a growing market trend for preferences for more compact
and diverse urban neighborhoods with greater accessibility to activities, destinations, and transit.

Applying Advanced Methodologies

OLS regression has been used for this research. There are several other appropriate
regression methods that may be applied to determine land use and transportation relationships
such as the weighted least squares (WLS), geographically weighted regression (GWR), or
maximum likelihood (ML). These methods should be explored since they typically produce
more robust and reliable models as compared to the OLS regression for analyzing relationships
across space. They provide more comprehensive interpretations that make it possible to capture
complex interactions among land use and travel variables. For example, structural equation
(SEM) modeling can be used to capture the effects of different variables on one another, as well as direct and indirect effects. Advanced methodologies can also control for residential self-selection that can introduce bias into the results.

**Increasing Geographical Scope**

The study is limited in its geographic scope to households located within Hamilton County, and therefore is only based on a subset of the entire 8-county OKI based regional travel survey data with a sample size of 610 households. This was due to the fact that land use characteristics were not easy to obtain, compare, and standardize across all OKI counties. A more comprehensive analysis would include the entire sample of over 1,350 households and wider travel patterns, which would be a truer reflection of how metropolitan America travels by car, often traveling beyond regional boundaries. In land use and travel research, it is crucial to use disaggregate level data covering a large geographical area and a large representative sample size to avoid ecological fallacy, where inferences about individual travel behavior are often made based on studies using aggregated data.


Greater Cincinnati Household Travel Survey. 2009-10. Ohio Department of Transportation, Office of Statewide Planning and Research, and the Ohio-Kentucky-Indiana (OKI) Regional Council of Governments.


*Transportation Research Record* 1400, p 58–66.

*Conservation Law Foundation.*


*Climate Policy.* Vol. 3, No. 4, p 359-37.


OKI Regional Council of Governments. 2010. Mobile source emissions inventory for Cincinnati PM 2.5 nonattainment area. Prepared for the Indiana Department of Environmental Management, the Kentucky Division for Air Quality, and the Ohio Environmental Protection Agency.


Shoup, Donald C., 2005. The high cost of free parking. Planners Press, Chicago


http://nhts.ornl.gov/briefs/Carbon%20Footprint%20of%20Travel.pdf.


http://www.epa.gov/cleanenergy/energy-resources/refs.html#vehicles.
