A STATEWIDE ANALYSIS OF THE INTERACTION BETWEEN THE BUILT ENVIRONMENT AND TRAVEL BEHAVIOR USING GEOGRAPHICALLY WEIGHTED REGRESSION

By

RUSSELL ERIC PROVOST

A THESIS PRESENTED TO THE GRADUATE SCHOOL
OF THE UNIVERSITY OF FLORIDA IN PARTIAL FULFILLMENT
OF THE REQUIREMENTS FOR THE DEGREE OF
MASTER OF ARTS IN URBAN AND REGIONAL PLANNING

UNIVERSITY OF FLORIDA

2013

ACKNOWLEDGMENTS

I thank my family and friends who continued to encourage me to finish my thesis. I also thank Florida Department of Transportation for providing such a rich dataset for analysis. I especially thank the University of Florida community for six unforgettable years in Gainesville.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

y_i	Yearly VMT at household i
x_{iSES}	A vector of socioeconomic variables at household i
β_{SES}	The coefficients representing the estimated change in household i's yearly VMT from a one unit change in the vector of socioeconomic variables
x_{iTA}	The travel attitude of household i
β_{TA}	The coefficient representing the estimated change in household i's yearly VMT from the travel attitude variable
x_{iBE}	A vector of built environment variables thought to impact the quality of travel, quantity of travel needed, and the cost of vehicle travel
β_{BE}	The coefficients representing the estimated change in household i's yearly VMT from a one unit change in the vector of built environment variables
x_{iC}	An additional travel cost variable
β_C	The coefficient representing the estimated change in household i's yearly VMT from a one unit change in the travel cost variable
ε_i	Unobserved factors impact household yearly VMT
GIS	Geographic Information Systems
GWR	Geographically Weighted Regression
GHG	Greenhouse Gas
NHTS	National Household Transportation Survey
NTD	Neo-Traditional Development
TMC	Theoretical Minimum Commute
VMT	Vehicle Miles Traveled

Abstract of Thesis Presented to the Graduate School of the University of Florida in Partial Fulfillment of the Requirements for the Degree of Masters of Arts in Urban and Regional Planning

A STATEWIDE ANALYSIS OF THE INTERACTION BETWEEN THE BUILT ENVIRONMENT AND TRAVEL BEHAVIOR USING GEOGRAPHICALLY WEIGHTED REGRESSION

By

Russell Eric Provost

August 2013

Chair: Ruth Steiner
Cochair: Paul Zwick
Major: Urban and Regional Planning

Concerns about traffic congestion, air pollution, climate change, transportation revenue shortfalls, and obesity rates are coalescing to form a perfect storm that is challenging the way development and transportation investments occur. Confronting these challenges will require a paradigm shift in the way politicians and citizens understand the synergies between the built environment and travel behavior. Justifying policy changes to address these issues require a thorough understanding of the interactions between the built environment and travel behavior.

Current and past research has predominantly found that factors in the built environment including density, diversity, and design influence travel behavior. These models, however, assume that these relationships do not vary across geographical space, ignoring spatial non-stationarity. Spatial non-stationarity is the phenomenon when relationships between the dependent and independent variables vary across geographic space. This research affirms that there is a relationship between the built environment and travel behavior after controlling for socioeconomic variables, but that the directionality and magnitudes of these relationships often vary across the state of

Florida. It is also demonstrated that the proposed model explains a greater amount of variability in south Florida and the Tampa area than in north Florida. Regional measures of the built environment were found to have the strongest influence at reducing VMT, particularly in urban areas. This research demonstrates that non-stationarity is an important consideration in the study of transportation behavior.

CHAPTER 1
INTRODUCTION

Concerns about traffic congestion, air pollution, climate change, transportation revenue shortfalls, and obesity rates are coalescing to form a perfect storm that is challenging the way development and transportation investments occur. Confronting these challenges will require a paradigm shift in the way politicians and citizens think about and understand the synergies between the built environment and travel behavior. Justifying policy changes to address these issues requires a thorough understanding of the interactions between the built environment and travel behavior.

The interaction between the built environment and travel behavior is potentially the most studied subject in the field of transportation and land use planning. Researchers have conducted a plethora of studies ranging in research designs, variables, and results. The subject has inspired meta-analyses (e.g., Leck, 2006; Ewing & Cervero, 2001; Ewing & Cervero, 2010), congressional commissioned reports (e.g., National Research Council, 2009), books, and numerous journal articles. Despite the existence of this rich body of literature, areas of research related to these relationships still need to be explored. Thanks to the growing availability of built environment and transportation spatial data, opportunities exist to explore and add to the existing body of literature regarding the complex synergies between the built environment and travel behavior.

A majority of the research published regarding the built environment and travel behavior relies on global models to infer statistical relationships between the independent and dependent variables. Global models assume a constant relationship between the response and explanatory variables and ignore spatial non-stationarity.

Spatial non-stationarity is the phenomenon with which modeled relationships vary across geographic space. These spatial variations are hidden in traditional regression modeling, masking any regional differences in the behavior of regression coefficients and model performance. This significant hole in the literature leads to an important question; does the interaction between the built environment and travel behavior vary across the rural, suburban, and urban development gradients? By taking advantage of improved analytical techniques using geographic information systems (GIS), this thesis examines how the relationships between factors in the built environment and travel behavior vary across the state of Florida.

This research aims to answer two fundamental questions. The first step is to determine if there are associations between factors in the built environment and travel behavior while controlling for attitudes, socioeconomic variables, and travel costs throughout the entire state of Florida. The second step examines if these associations are consistent throughout the state of Florida. It is hypothesized that doubling the density, accessibility, and diversity in downtown Miami (in urban environment) will not have the same impact on travel behavior as doubling the density in Pahokee (a rural environment).

To examine these two research questions, three global OLS models are developed that model household vehicle miles traveled (VMT) while controlling for attitudes, travel costs, and socioeconomic factors. Once a viable global model is determined, two logarithmic transformations are undertaken for interpretability. Finally, to determine the presence of non-stationarity in the study area, a geographically weighted regression (GWR) model is developed and interpreted. Coefficients developed by the GWR model will be compared across rural, suburban, and urban municipalities to explore the differences in how the built environment impacts travel behavior throughout the State of Florida.

CHAPTER 2
LITERATURE REVIEW

Trends

This section examines the current trends that illustrate the importance of understanding the potential impacts of the build environment on travel behavior. The passage of the National Defense and Interstate Highway Act of 1956 signaled that subsidizing private automobile travel would be a priority of the federal government. With its passage, Congress "approved 41,000 miles of interstate highways and allocated $25 billion to be expended between 1957 and 1969 (Boarnet, 2011, p.198). This massive infrastructure investment, coupled with cheap energy, rising incomes, mass produced automobiles, and a cultural love affair with the private vehicle has created a car dependent populous. Although more recent federal legislation including the 2005 the Safe Accountable, Flexible, Efficient Transportation Equity Act: A legacy for Users (SAFETEA-LU) has allocated $52.6 billion to transit, the private automobile has maintained its hegemony over personal travel (Federal Transit Administration (FTA), 2012). The most recent federal transportation legislation, the Moving Ahead for Progress in the 21st Century Act (MAP-21), allocates a meager 2% of the authorized 105 billion dollars for "alternative transportation" projects (United States Department of Transportation (DOT), 2013[a]). This indicates that the Federal Government is intent at continuing its bias towards investments that favor private single occupancy vehicles.

Recently, however, the costs to society of our dependence on the private automobile have become increasingly apparent. Revenue streams cannot keep up with needed investments in surface transportation infrastructure. Despite attempts to alleviate congestion through increased federal spending, annual hours of delay continues to grow throughout America (Shoup & Lang, 2011). Aside from an aging and ever more expensive surface transportation network, concerns over climate change and greenhouse gas emissions continue to spark debate. The Federal Surface Transportation Policy and Planning Act of 2011, explicitly states two objectives; reduce the national per capita motor VMT annually and reduce carbon dioxide levels by 40% by 2030 (S. 326, 2011). Although this language was not incorporated into the MAP-21, signed into law by President Obama on July 6, 2012, congestion reduction and environmental sustainability are core elements of the latest transportation legislation (DOT, 2013[b]).

VMT

The growth rate of VMT in America far outpaces population growth. Between 1982 and 2007 it is estimated that VMT increased by 189% nationally (National Research Council, 2009). Although that pace is expected to slow, “The U.S. Department of Energy’s Energy Information Administration (EIA) forecasts VMT to increase by 59% from 2005 to 2030” still outpacing population growth by 23% (as cited in Ewing, Bartholomew, Winkerman, Walters, & Chen, 2007, p.52). Although the recent recession has managed to quell the annual growth in VMT for the first time since 1980, a recovery in the economy is likely to bring about a return to VMT growth (Puentes & Tomer, 2008).

Florida, perhaps more than any other state, has not been immune to the growing dependency on the private automobile. For example, according to the American Society for Civil Engineers, travel on Florida’s highways increased over 80% over seventeen years between 1990 and 2007 (2008). This unprecedented growth in VMT continues to put a strain on federal and state resources as infrastructure projects helplessly attempt to keep up with demand. More VMT also means more congestion which manifests itself as a household cost through wasted travel time and additional gas expenditures.

Funding and Costs

Shrinking revenues for new transportation projects and maintenance of existing surface transportation infrastructure throughout the County is a growing concern. The American Society of Civil Engineers estimate that in 2010 “deficiencies in America’s surface transportation systems cost households and businesses nearly $130 billion” (2011, p.1). These costs mainly include vehicle operating costs and travel time delays. This is up from nearly 51.8 billion dollars from the Transportation Institute’s estimate in 2005 (as cited in Blanco, Steiner, Peng, Shmaltsuyev, and Wang, 2010). Unfortunately, the Interstate 35 Bridge collapse in Minneapolis in 2007, although an extreme case, is an example of America’s struggle to maintain its existing surface transportation infrastructure.

According to the Center for Urban Transportation Research (CUTR), after examining the long range transportation plans of each Metropolitan Planning Organization in the State of Florida, 20 year unfunded transportation needs stand at $74.3 million statewide in 2008 (2012). States and the federal government rely primarily on receipts from fuel taxes to fund transportation projects. In Florida, “receipts from fuel taxes make up 68% of the [transportation] revenue portfolio” (CUTR, 2012, p. 11). Due to increases in fuel efficiency, it is projected that fuel tax revenue in Florida will grow at only 8% from fiscal year 1999/00 to fiscal year 2019/20 lagging well behind the projected 82% increase in VMT during the same time period (CUTR, 2012).

The emerging trend of increasing transportation project costs and dwindling transportation revenues spells trouble for the future of surface transportation infrastructure throughout the country. These estimates, however, assume the continuation of the status-quo appeasement of meeting capacity driven metrics that honor the “roads equal progress” mentality. Since the advent of the mass produced car, drivers have been able to ignore the marginal social cost of the private vehicle and the burning of fossil fuels. Emerging climate change legislation, however, is attempting to address the negative externalities of fossil fuel usage.

Emerging Greenhouse Gas Emissions Legislation

The United States decision not to ratify the Kyoto Protocol in December of 1997 has not shielded it from the changing political landscape regarding climate change. On April 2, 2007 the Supreme Court in Massachusetts v. United States Environmental Protection Agency (EPA), 549 U.S. 497, declared that greenhouse gasses (GHGs) are pollutants, and therefore regulated under the Clean Air Act (CAA) (EPA, 2009). The Supreme Court directed the EPA to determine the contribution of GHGs from new motor vehicles to air pollution, therefore endangering the public welfare. Nearly two years after this landmark decision, the EPA “officially adopted the position that “greenhouse gases contribute to air pollution that may endanger public health or welfare” opening up the door to GHG regulation at the federal level (EPA, 2009). Some states, however, have already begun regulating GHG emissions.

California’s passage of the Global Warming Solutions Act (AB 32), the nation’s first global warming legislation, in 2006 has appeared to have caused reverberations throughout the political landscape in this Country. AB 32 requires the state to reduce GHG emissions by 27% in 2020. Preceding this legislation, however, Governor Schwarzenegger issued Executive Order 3-05, requiring California to reduce its “GHG emissions to 2000 levels by 2010, reducing emissions to 1990 levels by 2020, and reducing emissions to 80% below 1990 levels by 2050" (Shabeen et al., 2009). Senate Bill 375 was signed into law by Governor Schwarzenegger in 2008 which specifically targets emission standards in the transportation sector and procedures to meet those standards. According to the legislation, even after considering increases in the availability of low carbon fuels and increases in fuel efficiency standards, "it will be necessary to achieve significant additional [GHG] reductions from changed land use patterns and improved transportation (Sustainable Communities and Climate Protection Act of 2008, 2008). The bill requires each region within the State to incorporate reduction targets into their regional transportation plan culminating in a sustainable communities strategy (Shaheen, et al., 2009). The bill goes on to state that planning models used to asses transportation infrastructure decisions must be updated to "assess the effects of policy choices, such as residential development patterns, expanded transit service, and accessibility" on air quality (Sustainable Communities and Climate Protection Act of 2008, 2008).

Other states have followed California's lead. Governor Charlie Christ of Florida signed three executive orders aimed at curbing climate change. Executive order 07-127 requires "a reduction of emissions to 2000 levels by 2017, to 1990 levels by 2025, and by 80% of 1990 levels by 2050" (Florida Department of Environmental Protection, 2009). In 2008 the Florida legislature strengthened and showed support for the governor's executive orders by passing House Bill 697 requiring consideration of greenhouse gases and energy efficiency in local comprehensive plans (Florida Department of Community Affairs, 2009). According to the Governor's Action Team on

Energy and Climate Change (2008) there are 21 states, including Florida and California, that have climate action plans underway or completed.

The transportation sector is responsible for 28% of the United States' GHG emissions (Ewing, et al.,2007). To date, particularly at the federal level, GHG reduction strategies in the transportation sector have been aimed at reducing the reliance of carbon intensive fuels, and improving the fuel efficiency of vehicles. Future growth in vehicle miles of travel, however, is anticipated to outweigh any reduction in GHG emissions created by such efforts. For example, despite Congress' passage of legislation mandating tougher fuel economy standards to 35 miles per gallon (MPG) by 2020 and California's low carbon standard for combustion fuels, CO_2 emissions from cars and light trucks would be 40% above the 1990 level in 2030 even if these standards were adopted nationwide (Ewing, et, al., 2007).

The Built Environment and Travel Behavior

Many in the urban planning and transportation field have suggested that the built environment can serve as a means to reduce demand of the private vehicle and help address the greenhouse gas and funding issues raised in the prior sections. The first section attempts to clarify what is meant by the built environment and travel behavior. Then, theoretical frameworks are examined that attempt to understand and conceptualize travel behavior. Finally specific studies are reviewed that employ various forms of the theoretical frameworks and concepts discussed.

Definitions

In order to move forward in the discussion of the built environment and travel behavior, one should have a clear understanding of what underlying concepts are being conveyed when using the terms "the built environment" and "travel behavior". Although general concepts can be discussed, particularly regarding the built environment, methods of operationalizing these concepts vary significantly as will be seen in later sections. It is still useful, however, to begin the discussion with general understanding of the two main variables in this study.

The built environment is a somewhat nebulous concept that invokes many different feelings for different people and hence the difficulty of objectively measuring its components. Some definitions are more abstract than others. For example, Carmona, Heath, Oc, & Tiesdell described the built environment as being “experienced as a dynamic, emerging, unfolding temporal sequence” (2003, p.134). They go on to describe urban design and the built environment consisting of six dimensions: morphological, perceptual, social, visual, functional, and temporal (Carmone, et al., 2003). Many of these dimensions are abstract by nature and good quantitative research demands more objective concepts.

Handy took a more objective approach and conceptualized the built environment using three components; land use patterns (“the spatial distribution of human activities”), the transportation system (“the physical infrastructure and the services that make up the transportation system”), and design (“the aesthetic qualities” of the environment) (2005, p.5). Cervero and Kockelman took a similar, but slightly more precise approach by conceptualizing the built environment using three dimensions: density, diversity, and design (1997). Later, destination accessibility and distance to transit were added to capture more dimensions of the built environment (Ewing & Cervero, 2010) and the totality of the built environment descriptors were coined “the five

D’s. Despite gaining traction, researchers continued to operationalize individual components of the five 5’s in number of ways (Table 2-1).

Travel behavior also has many components. Mode choice, trip distance, vehicle miles traveled (VMT) (a composite of vehicle trip length and vehicle trip frequency), and trip chaining/complexity have all been the subject to investigation. For the purposes of the National Household Travel Survey, trip chaining is defined as “any travel between two anchors (we call this a tour, such as between home and work) that is direct, or has an intervening stop of 30 minutes or less” (NHTS, 2001, p.2). The individual or household is frequently the subject of such travel behaviors. It is important to note that factors in the built environment may impact each of these behaviors differently.

Theoretical Frameworks

Travel behavior is a complex phenomenon which requires knowledge of an array of research fields and concepts. A robust conceptual model, as Acker, Van Wee, & Witlox described, would “involve combining and linking theories stemming from not only microeconomics, but also from transport geography and social psychology” (2010, p.2). Early frameworks were very aggregate in nature and lacked behavioral content and interdisciplinary frameworks. The now ubiquitous “four-step model” was crude and “oriented almost exclusively toward analysis of long-term, capital-intensive expansion of the transportation system, primarily in the form of highways” (Pas as cited in Cervero, 2006, p.285). After decades of accommodating the vehicle at all costs, including displacing huge numbers of inner city residents, the externalities of single-occupancy vehicle dependency began to mount. Beginning in the 1980s the “goal shifted from forecasting travel to influencing travel, and, as such, it became necessary to conceptualize travel as the outcome of a host of decisions made by the traveler (Boarnet, 2011, p.199).

With the growing popularity of planning concepts such as transit oriented development, smart growth, new urbanism, and neo-traditional design, planners began to justify particular planning arrangements as a method to reduce automobile dependency. In order to justify these claims, more decentralized behavioral based models had to be devised. Boarnet and Crane invoked the theory of microeconomics and the derived consumer demand theory that follows the logic that travel is a derived demand in which “households choose the number of trips by each mode to maximize a well behaved utility function, subject to their time budget” (2000, p.826). The built environment, therefore, is thought to influence the price of travel, and therefore impact the perceived disutility of particular forms of travel (Boarnet & Crane, 2000). An extension of the utility maximizing theory is the activity-based approach. Handy stated that the “activity-based approach takes its starting point that the demand for travel is derived from the demand for activities” and offers improvement over the utility-maximizing framework by recognizing “the relevance of uncertainty, the importance of habit and thresholds, the role of constraints, and the influence of levels of adequate information and knowledge” (Goodwind & Hensher, as cited in Handy, 2005, p.11). With activity-based frameworks, the focus shifted from attempting to understand “travel patterns” in a vacuum to understanding “activity patterns” (Handy, 2005). As with the utility-maximizing framework, the built environment is thought to influence the costs of various modes of transportation and the disutility of each.

Chatman surmised that there are two underlying assumptions when studying the built environment and travel behavior; “travel choices are determined by individual and household preferences for travel that vary with socioeconomic characteristics and urban form” and “individuals maximize utility over trips subject to a time budget constraint” (2005, p.9). Both approaches have their share of weaknesses with the first omitting trip time or money cost, and the second “often neglects variances in direct utility due to built environment variation, because speed and distance are assumed to be the mechanism through which any influences of the built environment on travel behavior would occur” (Chatman, 2005, p.10). The question then becomes, is the built environment’s most influential mechanism in influencing travel behavior its impact on travel costs, (direct utility) or through the quality of travel (indirect utility). Chatman argued that the built environment impacts travel behavior “by influencing three types of travel characteristics; the qualities of travel that directly affect the utility of the travel experience; the quantity of travel inputs needed to produce out-of-home activities; and the per-unit prices of travel by different modes” (2005, p.15).

All of the aforementioned conceptual models assume that travel is an indirect demand. Some research has shown, however, that certain travel may serve as a positive utility, giving credence to the adage that life is a journey, not a destination. For example, Mokhtarian and Salomon’s examined more than 1900 residents in the San Francisco Bay Area and found that “three-quarters of the sample reported sometimes or often traveling “just for the fun of it”. More than two-thirds disagreed that “the only good thing about traveling is arriving at your destination” (2001, p.716). The idea that travel may offer positive utility adds complication and uncertainty to the “travel time minimizations principle that underlies a great deal of policy-making as well as virtually all regional travel demand forecasting models" (Mokhtarian & Chen, 2003, p.1).

The theory of planned behavior offers insight into human action and travel behavior. According to the theory of planned behavior, "human action is guided by three kinds of considerations; beliefs about likely consequences of the behavior (behavioral beliefs), beliefs about the normative expectations of others (normative beliefs), and beliefs about the presence of factors that may further hinder performance of the behavior (control beliefs)" which leads to a behavioral intention (Bamberg, Arjzen, & Schmidt (p.175). Although this theory has performed fairly well in empirical studies, habitual behavior adds uncertainty to the theory of planned behavior's ability to predict behavior. It was found that "the frequency with which a behavior has been performed in the past more accurately predicts its future frequency of performance than does stated intention" (Garling, Gillholm, & Garling, 1998, p.131).

These theories, although not exhaustive, provide for a solid foundation when interpreting empirical studies examining travel behavior. Theory aids in deciphering results that may conflict with stated hypothesis. For example, Chatman's theoretical framework deconstructed the role of the built environment on travel behavior into three components: the qualities of travel, the quantity of travel needed, and the per-unit price of travel. Using this framework, one can conjecture how density may impact each of the components. The following section reviews empirical studies examining travel behavior across various disciplines.

Empirical Studies

Researchers have relied on several typologies over the past two decades when investigating the built environment and travel behavior. According to Crane, some of the more relevant variations include the travel purpose under study, the nature and level of detail in the data, and the how the characterization of the built environment is operationalized (as cited in Leck, 2006). The lack of a standardized method for defining dependent and dependent variables has made it difficult to compare results across the myriad of empirical studies dealing with the role of the built environment on travel behavior. For example, in a meta-analysis conducted by Ewing and Cervero, of the 31, 23, 22 , and 22 studies reviewed that examined VMT with respect to density, diversity, design, and destination accessibility respectively, there were 9 methods of operationalizing density, 11 methods of operationalizing diversity, 14 methods of operationalizing design, and 8 methods of operationalizing accessibility (2010).

Aggregate studies

A renewed interest in the impact of the built environment and travel behavior surfaced in the early 1990s with the foundation of the Congress for New Urbanism. The movement, conceived by architects Peter Calthorpe, Andres Duany, Elizabeth Plater-Zyberk, and others, promulgated transit-oriented development and neo-traditional development (NTD) as a means to reduce demand for the private vehicle (Calthorpe & Fulton, 2001). Earlier studies were fairly aggregate and crafted to examine the impact of these generalized concepts on travel behavior. Often neighborhoods were characterized as being “neo-traditional” versus contemporary suburbia. Typically these aggregate studies found a relatively strong relationship between neighborhood type and travel behavior.

Quasi-experimental designs typically find the strongest relationships between neighborhood design and distance traveled (Ewing & Cervero, 2010). Guiding principles such as gridded street networks, mixed-use neighborhood centers, and pedestrianfriendly environments provide a higher percentage of mode split, and higher internal capture rates. Levinson and Kumar (1997) suggested that density may be used as a substitute for city size. They analyzed 38 US cities to investigate the effects of residential density on travel behavior. Their regression analysis showed that distance and time are negatively related with density while auto travel time seems to have a threshold density at 10,000 people per square mile. Once density exceeds 10,000, auto travel time shows positive associations with density. They argue that beyond a certain density level automobile travel is less attractive because of increasing traffic congestion.

The works of Handy (1996), Ewing et al. (1994), and Rutherford (1996) suggested neighborhoods designed with NTD principles produce both shorter trips and fewer trips when compared to conventional suburban subdivisions. Shay & Khattak (2005) found that people in NTDs “make fewer auto trips and travel about 14 miles less per day” compared to residents of a conventional cookie cutter suburban neighborhood (p. 10). No differences were found, however in auto ownership. Cervero and Radisch (1996) discovered that residents of a pre-war neighborhood “were five times more likely to go to a store or other non-work destination by foot or bicycle than” their modern, post-war suburban neighborhood counterpart (p.122). Interestingly, the number of non-work trips taken was statistically equal between the two neighborhoods, but residents of the urban neighborhood substituted many of their potential driving trips with walking trips.

Other studies suggest, however, that residents of NTD neighborhoods make more trips than their conventional neighborhood counterparts. A study commissioned by the Oregon Transportation Research and Education Consortium (2011) found residents of NTDs made more trips than non NTD residents, however, no difference in VMT was found, suggesting NTD residents make more internal and non-motorized trips. Although the neighborhood type dummy variable was the best predictor of total trip-making, the "NTD dummy variable was not significant for non-motorized trips when the built-environment variables were included" suggesting "regardless of neighborhood type, walking and cycling trips might be promoted through improved street connectivity and increased commercial activity" (p. 54).

Treating neighborhood type as a dummy variable allowed the researches to assess the "intrinsic" value of neighborhood design on travel behavior. Findings as these suggest that quasi-experimental designs make "no effort to isolate the effects of specific land use features and indeed factors like density and mixed u-uses are accepted as co-dependent and mutually reinforcing" (Cervero, 2003, p.121). Geographical information systems have made it possible for a myriad of disaggregate studies to be published with varying degrees of sophistication, methods, and variables.

Disaggregate studies

Disaggregate studies tend to find that the built environment has a modest impact on travel behavior. According to Ewing and Cervero (2010) over 200 studies examine the relationship between the built environment and travel behavior that employ various levels of sophistication, variables, controls, and data sources. Faced with limitations in creating true experimental designs (you cannot randomly select and relocate a group of households into a rural or urban area and observe their changes in travel behavior), establishing causality between the built environment and travel behavior has been difficult. Nevertheless, the majority of studies find a correlation between built environment variables and travel behavior.

Many studies find accessibility (operationalized in a number of ways) to be the most influential built environment variable in regards influencing travel behavior. Kockelman analyzed VMT per household using only socioeconomic variables (household size, auto ownership, and income) in a base model, and then added built environment variables to ascertain if the model's performance improved. The model that included the built environment variables (accessibility, and land use mix) improved the models and “unexplained variation was reduced substantially” (Kockelman, 1991, p.27). Accessibility was found to be the strongest influence on household VMT with an elasticity of -.31 (a 100% increase in accessibility reduces VMT by 31%).A similar conclusion was made by Ewing and Cervero in their meta-analysis of 50 disaggregate studies that examined travel and the built environment. The weighted elasticities of VMT with respect to density, diversity, design, destination accessibility, and distance to transit estimated in the study reveal a very modest impact of each variable on VMT. Destination accessibility (operationalized as distance to downtown) incurred that largest impact with a weighted average elasticity of VMT of -.22. Neither density, diversity, nor distance to transit reached a weighted average elasticity of greater than -.09. Ewing and Cervero concluded, however, that “the combined effect of several such variables on travel could be quite large (Ewing & Cervero, 2010, p.275).

Bento and Cropper found that features in the built environment such as city shape, road density, population centrality, distribution of employment, and transit availability have marginal impacts on VMT. For example “a 10% change in city shape, road density, rail supply (for rail cities) and jobs-housing balance is to change average annual miles driven by at most .7% for each variable” (Bento & Cropper, 2005, p.475).

There appears to be a synergistic relationship between the variables, however, and changing each variable in concert with one another can have a relatively large impact on travel behavior. Bento and Cropper estimated a 25 % reduction in household VMT when a hypothetical family moves from Atlanta, Georgia to Boston, Massachusetts (Bento & Cropper, 2005).

Many researchers have discovered that the spatial resolution in which the built environment is measured is an important consideration when estimating travel demand models. Steiner et, al. (2010) used highly disaggregate data to determine the influences of the built environment on trip lengths. Findings suggested that the same built environment variables at the parcel, neighborhood, and regional scales can impact trip lengths differently depending on if the trip is being produced or attracted to the particular location. For example, non-work trips were found to be shorter if produced at a location closer to a regional activity center (a hub of commercial activity within the region). A location, however, that is closer to a regional activity center will attract longer non-work trips. This research demonstrated not only the importance of examining the built environment at both the trip origin and destination, but also the interrelationships between the parcel, neighborhood, and context within the region.

Susan Handy (1993) also recognized the importance of differentiating the influences of various spatial scales on travel behavior. Using a conventional exponential form of the gravity model to calculate local and regional accessibility, Susan Handy estimated the relative importance of both measures when analyzing travel behavior. She defined local accessibility as ease of access to “convenience establishments, such as supermarkets, drugstores, dry cleaners” (p.5). Regional accessibility is defined as access to “regional retail centers, such as suburban shopping malls or downtown commercial areas, which offer a wide range of “comparison goods”. Results indicate that although both measures impact travel behavior, regional accessibility appears to be more influential.

Many researchers, however, raised concerns with the issue of self-selection. Bhat and Guo (2007) admonished that “the assumption that households and individuals locate themselves in neighborhoods and then, based on neighborhood attributes, determine their travel behaviors” is devoid of reality (p.509). This is an important consideration because in the context of the built environment and travel “suburbanites tend to be more affluent, have more cars, live in a larger household, be more auto-oriented, and prefer larger space than their counterparts in urban areas, a result of residential self-selection” (Cao, Xu, & Fan, 2010, p.800). If residents self select into neighborhoods that suit their travel needs, results from studies could be biased.

The research suggests that attitudes do have an impact on travel behavior. An experiment that used K-means clustering to group over 600 individuals into six discernible groups based solely on attitudes found that the average VMT of each group was significantly different from one another. Of the socioeconomic variables measured, only education was significantly different across the groups suggesting “attitudes and opinions largely cut uniformly across demographic characteristics” (Anable, p.71). Although attitudes can impact ones’ travel behavior, research suggests that factors in the built environment can curtail or exasperate travel behavior manifestations of these attitudes.

Studies suggest that even after controlling for attitudes, the built environment plays an important role in determining one's travel behavior. Using propensity score matching to pair "identical" households (based on attitudes and demographics) in urban and exurban areas of Raleigh, North Carolina, Cao, Xu, & Fan concluded "if a randomly-selected individual moves from an inner-ring suburb to an exurb, we expect an increase of 8.420 miles in VMD" and that "self-selection plays a negligible role between this pair of locations" (p.803). Self selection becomes more influential, however, if the comparison is made between households located in the inner-ring suburb and urban area. In this scenario, self-selection accounted for 50% of the increase in VMT of inner-suburbanites compared to urbanites. This suggests that attitudes have a bigger role to play with regards to travel behavior for individuals living in urban or semi-urban environments. Zhou and Kockelman conducted a similar study that attempts to simulate a treated/untreated approach to test the impact of a hypothetical move from a suburban area to a rural area. Findings suggested that "a randomly selected household is expected to increase its daily VMT by 17 miles when living in a rural or suburban neighborhood, as compared to living in the CBD of urban neighborhood" (p.10). Researchers estimated that "self-selection accounts for 42% of observed VMT differences across Austin households in suburban or rural versus CBD or urban zones" (p.10).

Another attempt to isolate the importance of attitudes and self selection on travel behavior is a study conducted by Schanen and Mokhtarian (2005) that "investigates to what degree a lack of congruence between physical neighborhood structure and preferences regarding land use near one's home location affect distance traveled" (p.127). Using principal component analysis with data obtained from a 14 page questionnaire targeting attitudes, the authors identified four basic traveler types to compare their travel habits; true urbanites, dissonant urban dwellers, true suburbanites, and dissonant suburbanites. Researchers conclude that “the physical land use structure appears to exert a stronger influence on distance traveled than do preferences toward land use” (p.150). In a thorough review of the literature, Cao, Mokhtarian, and Handy’s analysis of 38 empirical studies found that “virtually all” of the examinations found a statistically significant influence of the built environment remained after accounting for self-selection (2006).

In sum, previous literature suggests that travel behavior can be moderated by factors in the built environment. Although the review presented here is certainly not exhaustive and concepts such as internal capture, trip chaining, and tour complexity have gone unmentioned, certain generalizations can be made. One is the importance of understanding the nexus between the built environment and travel behavior in light of several disturbing trends; climate change, ageing infrastructure, and shrinking revenue. With climate change legislation becoming reality, local policy makers will need to invoke a balanced approach to meet greenhouse gas reduction targets. Justifying the built environment as one part of the solution requires unambiguous results from the research community.

In reviewing the literature presented here, a few themes crystallize. First is the lack of standard definitions when operationalizing built environment variables. Although it appears accessibility is the most effective at reducing VMT, it is difficult to separate the importance of the concept with how it is being measured. It is also important to consider spatial scale. The built environment can be operationalized at the parcel, neighborhood, and regional scales. The interdependency and different impacts of these scales are important to consider. Finally, the nature of the phenomenon under study makes it difficult to conclusively make a causal link between the built environment and travel behavior. Despite the limitations, advances in the field have attempted to mimic a true experimental design through the use of propensity score matching. Results from these methodologies suggest a causal link can be implied.

The absence of any acknowledgement of the potential existence of spatial non-stationarity within the body of research presented leaves a void in the otherwise robust set of literature examining travel behavior and the built environment. Spatial non-stationarity is the idea that "there might be intrinsic differences in relationships over space or that there might be some problem with the specification of the model from which the relationships are being measured and which manifests itself in terms of spatially varying parameter estimates" (Brunsdon, Fotheringham, & Charlton, 1996, p.282). Every piece of literature reviewed assumes a global model when isolating the effects of the built environment on travel behavior. For example, the elasticities estimated by Ewing and others suggest that doubling the density, accessibility, and diversity would have the same impact on travel behavior in rural Florida as it would in downtown Miami. Ali, Patridge, & Olfert (2007) concluded that global models such as OLS "ignores one of the core principles of regional science: spatial location matters" (p.301).Brunsdon, Fotheringham, & Charlton (1996) proposed a technique call geographically weighted regression (GWR) to address spatial non-stationarity. This paper attempts to utilize the GWR method to augment the existing built environment/travel behavior global models.

Chapter 2 demonstrates that reducing VMT nationally is an important endeavor for many reasons. The growing acknowledgment that an increased reliance on the private automobile will continue to put pressure on budgets and the environment has sparked a myriad of studies investigating potential methods to reduce VMT. Many of these empirical studies have focused on the role of the built environment at achieving a reduction in demand for the private automobile. In many instances, evidence supports that the built environment can impact one's travel behavior after controlling for self selection. These studies, however, assume these relationships are consistent across geographical space, ignoring spatial non-stationarity.

Table 2-1. Common operationalizations of the built environment

Variable	Operationalization
Density	Net residential density (number of residential units/residential area) Gross residential density (number of residential units/total area) Population density(total population/total area) Employment density(total jobs/total area)
Diversity	Entropy (see Cervero & Kockelman, 1997) Dissimilarity index (see Cervero & Kockelman, 1997) Proportion of each land use type
Design	Connected node ratio Percentage of 4-way intersections Block length Pedestrian route directness Intersection density
Destination Accessibility	Job accessibility by auto Job acessilbibilty by transit Various gravity model iterations (see Bhat et al., 2000 for literature review)

CHAPTER 3
METHODOLOGY

This methodology seeks to determine the correlation between the built environment and travel behavior. The built environment is assumed to impact travel behavior through the three mechanisms established by Chatman: “the qualities of travel that directly affect the utility of the travel experience, the quantity of the travel inputs needed to produce out-of-home activities, and the per unit prices of travel by different modes” (2005, p.15). Although data availability limits direct measurement of some of these mechanisms, it is argued the available resources provide enough information to formulate a methodology that reflects this conceptual model. As stated earlier, this methodology also seeks to determine if the relationship between the built environment and travel behavior, via these mechanisms, is constant across Florida. For interpretation purposes, three global models and one GWR model are developed.

Model Development

In this study, household VMT is first modeled using a global OLS linear regression structure. The residents of the household must have maintained tenure for at least a year. Also, the house had to have been geocoded to at least the intersection (as opposed to the zip code as some had been). After applying these restrictions,9985 households were available for analysis. The base model is as follows;

$y_i = \beta_0 + \beta_{SES}x_{iSES} + \beta_{TA}x_{iTA} + \beta_{BE}x_{iBE} + \beta_C x_{iC} + \varepsilon_i$ (see the list of abbreviations for definitions).

Two additional variations of the base model are also developed for further interpretation of the model’s coefficients. A log-linear model is developed using the base model in which the natural logarithm of household yearly VMT is the dependent variable;

$Ln(y_i) = \beta_0 + \beta_{SES}x_{iSES} + \beta_{TA}x_{iTA} + \beta_{BE}x_{iBE} + \beta_C x_{iC} + \varepsilon_{i.}$

According to UCLA Statistical Consulting Group (2013), the percentage increase in the outcome variable from a one unit increase in a independent variable can be estimated by calculating the exponentiated value of the variable's coefficient ($\exp(\beta)$) in a log-linear regression model.

The second variation of the base model is the log-log transformation. The log-log model is developed using the base model in which the natural logarithm of the dependent variable (yearly household VMT) and independent variables are taken;

$Ln(y_i) = \beta_0 + \beta_{SES}Ln(x_{iSES}) + \beta_{TA}x_{iTA} + \beta_{BE}Ln(x_{iBE}) + \beta_C\ Ln(x_{iC}) + \varepsilon_{i.}$

According to UCLA: Statistical Consulting Group(2013), the percentage change in the outcome variable from a corresponding percentage change in a predictor variable can be calculated by raising the percentage change in the independent variable by the variable's coefficient ((x_iBE2/x_iBE1)^β_{BE}). These interpretive concepts will be applied to the VMT model in the subsequent results section.

A GWR model is developed that allows "model coefficients to vary regionally" (Mitchell, 2005, p.219), in order to determine how relationships between factors in the built environment and travel behavior vary across the rural, suburban, and urban gradients of Florida. GWR reduces the sphere of influence when determining model outputs to a local and or regional scale dependent upon a prescribed kernel. GWR is employed and takes the following form;

$y_i(g) = \beta_0 + \beta_{SES}(g)x_{iSES} + \beta_{TA}(g)x_{iTA} + \beta_{BE}(g)x_{iBE} + \beta_C(g)x_{iC} + \varepsilon_i$

where the model parameters are the same as previously described for the base global regression model with the additional *g* parameter indicating that the "predicted values and coefficients are for a single geographic location (Mitchell, 2005, p.219).

Data and Variables

The 2009 National Household Transportation Survey (NHTS) provided a rich set of variables for this study including the dependent variable, yearly household VMT. The NHTS was initiated in 1969 (formerly known as the National Personal Transportation Survey) and collected every five to seven years throughout the Country. The NHTS is indented to provide "information to assist transportation planners and policy makers who need comprehensive data on travel and transportation patterns in the United States "and collects information on daily trips taken in a 24-hour period. (Federal Highway Administration, 2013). States and Metropolitan Planning Organizations (MPOs) have the opportunity to purchase and participate in the add-on program making larger and more complete samples available that allow for more accurate modeling. Florida Department of Transportation (FDOT) decided to participate in the 2009 NHTS add-on program. The result was a geographic stratified sample of over 14,000 households throughout the state of Florida (Figure 3.1). The add-on includes the travel diary, household and personal socioeconomic data, information regarding perceptions and attitudes, vehicle data, and the locations of each household, workplace, origin and destination.

The purpose of this study is to isolate the impacts of the built environment on travel behavior. To isolate these impacts, several socioeconomic variables are incorporated into the global and local models (Table 3-1). Total Household income was reported via 18 categories. The first category represented an income of $5,000 or less with each subsequent category increasing by $4,999 ($5,000-$9,999, $10,000-$14,999, etc.) until a category of $100,000 or more is reached. The methodology derives a semi-continuous variable by taking the midpoint of each income category. The values $5,000 and $100,000 are utilized for the bottom and top categories respectively. Additional control variables in the global and local models are household size, the number of workers, head of household retirement status, the number of drivers, the number of kids, and the number of commercial vehicles owned by the household.

The global and local models attempt to control for self-selection. As part of the interview process, the NHTS survey asked each head of household “what is the most important reason you chose your current home location” (National Household Travel Survey, 2009, p.5)? The respondent could choose from a set of predefined answers or respond in an open-ended format. The attitude dummy variable was coded one if the respondent answered with a “convenient” or “close to” statement, signifying that the household may have self selected into the neighborhood due to travel preferences and attitudes. All other answers, including the cost/price of the home, the school system, and home or lot size were coded with a zero.

The model includes two variables that are believed to influence the quantity of the travel needed to satisfy the desired out-of-home activities of each household. Accessibility is “broadly defined as the ease with which activities at one place can be reached from another via a particular travel model” (Liu & Zhu, 2004, p. 105). Accessibility in the global and local models represents the ease of travel to shopping and office establishments from an individual household. To calculate the accessibility index for each household in the NHTS survey, a 2010 statewide parcel dataset was collected for the state of Florida. Retail and office parcels were extracted from the larger database leaving 177,865 records for analysis. Each parcel record contains the total conditioned square footage space on the property.

An origin- destination (OD) matrix was calculated for each NHTS household with the household serving as the origin and each retail/office parcel centroid serving as the destination. Due to the unmanageable size of each OD matrix, a network search distance of 6.3 miles, which represents the average shopping trip distance in the NHTS, was applied (Florida Department of Transportation, 2010). A routable transportation network that contains the travel cost in minutes to traverse each link was used to calculate the amount of time it takes to travel by automobile to each retail/office parcel within 6.3 miles of the NHTS household (Figure 3-2). Once the cumulative opportunities (square footage) and travel costs (minutes) were extracted from the datasets, the conventional Hansen accessibility formula based on the gravity model was applied to each NHTS household (Table 3-1).

The accessibility variable described above provides insight into the character of the immediate neighborhood around each NHTS household. It does not however, capture the spatial structure of the region. The theoretical minimum commute (TMC) represents the “distance that each worker would have to cover in order to find a job as close to home as possible under the assumption that actual residential locations and job locations are maintained and the total distance travelled (by all workers together) is minimized” (Brussauw, Derudder, & Wilcox, p.43, 2011). Unlike the tradition jobs-housing ratio which is insensitive to its context within the region, the TMC is a proxy of the urban structure at the regional scale (Horner, 2006).

To calculate the TMC (Table 3-1) for each NHTS household, Census' Longitudinal Employer-Household Dynamics (LEHD) were extracted for the state of Florida from the "OnTheMap" (http://onthemap.ces.census.gov/) application. The data contained the number of employees and employers in each income category (less than $1250/month, between $1250 - $3333/month, and more than $3333/month) residing within each census block in 2009 for the entire state of Florida. Using a customized tool in ArcGIS Desktop, the optimum allocation of employees between each census block was determined for each income category. The customized tool relied upon the Network Analyst extension and a linear optimization algorithm to assign each employee to an employer in such a way that minimized the total distance traveled statewide, while satisfying the total supply of employees (Figure 3-3). The destination census tract in the example provided in Figure 3-3 contains over 33,000 jobs making between $1250 and $3333 per month. The lines indicate the flow of employees falling within that income category into the census tract to meet the demand of employers in the destination census tract. Due to the unmanageable size of each OD matrix using census blocks, the data was aggregated to the census tract. Intrazonal trips were assigned a distance of SQRT(census area/PI) following the procedure undertaken by Frost, et al., 1998. The total distance for each census tract was added together and divided by the number of employees to obtain the MTC.

This process was repeated three times for each income category. This guaranteed that employees earning a particular wage were assigned a job who paid a similar wage. The TMC for each income category was then interpolated using the Natural Neighbor interpolation technique within the Spatial Analyst Extension for ArcGIS

Desktop. This technique finds the closest subset of input samples to a query point and applies weights to them based on proportionate areas to interpolate a value (Sibson, 1981).This interpolation method is very local in nature and produced lower root mean square prediction errors than the Inverse Distance Weighted and Kriging interpolation methods. Once the continuous TMC surfaces were interpolated, the values were extracted to the NHTS households where the three TMC values for each income category were averaged for the final TMC variable for the global and local regression models.

Cost is an important mechanism through which the built environment can impact travel behavior. Although variables such as density can serve as proxies for cost (denser areas are thought to be more prohibitive on the private vehicle and more accommodating to transit), this methodology attempts to directly measure a trip delay ratio. Within the NHTS, respondents were asked to report the total time each recorded trip took to complete. This value was compared to the “optimal” travel time. The optimal travel time was calculated using a statewide routable network that includes the time to traverse each link.

Each recorded trip in the NHTS includes the geocoded origin and destination. The optimal travel time for each trip was calculated using the Network Analyst Extension in ArcGIS Desktop. The reported travel time was then divided by the optimal travel time. This travel delay ratio is less than one when the reported travel time is less than the optimal travel time and greater than one when the reported travel time is larger than the optimal travel time. Larger ratios imply a greater cost associated with the particular trip. The travel delay ratio was calculated for each trip in the NHTS and averaged for each household and included in the local and global regression models.

Density was calculated using 2010 census blocks. The number of residential units in each census block was divided by the total area to obtain the gross residential density. The vector polygons were then converted to a raster with 100 square meter cells. To avoid a hard edge between census blocks, focal statistics was applied to calculate the mean value of each cell within a rectangle neighborhood of three cells. The values were then extracted to the NHTS households for inclusion in the global and local regression models.

The dependent variable, total household VMT, was derived from the vehicle database included in the NHTS. The vehicle database included information about each of the NHTS household's vehicles. Vehicle owners were asked to record the VMT during the past year for each of the vehicles owned. Vehicles owned for less than a year were extrapolated. Households who moved to the current location within the past year of the NHTS were removed from the analysis. Household VMT was calculated from adding together individual vehicle's VMT belonging to the same household.

Table 3-1. Model parameters

Variable	Model Parameter	Calculation	Source
Household Income	x_{iSES}	Midpoint of recorded income range	NHTS
Household size	x_{iSES}	Number of household members	NHTS
Number of household workers	x_{iSES}	Number of employed household members	NHTS
Household retirement status	x_{iSES}	Binary variable (1,0) coded 1 if head of household reported as retired	NHTS
Number of household children	x_{iSES}	Number of children 18 years of age or younger	NHTS
Number of household commercial vehicles	x_{iSES}	The number of reported commercial vehicles owned by the household	NHTS
Household travel attitude	x_{iTA}	Binary variable (1,0) coded 1 if the head of household indicated proximity to destinations was the main reason for staying in/purchasing the house	NHTS
Accessibility	x_{iBE}	$Ai = \sum_{j=1}^{n} dj\ e^{-tij}$ where, Ai= Accessibility index for household j. dj= parcel attractiveness (square feet) t_{ij} = the network travel time to reach parcel *j* from household *i*	Derived from parcels

Table 3-1. Continued

Variable	Model Parameter	Calculation	Source
Theoretical minimum commute	x_{iBE}	Minimize H $=\sum_{i=1}^{n}\sum_{j=1}^{n} d_{ij}\, t_{ij}$ given: $\sum_{i=1}^{n} t_{ij} = O_i$ where, H = total distance traveled within the state of Florida to match workers and jobs within the same income category. n = number of census tracts O_i= number of workers in census tract i D_j = number of jobs in census tract j d_{ij}= network distance between centroids of census tract $i$and census tract j t_{ij}= number of trips between census tract i and census tract j	Derived from Census LEHD data
Travel Delay Ratio	x_{iC}	$(\sum_{k=1}^{n} rt_{ij} / ot_{ij})/t_i$ where, rt_{ij} = the reported travel time for trip k between origin i and destination j ot_{ij}= the calculated optimal travel time for trip k between origin i and destination j t_{ij}= the number of trips reported for household i	Derived from NHTS
Density	x_{iBE}	The number of household units per square mile	Derived from 2010 Census blocks

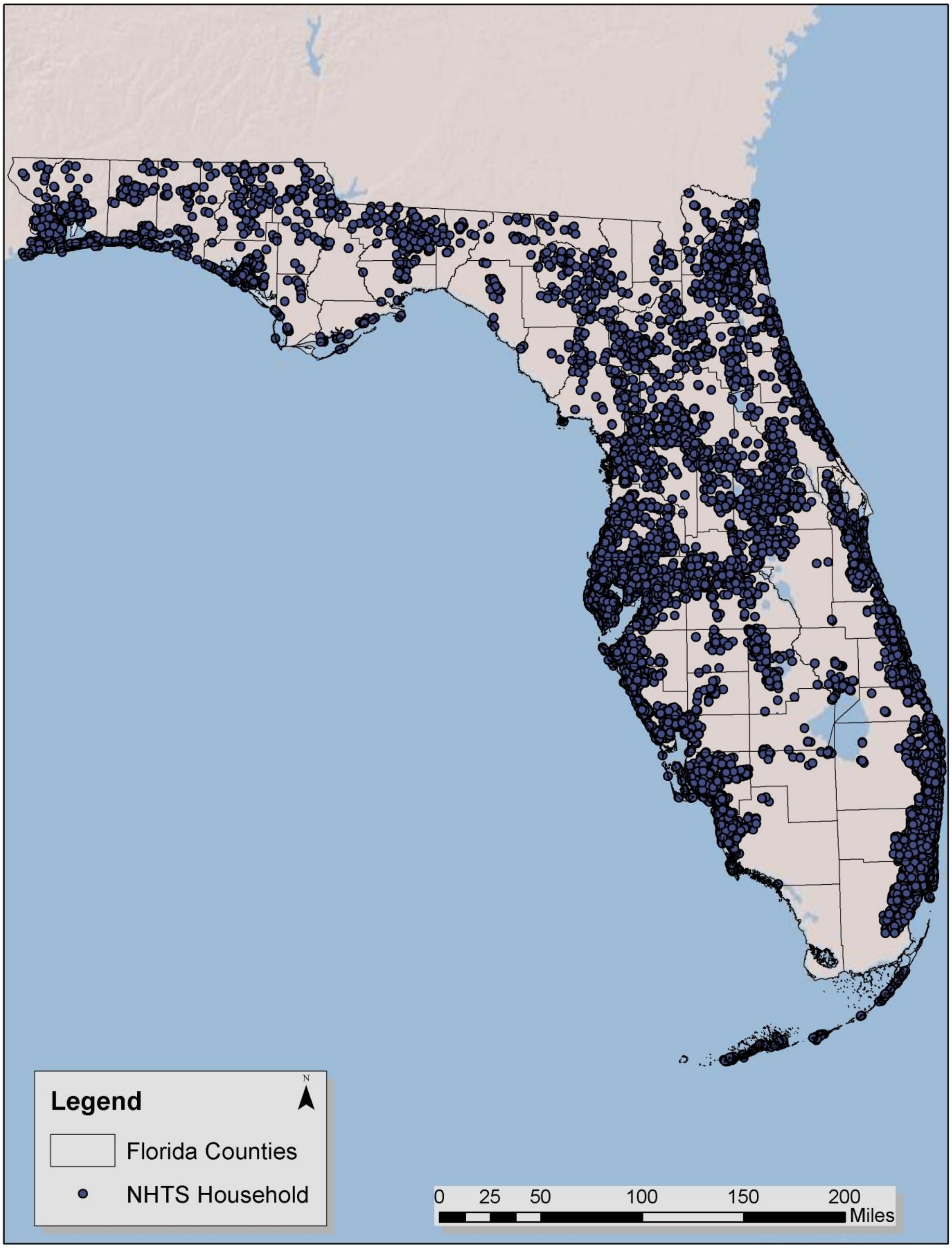

Figure 3-1. Geocoded households from the NHTS add-on

Figure 3-2. Accessibility search area based on the average NHTS shopping trip length

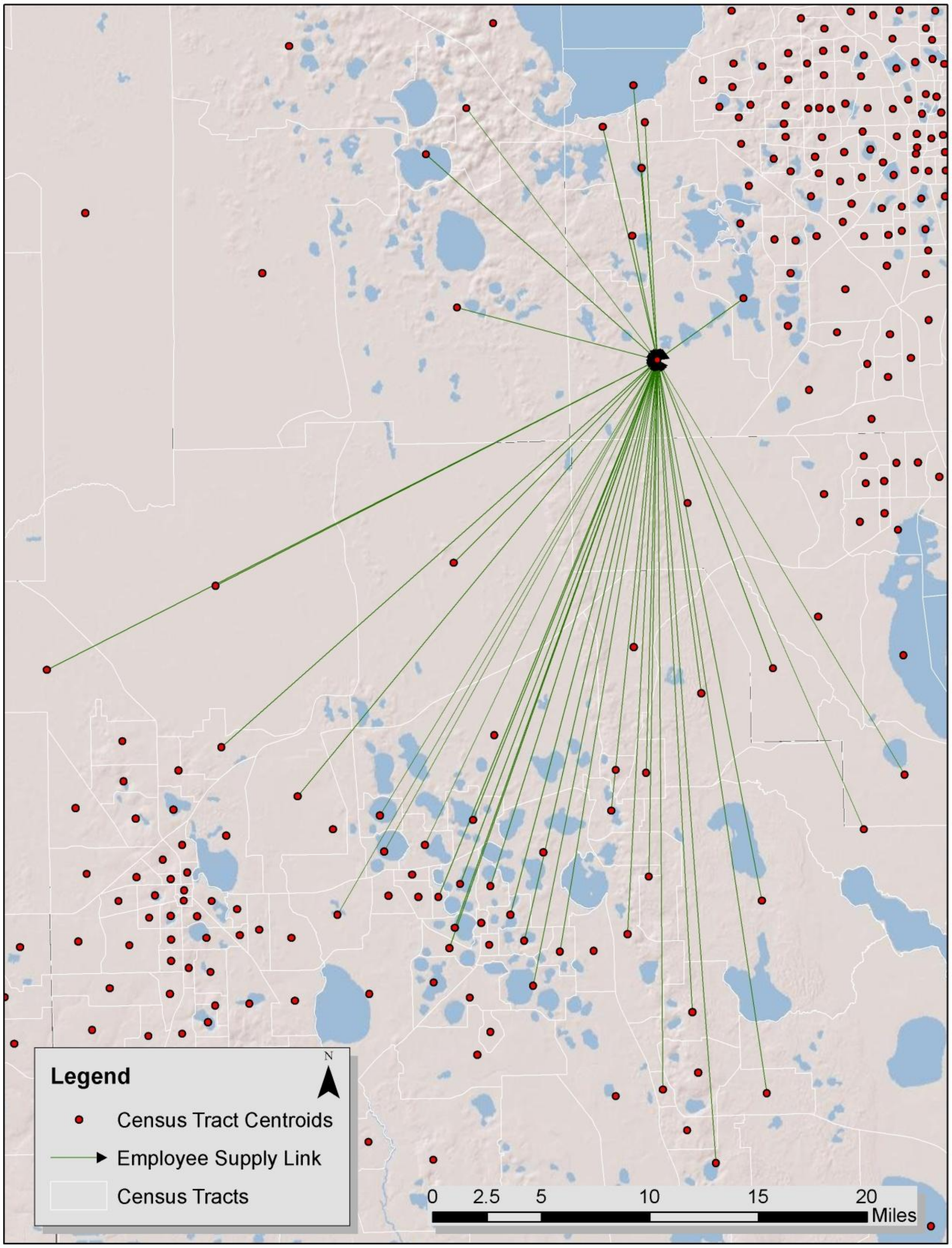

Figure 3-3. Flow of employees between census tracts

CHAPTER 4
RESULTS

For comparative and interoperability purposes, findings from the three global regression models are first discussed followed by the results from the GWR model. As with the prevailing body of literature, findings suggest a correlation between the built environment and travel behavior, but global models may inhibit a robust interpretation of the interaction between the two. The built environment variables are highly skewed throughout the State as indicated by the standard deviation (Table 4-1). Overall, GWR models perform slightly better due to a reduction in unexplained variation when predicting household VMT. The GWR model, however, performs best in Southeast Florida and the Tampa area. The GWR models indicate there is variation across the State of Florida with regards to model coefficients, and in some instances, change directionality. All coefficients are deemed significant at the 95% confidence interval and are non-standardized.

Linear-Linear Global Regression Model Summary

Overall model performance is indicated by the adjusted r-squared value, and the Joint Wald Statistic. The adjusted r-squared value of the linear-linear OLS model is .43 indicating the model explains 43% of the variability among household's yearly VMT (Table 4-2). The Joint Wald Statistic's 95% confidence level probability is zero, indicating the model is statistically significant. Additional model statistics are the Koenker's studentized Bruesch-Pagan (BP) statistic and the Jarque-Bera statistic. The BP statistic assess if non-stationary (model coefficients vary across space) and/or heteroscedasticity exists (the relationship between the dependent and independent variable is not consistent throughout the dataset). The BP statistic's 95% confidence level probability is zero, indicating non-stationary and/or heteroscedasticity exists. Finally, the Jarque-Bera statistic assesses model bias, and when significant, indicates the residuals are not normally distributed signifying model misspecification. The Jarque-Bera statistic's 95% confidence level probability is zero, indicating the results should be interpreted with caution because one or more key variables are missing from the model.

In a traditional OLS regression model, coefficients are interpreted as indicating the expected change in the dependent variable (household VMT) from a one unit change in the independent variable when all other covariates are held constant. All of the variables are statistically significant with the exception of the attitude dummy variable. All coefficients indicate the expected directionality. An increase in a household's income, size, workers, vehicles, and commercial vehicles correlates with higher household VMT. For example, for every additional worker, a household can expect an increase in yearly VMT of just over 2,460 miles. Increasing a household's vehicle count by one will increase the yearly VMT by 3,368 miles. If a head of household is retired, that household is estimated to reduce its yearly VMT by 2,010 miles.

An increase in one unit of accessibility (a unitless variable) reduces yearly household VMT by .002 miles. To put this in perspective, a NHTS household in downtown Miami was measured to have an accessibility index of 1,418,125.5. A NHTS household in rural Belle Glade was measured to have an accessibility index of 212,929 resulting in a difference of 1,205,196.5 (Figure 4-1). Holding all other variables constant, the Miami household's more accessible location results in a yearly VMT of 2,410.4 miles less than the Belle Glade household. An increase in one residential unit per acre reduces yearly VMT by 39.2 miles. To put this in perspective, a NHTS household in downtown Tampa was estimated to have a gross residential density of 9.15 units per acre. A NHTS household in rural Greenville was estimated to have a gross residential density of .65 acres, a difference of 8.5 units per acre (Figure 4-1). Due to this difference in densities, the household in Greenville can expect to incur 333.2 VMT more per year, all other things being equal.

A one mile increase in the minimum commute, an indicator of the job-housing balance throughout the region, increases yearly household VMT by 75.7 miles. For example, a NHTS household in Miami Beach was estimated to have a minimum commute distance of .36 miles. A NHTS household in rural Madison was estimated to have a minimum commute of 48.8 miles, a difference of 48.44 miles (Figure 4-1). All other things being equal, the better regional jobs-housing balance in the Miami Beach area affords a savings of 3,666.9 miles a year compared to a household located in the Madison area. Finally, an increase in one unit in the travel delay ratio, an indicator of travel cost, decreases yearly VMT by only .56 miles. A household with a travel delay ratio of five, which would indicate a household experiences on average travel delays equaling five times the amount of time during optimal conditions, would incur 2.8 VMT less per year than a household who experiences no delays. Although seemingly inconsequential, the variable's directionality and statistical significance affirms the hypothesis that higher costs, as measured in travel delay, reduces travel.

Log-Linear Global Regression Model Summary

In the log-linear model the dependent variable, household yearly VMT, has been log transformed. Overall model performance is reduced slightly with the adjusted r-squared value falling to .38 indicating the model explains 38% of the variability in the log of household VMT (Table 4-2).The Joint Wald Statistic's 95% confidence level probability is zero, indicating the model is statistically significant. The BP statistic's 95% confidence level probability is zero, indicating non-stationary and/or heteroscedasticity exists. The Jarque-Bera statistic's 95% confidence level probability is zero, indicating the results should be interpreted with caution because one or more key variables are missing from the model.

When the outcome variable is log transformed, binary (dummy) variables can be interpreted as the ratio of the geometric means for the two groups by taking the exponentiated value of the coefficient. For continuous variables, the exponentiated value of the coefficient can be interpreted as the percentage increase in the dependent variable from a one unit increase in the independent variable. In the log-linear model, all of the variables are statistically significant with the exception of the attitude dummy variable and the trip delay ratio. All coefficients indicate the expected directionality. An increase in a household's income, size, workers, vehicles, and commercial vehicles correlates with higher household VMT.

For example, a household whose head is retired is expected to have a yearly VMT geometric mean 15% less than a household with a non-retired head of household ($e^{-.16801}$). Increasing a household's vehicle count by one will increase the yearly VMT by 27% ($e^{.235759}$). For every additional worker, a household's yearly VMT can be expected to increase 17% ($e^{.156321}$). Similar interpretations can be made for all of the variables.

The accessibility coefficient is rounded to six decimal places and therefore is reported to be zero despite being statistically significant. Statistically significant variables do not often have a coefficient of zero, however, its interpretation makes sense in the log-linear regression framework. Accessibility is a unitless measure with each increment increase in its measurement representing little change. As noted above, the accessibility index of the rural town of Belle Glade, Florida is 212,929, The accessibility index of Downtown Miami is 1,205,196.5. Therefore a one unit increase in the accessibility index is inconsequential, and should not be expected to reduce the percentage of yearly VMT by a measurable amount. Therefore, a one unit increase in accessibility can be expected to decrease yearly VMT by 0%.

An increase in one residential unit per acre reduces yearly VMT by .5%($e^{\cdot -004807}$). Returning to the previous density example, a NHTS household in downtown Tampa was estimated to have a gross residential density of 9.15 units per acre. A NHTS household in rural Greenville was estimated to have a gross residential density of .65 acres, a difference of 8.5 units per acre (Figure 4-1). According to the log-linear model, ceteris paribus, the household's yearly VMT located in Tampa Bay is estimated to be 4.25% less than the household located outside of Lake City due to the difference in density.

Finally, a one mile increase in the region's minimum commute increases a household's yearly VMT by .5%($e^{\cdot 004627}$). Returning to the previous example, a NHTS household in Miami Beach was estimated to have a minimum commute distance of .36 miles. A NHTS household in rural Madison was estimated to have a minimum commute of 48.8 miles, a difference of 48.44 miles. According to the log-linear model, ceteris paribus, the household's yearly VMT located in Tampa Bay is estimated to be 25% less than the household located outside of Lake City due to the difference in the average minimum commute.

Log-Log Global Regression Model Summary

In the log-log model, the dependent variable and the continuous independent variables have been log transformed. The adjusted r-squared value is .40 indicating the model explains 40% of the variability in the log of household VMT (Table 4-2).The Joint Wald Statistic's 95% confidence level probability is zero, indicating the model is statistically significant. The BP statistic's 95% confidence level probability is zero, indicating non-stationary and/or heteroscedasticity exists. The Jarque-Bera statistic's 95% confidence level probability is zero, indicating the results should be interpreted with caution because one or more key variables are missing from the model.

In a log-log model, coefficients of log transformed independent variables can be utilized to calculate the percentage change in a household's yearly VMT from a percentage change in an independent variable. This ratio is often referred to as an elasticity and is used extensively in economics. In the log-log model, discrete variables such as household size, household workers, household vehicles, household commercial vehicles, and household children were not log transformed. Discrete variables were omitted from being log transformed because of the difficulty with dealing with zero values. Continuous variables such as accessibility, density, minimum commute, and trip delay ratio were transformed and can be interpreted as elasticities. All variables demonstrated the expected directionality, but unlike the previous models, the average minimum commute distance was not statistically significant.

Since the control variables and dummy variables are discrete, and therefore not log-transformed, the results are the same from the log-linear model discussed above.

The income variable was transformed, however, and can be interpreted as an elasticity. A 10% increase in household income is associated with a 2.9% increase in household yearly VMT. Household income had the largest elasticity among the variables that were log transformed.

A 10% increase in accessibility reduces yearly household VMT by only .2%. Although seemingly small, downtown Miami's accessibility index is 466% larger than Belle Glade's accessibility index. According to the log-log linear model, ceteris paribus, the 466% increase in accessibility reduces household yearly VMT by 9.8% (-.021*466). A 10% increase in gross residential density reduces yearly VMT by .4%. Although this is a highly inelastic relationship, context is needed. Returning to the example given in the linear-linear model summary, a household in Tampa, Florida was estimated to have a gross residential density of 9.15 units per acre. A household in rural Greenville, Florida was estimated to have a gross residential density of only .65 units per acre. The density of the Tampa household is 1308% higher than the Greenville household corresponding to a 52% decrease in yearly household VMT (-.038 * 1380).

Although insignificant in the log-log model, the minimum commute results are discussed. A 10% increase in the average minimum commute increases yearly VMT by .145%. Although these findings may seem insignificant, context is needed to interpret the results. Returning to the example examined in the linear-linear model summary, a household in Miami Beach was estimated to have an average minimum commute of .36 miles and a household in rural Madison County in Northern Florida was estimated to have an average minimum commute of 48.8 miles. The Madison County household's minimum commute is 13,456% more than the minimum commute for the Miami Beach household corresponding to a 195% increase in yearly VMT, all other things being equal.

Finally, a 10% increase in the average trip delay ratio decreases yearly VMT by .7%. To put this in perspective, a household in downtown Miami was estimated to have a travel delay ratio 266% greater than a household in High Springs (7.5 versus 2.3). According to the log-log model, ceteris paribus, the Miami household's yearly VMT is 18.6% less than the household in High Springs due to the differences in the travel delay ratio, a surrogate for travel costs.

Linear-Linear GWR Regression Model Summary

The previous models ignore non-stationarity, the phenomenon where regression coefficients vary across geographic space. To assess if this is occurs in the NHTS dataset, a GWR model is developed. Only variables found to be significant in the linear-linear OLS model were incorporated into the two GWR models. The adjusted r-squared value for the overall linear-linear GWR model is .44, indicating the model explains 44% of the variability among household's yearly VMT. This is a very slight improvement over the OLS model's r-squared value of .43. One useful way of comparing two or more regression models is the Akaike's Information Criterion (AIC). AIC is a relative measurement with smaller values representing a better goodness of fit. The AIC value for the linear-linear OLS model is 209,023. The AIC value for the linear-linear GWR model is 208,937 indicating it is superior to the global OLS model.

In a GWR analysis, a local model is developed for every observation in the dataset. Model coefficients and outputs are calculated based on a kernel that imposes an extent around the unit under analysis. The kernels for this GWR model were designed to minimize the AIC while being dynamic in nature. From each of the local regression models a local r-squared value is calculated (Figure 4-2). The points in dark green represent households whose r-squared values are larger than .5 (the r-squared value for the linear-linear OLS model was .43). Generally speaking, the model fits better south of Orlando including in large urban areas of Tampa, and Southeast Florida. Interestingly, the one major exception is an area just north of Miami including Miami Beach, Hialeah, Miramar, and Hollywood. The model largely underperforms north of Orlando including Jacksonville, Tallahassee, and Pensacola. While examining the following coefficient surfaces, please keep in mind that orange and red areas typically represent relationships not expected or that are not found in the literature.

Examining the accessibility coefficient surface, an interesting pattern arises (Figure 4-3). The coefficient for the accessibility index in the linear-linear OLS was -.02; a one unit increase in the accessibility index reduces yearly VMT by .02 miles. Areas in yellow illustrate where accessibility reduces VMT less than what was estimated in the global model. Areas in red delineate neighborhoods where there is a positive relationship between VMT and accessibility, that is, neighborhoods with greater accessibility increases a household's yearly VMT. Accessibility's negative relationship with VMT is greater than the estimated relationship in the global OLS model in the areas delineated by the two shades of green.

For the most part, positive relationships between accessibility and VMT are concentrated around major urban areas throughout south Florida and the rural/suburban area of south-central Florida including Sebring, Lake Placid, and Avon Park. A positive relationship implies that an increase in neighborhood accessibility, and indicator of access to office and commercial activity, increases household VMT. This relationship is contrary to what is stated in the literature and estimated in the global OLS models. Neighborhood accessibility appears to play a key role in reducing VMT in the Daytona Beach, Port Charlotte and Pensacola areas.

The density coefficient surface is also intriguing. The coefficient for gross residential density in the linear-linear OLS model was -39.2; a one unit increase in the residential density reduces yearly household VMT by 39.2 miles. In the GWR model, however, there is great variability in the density coefficient across the state of Florida (Figure 4-4). Areas in red indicate a positive relationship between density and VMT,that is, an increase in residential density increases VMT. This primarily occurs in Southeast Florida and around Lakeland. Areas in burnt orange exhibit a negative relationship between density and VMT but at a rate less than the OLS estimated. This primarily occurs around Venice in Southwest Florida.

The remainder of the colors signifies a stronger negative relationship between density and VMT than was estimated in the OLS model. Density appears to be an important mechanism to reduce VMT in the Tallahassee area with coefficients reaching -1,595 indicating a one unit increase in density reduces household VMT by 1,595 miles per year. Density also plays a key role in reducing VMT around the Sebring, Lake Placid, and Avon Park areas. Interestingly, this is the same area where there was a positive relationship between accessibility and VMT.

The average minimum commute, a regional indicator of jobs-housing balance, also varies across Florida (Figure 4-5). The minimum commute coefficient in the linear-linear OLS model was 75.7; a one mile increase in the average minimum commute increases household VMT by 75.7 miles. The larger the minimum commute, the more unevenly jobs and housing within the same income category occur throughout the region. Areas in red indicate a negative relationship between the average minimum commute and VMT. This primarily occurs within the interior of south Florida, a primarily rural area. Areas in orange indicate a positive relationship between the average minimum commute and VMT but at a smaller rate than indicated by the OLS model.

Of particular note are the areas in green which represent a highly positive relationship between average minimum commute and VMT. Major urban areas including Orlando, Tampa, and most of Southeast Florida indicate that the minimum average commute plays a major role in determining household VMT. Dark green areas indicate that a one mile increase in the average minimum commute increases yearly VMT by up to 826.7 miles. This seems to indicate that regional indicators may better model VMT in large urban areas than neighborhood oriented statistics.

Finally, the travel delay ratio, a surrogate for trip cost, coefficient surface appears to be more random (Figure 4-6). The travel delay ratio coefficient in the linear-linear OLS model was -.56, indicating a one unit increase in the travel delay reduces VMT by .56 miles. Areas in orange and red indicate a very small negative relationship between the travel delay ratio and VMT (-.56 – 0) or a positive relationship. Areas in yellow and green signify a negative relationship greater than that estimated by the global OLS model.

No clear pattern arises from the coefficient surface. Of particular interest is Pinellas County just east of Tampa. Pinellas County is estimated to have a strong negative relationship between the travel delay ratio and VMT, indicating travel cost, such as congestion, is an important determent of VMT. Other urban areas estimated to have a strong negative relationship is Miami and Stuart. This also occurs in relatively rural areas, however, including Levy, Dixie, and Eastern Marion Counties.

Table 4-1. Descriptive Statistics of Study Sample

Variable	Mean	Standard Deviation
Household VMT	16,884.2	11,242.5
Household Income	55,743	30,484
Household size	2.2	1.1
Workers per household	.88	.85
Children per household	.34	.79
Number of household commercial vehicles	.03	.18
Accessibility	168008	295352.6
Theoretical minimum commute	9.4	10.5
Travel Delay Ratio	6.6	191.3
Density	3.1	4.8

Table 4-2. OLS Model Outputs

Output	Linear-Linear	Log-Linear	Log-Log
Intercept	1031.064	8.259	5.810
Accessibility Coefficient (t-statistic)	-0.002 (2.884)*	0 (-5.838)*	-0.021 (-5.350)*
Density Coefficient (t-statistic)	-39.150 (-2.067)*	-0.005 (-3.105)*	-0.038 (-5.290)*
Average Minimum Commute Coefficient (t-statistic)	75.662 (8.666)*	0.005 (6.484)*	0.014 (1.808)
Travel Delay Ratio Coefficient (t-statistic)	-0.557 (-1.252)*	-0.000063 (-1.735)	-0.069(-6.477)*
Household Income Coefficient (t-statistic)	0.073 (23.017)*	0 (6.484)*	0.290 (26.546)*
Household Size Coefficient (t-statistic)	1776.567 (10.91)*	0.147 (11.062)*	0.147 (11.175)*
Household Workers Coefficient (t-statistic)	2460.934 (16.41)*	0.156 (12.753)*	0.153 (12.59)*
Household Vehicles Coefficient (t-statistic)	3367.92 (28.956)*	0.236 (24.8)*	0.226 (24.044)*
Household Kids Coefficient (t-statistic)	-705.360 (-3.35)*	-0.092 (-5.357)*	-0.091 (-5.355)*
Household Commercial Vehicles Coefficient (t-statistic)	2032.658 (4.243)*	0.102 (2.60)*	0.097 (2.507)*

Table 4-2. Continued

Output	Linear-Linear	Log-Linear	Log-Log
Retired Dummy Coefficient (t-statistic)	-2010.136 (-8.28)*	-0.168 (-8.469)*	-0.168 (-8.532)*
Attitude Dummy Coefficient (t-statistic)	-250.561 (-1.205)	-0.015 (-0.888)	-0.012 (-0.708)
R-Squared Value	.43	.38	.40

* Significant at the 95% Confidence Interval

N = 9985

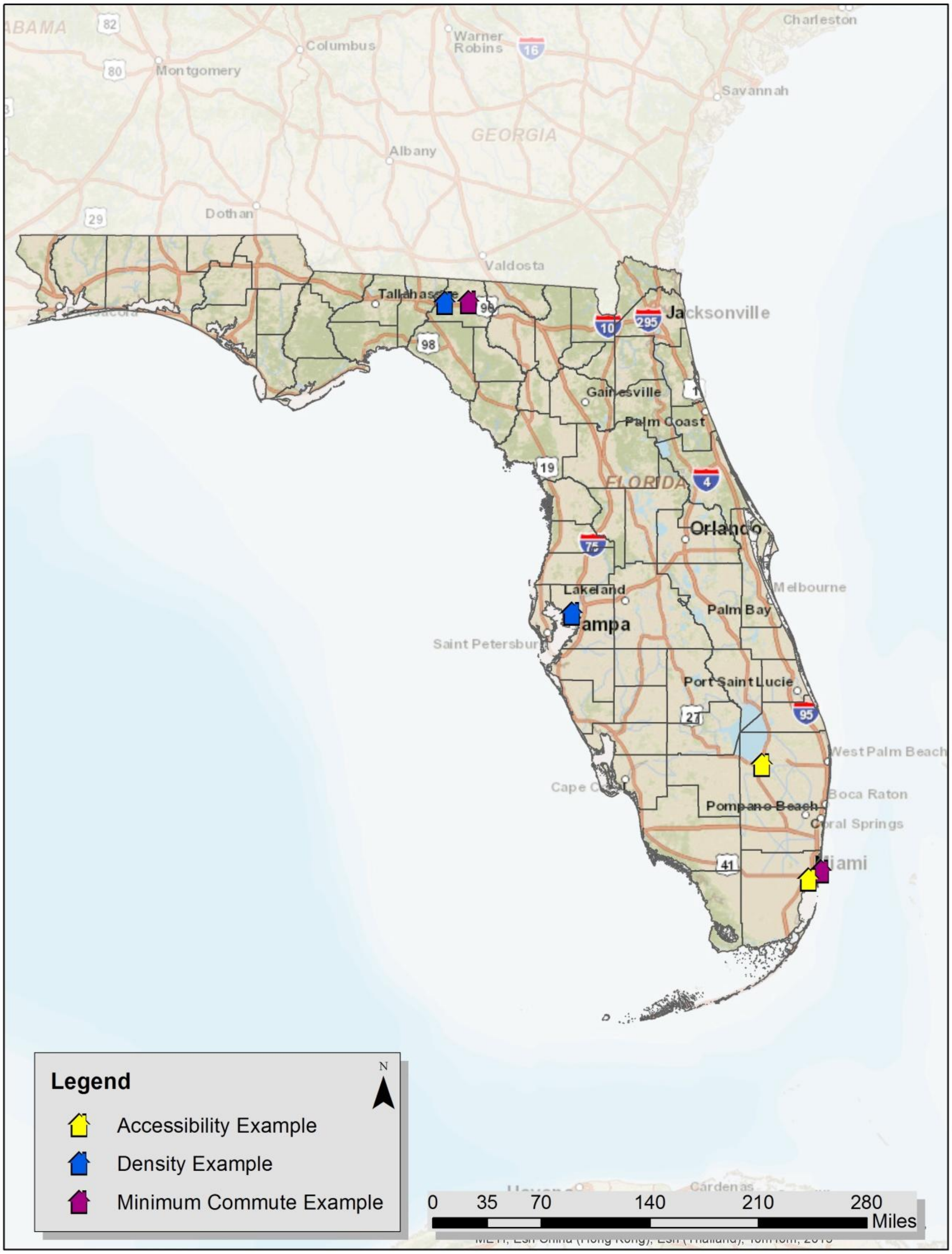

Figure 4-1. Location of examples describing land use coefficients

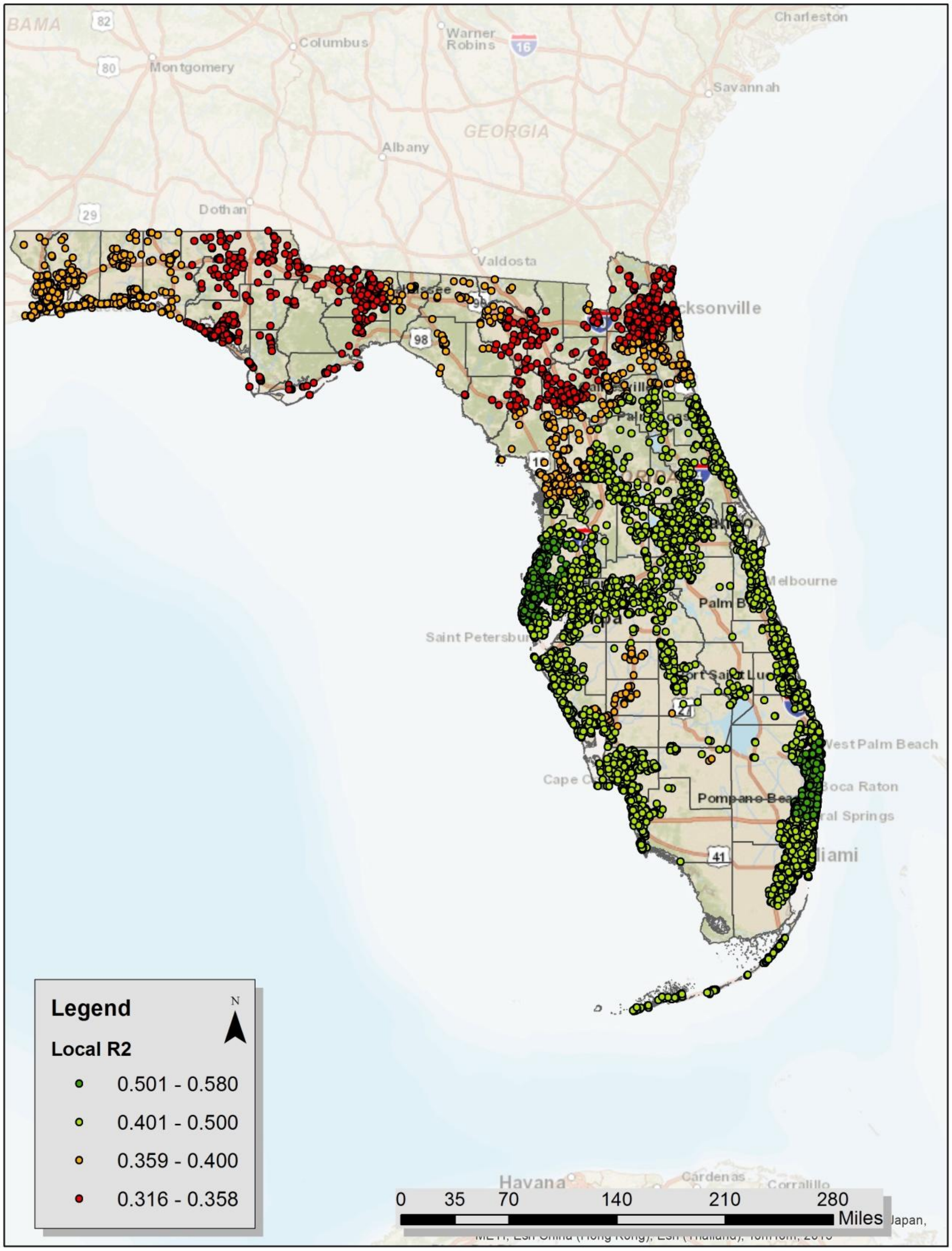

Figure 4-2. Localized R-Squared values from the GWR model

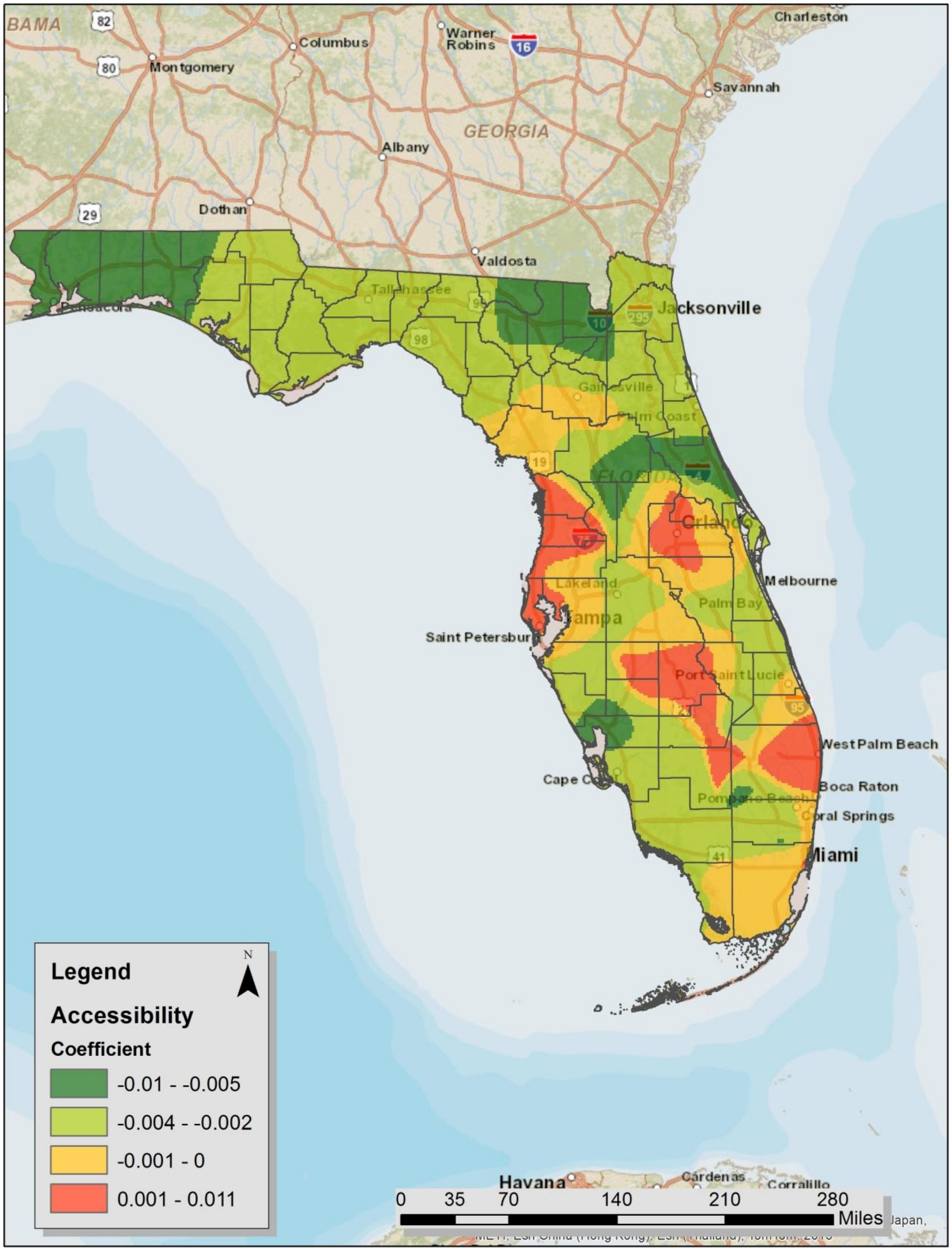

Figure 4-3. Accessibility coefficient surface

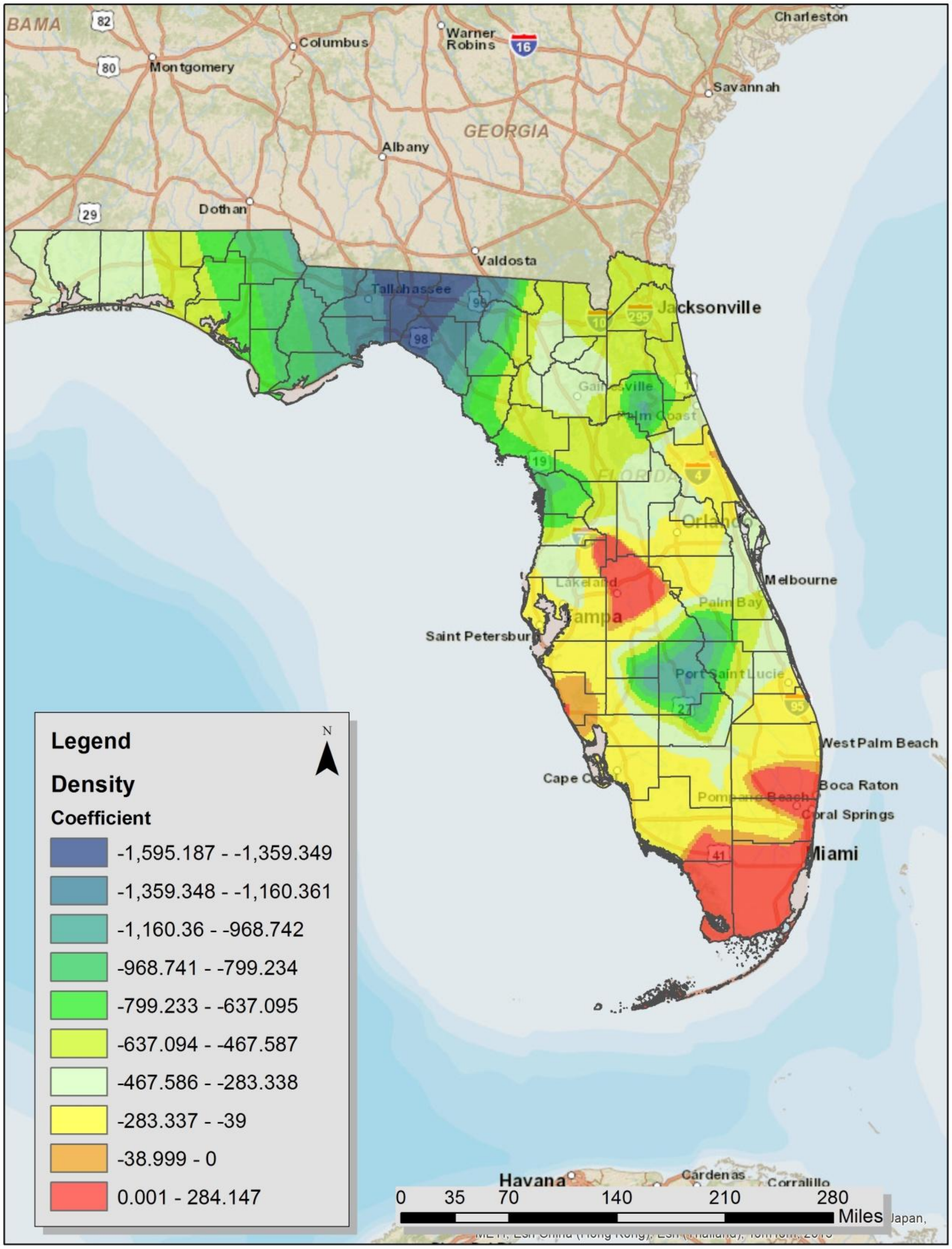

Figure 4-4. Density coefficient surface

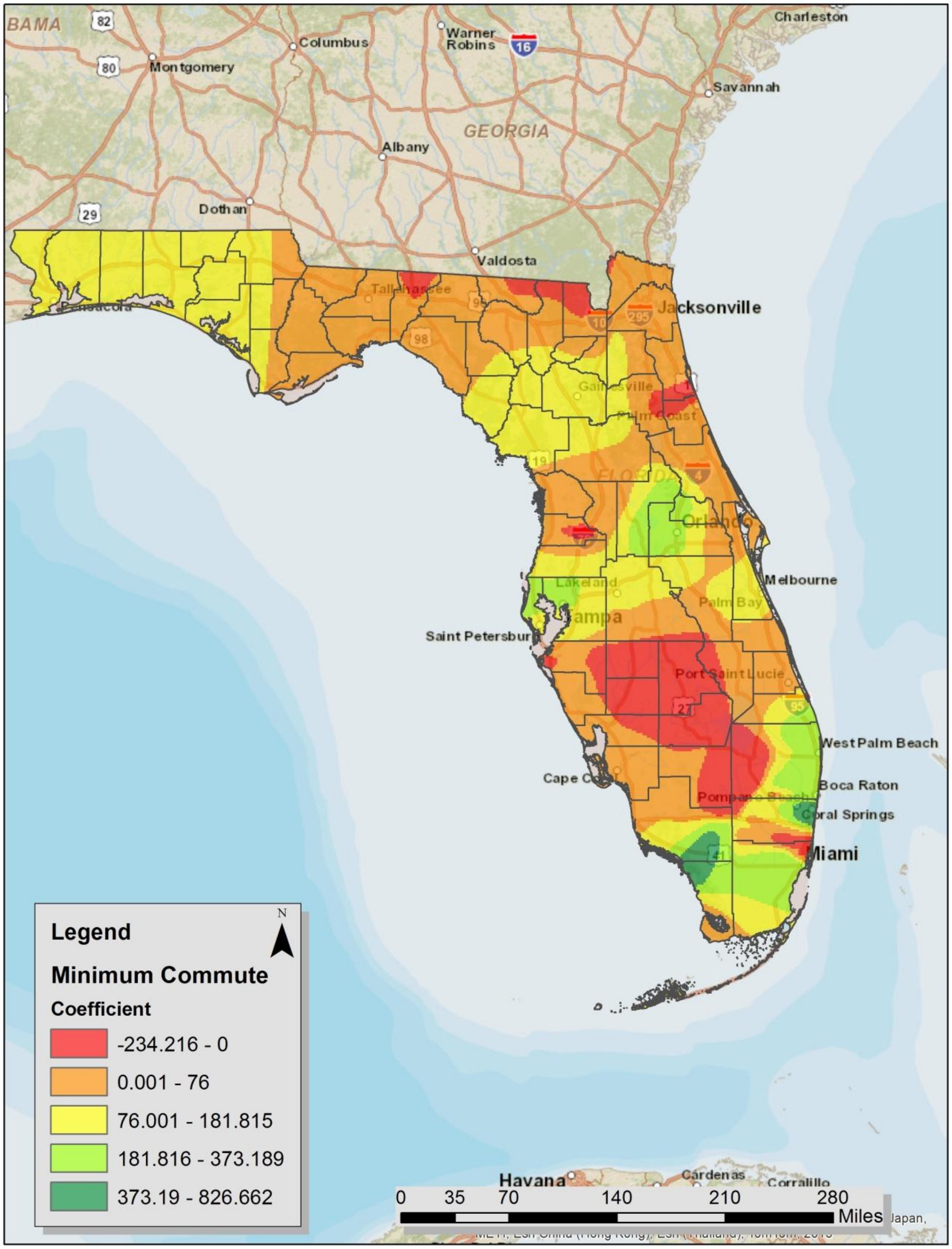

Figure 4-5. Minimum Commute coefficient surface

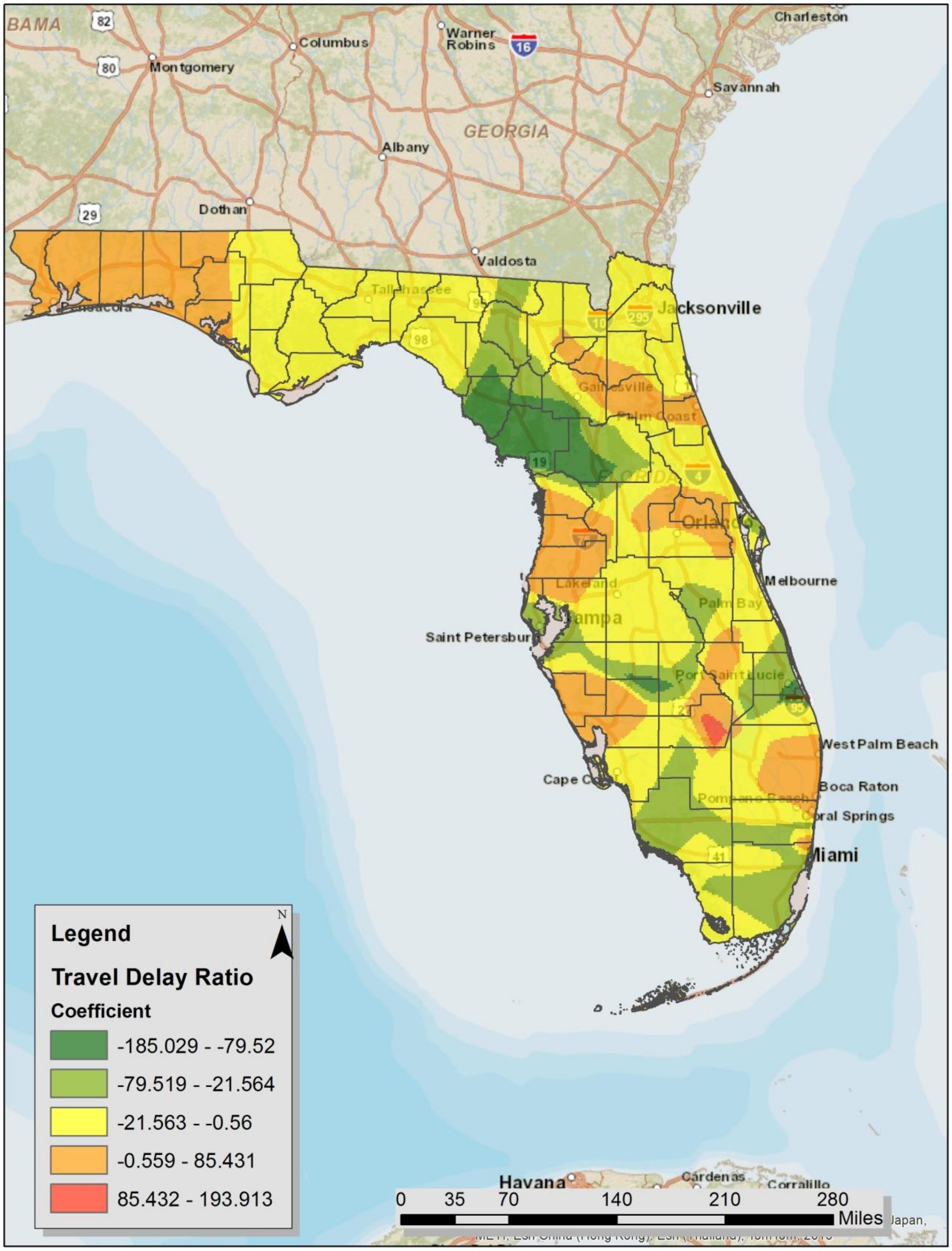

Figure 4-6. Travel Delay coefficient surface

CHAPTER 5
DISCUSSION

Florida is a peninsula which provides an excellent geographic space to conduct spatial analysis because it lacks anthropogenic influence along a majority of its borders. The three global OLS models developed demonstrated and reaffirmed that, after controlling for socioeconomic variables, the built environment impacts travel behavior. The methodology failed, however, to construct an adequate measure of attitudes in an attempt to control for self selection. The dummy variable “attitudes” was constructed from answers to a question in the NHTS designed to capture the main reason the head of household moved to their current residence. There could be a number of explanations for this failure; one being the question only reflected the head of household’s views. All of the built environment variables’ coefficients demonstrated the expected directionality according to the literature.

For each of the global models, an example provided context for the implications of the model’s findings. The contexts illustrated examples of the built environment on opposite ends of the rural/urban spectrum in Florida. In all cases the average minimum commute, an indicator of regional accessibility and/or job-housing balance, appeared to be the most influential at reducing VMT. This supports Handy’s findings that regional accessibility was a better predictor of travel behavior than neighborhood accessibility (Handy, 1993). The magnitudes of the elasticities derived from the log-log OLS model were small with none reaching the greatest magnitude found by Ewing of .39 (Ewing & Cervero, 2010). The density elasticity with respect to VMT was -.04, exactly what was estimated by Ewing and Cervero’s work. The accessibility elasticities, however, were significantly smaller that others estimated.

Just relying on the absolute magnitude of the coefficients and/or elasticities, however, is meaningless. Despite the small overall magnitude of the coefficients, their “real world” application provides insight into their influence. For example, the difference in density between urban Tampa and rural Greenville reduces yearly VMT by 52%, all other factors being the same. Although this is an extreme example of the urban/rural spectrum in Florida, it does provide insight into density’s importance. It must be noted that density is often seen as a surrogate for other hard to measure variables such as walkability, parking costs, and transit availability. These variables were not directly measured in this study but are assumed to vary with density.

Although the global models demonstrate the expected directionalities from all of the built environment variables, a closer examination using GWR reveal some interesting trends. The coefficient surfaces clearly demonstrate that non-stationarity exists in the model. Also, by mapping the localized r-squared values, it is clear that the model proposed in this research fits better in southern Florida and the Tampa area. The model fits the least in the major college towns of Gainesville and Tallahassee, and also the military town of Jacksonville. It is possible that these unique populations necessitate different models to explain travel behavior.

In some instances in the coefficient surfaces, neighborhood variables such as density and accessibility to shopping impact VMT in the opposite direction that was estimated in the global OLS models and found in the literature. Large portions of Orlando, Tampa, and Southeast Florida have a positive relationship between accessibility and VMT suggesting an increase shopping opportunities within six miles of the household increases VMT. There is also a positive relationship between density and

VMT in Southeast Florida. Perhaps within these areas, accessibility and density are largely uniform and other factors at measuring urban form must be devised. Many of these same areas, however, have a highly positive relationship between minimum commute and VMT suggesting that regional job accessibility is an important mechanism to reduce VMT in urban areas.

Rural areas provide a less amount of discernable patterns. One generalized pattern is that minimum commute often does not have a positive relationship with VMT. This suggests that the regional measure of job-housing is not a viable mechanism to reduce VMT in rural areas. Again, these findings could be from a lack of variability in the jobs-housing balance in rural areas to decipher a viable relationship. Density and accessibility, for the most part, demonstrated the expected directionality in rural areas with varying degrees of magnitude. Density was particularly useful at reducing VMT in the Tallahassee and Sebring/Lake Placid areas. If density is in fact an intermediate variable as the literature suggests, other factors such as transit, parking supply, and crime may be important determinants of VMT in these areas.

Although the GWR analysis demonstrates coefficients can reverse their directionality, a closer examination of the model outputs indicate that this should be interpreted with caution. Using the standard error of the coefficients in the GWR output to calculate the regression coefficient 95% confidence interval reveals that many of the confidence intervals are quite large, and include positive and negative values. For example, an observation with a density coefficient of 281.6, an unexpected positive relationship, has a 95% confidence interval of $-219.61701 \le \beta \le 782.79101$. As indicated by this very large confidence interval, we could still expect the coefficient for this observation to be negative. Another caveat of interpreting GWR is the possibility of variables, although found to be significant in the global models, are not statistically significant in the local model.

By utilizing GWR, researchers and policy analysts can differentiate between areas where models are accurate and need adjustment. GWR provides a starting point to uncover unique relationships that would otherwise be overlooked using global regression techniques. In this study, it was demonstrated that traditional neighborhood built environment variables may not capture the necessary information in built-out urban areas. Other variables may need to be devised. Modeling travel behavior is difficult due to the unique travel situations of the respondents. Answers to cross sectional studies regarding travel behavior can also be suspect especially when respondents are asked to recall certain travel information like the amount of miles driven within the past year for each vehicle owned. Nevertheless, this exercise provided insight into the varying relationship between the built environment and travel behavior across Florida.

CHAPTER 5
CONCLUSION

This thesis utilizes a statewide travel survey to conduct statistical analysis of the relationship between the built environment and travel behavior. First, current trends that demonstrate the saliency of the subject were discussed. Second, conceptual frameworks were examined that outlined the building blocks for an in depth examination of the subject. Third, empirical studies were reviewed to summarize the prevailing trends found in the literature. Fourth, the methodology section outlined the construction of three global OLS models and one GWR model.

Attitudes, travel costs, and socioeconomic variables were controlled for in the models. The built environment was presumed to influence travel behavior through “the qualities of travel that directly affect the utility of the travel experience, the quantity of the travel inputs needed to produce out-of-home activities, and the per unit prices of travel by different modes” (2005, p.15). The global models, which assume constant relationships between the independent and dependent variables across space, affirmed this hypothesis. It was also hypothesized that these relationships would vary across the state of Florida. By utilizing GWR, it was clearly demonstrated that the relationships between factors in the built environment and travel behavior incur non-stationarity.

Future research should not ignore non-stationarity and more work needs to concentrate on the varying degrees of model goodness of fit across geographic space. If research is to inform policy decisions, a one size fits all model cannot be assumed. Also, as this study demonstrates, larger regions should be the focus of empirical research so that context can be given and model implications can clearly be articulated. This research provides the one of the few statewide analysis of the relationship between the built environment and travel behavior that maps out and clearly identifies non-stationarity in regression analysis for this subject. It is urged that future research on this subject matter utilizes the growing spatial statistical tools now available. Only then can more precise models be developed.

This research is just the first step in developing a robust travel demand model. Future research will focus on determining the mechanisms that make the proposed model fit better in south Florida and Tampa than north Florida. Other built environment variables should be developed for urban areas that capture subtleness that perhaps density and neighborhood accessibility cannot. Research that utilizes GWR is adaptive in nature, and requires the analyst to adjust the models as results dictate. This research is step one in that process.

LIST OF REFERENCES

Ali, K., Partridge, M., & Olfert, R. (2007). Can Geographically Weighted Regressions Improve Regional Analysis and Policy Making? *International Regional Science Review*, *30*(3), 300–329.

American Society of Civil Engineers. (2008). *Report Card for America's Infrastructure*. Retrieved from http://www.infrastructurereportcard.org/state-page/florida

American Society of Civil Engineers. (2011). *Failure to Act: The Economic Impact of Current Investment Trends in Surface Transportation Infrastructure*. Reston, VA. Retrieved from http://www.asce.org/uploadedFiles/Infrastructure/Report_Card/ASCE-FailureToActFinal.pdf

Anable, J. (2005). "Complacent Car Addicts" or "Aspiring Environmentalists"? Identifying Travel Behavior Segments Using Attitude Theory. *Transport Policy, 12,* 65–78.

Bamberg, S., Ajzen, I., & Schmidt, P. (2010). Choice of Travel Mode in the Theory of Planned Behavior: The Roles of Past Behavior, Habit, and Reasoned Action. *Basic and Applied Social Psychology, 25*(3), 175–187. Retrieved from http://dx.doi.org/10.1207/S15324834BASP2503_01

Baussauw, K., Derudder, B., & Witlox, F. (2011). Measuring Spatial Separation Processes Through the Minimum Commute: the Case of Flanders. *European Journal of Transport and Infrastructure Research*, 11(1), 42–60.

Bento, A., Cropper, M., Mobarak, A., & Vinha, K. (2005). The Impact of Urban Spatial Structure on Travel Demand in the United States. *The Review of Economics and Statistics*, 87, 466–478.

Bhat, C., & Guo, J. (2007). A Comprehensive Analysis of Built Environment Characteristics on Household Residential Choice and Auto Ownership Levels. *Transportation Research Part B*, 41, 506–526.

Bhat, C., Kockelman, K., Chen, Q., Handy, S., Mahmassani, H., & Weston, L. (2000). *Urban Accessibility Index: Literature Review,* (pp. 1–84). Austin, Texas.

Blanco, A., Steiner, R. L., Peng, Z.-R., Shmaltsuyev, M., & Wang, R. (2010). *The Economic Cost of Traffic Congestion in Florida* (p. 217). Gainesville, FL. Retrieved from http://www.dot.state.fl.us/research-center/Completed_Proj/Summary_OP/FDOT_BDK75_977-19_rpt.pdf

Boarnet, M. (2011). A broader Context for Land Use and Travel Behavior, and a Research Agenda. *Journal of the American Planning Association*, *77*(3), 197–213.

Boarnet, M., & Crane, R. (2000). The Influence of Land use on Travel Behavior: Specification and Estimation Strategies. *Transportation Research Part A*, 35, 823–845.

Brundson, C., Fotheringham, S., & Charlton, M. (1996). Geographically Weighted Regression: A Method for Exploring Spatial Nonstationarity. *Geographical Analysis*, *28*(4), 281–298.

Calthorpe, P., & Fulton, W. (2001). *The Regional City*. Washington, DC: Island Press.

Cao, X., Mokhtarian, P., & Handy, S. (2008). *Examining the Impacts of Residential Self-Selection on Travel Behavior: Methodologies and Empirical Findings* (pp. 1–56). Davis, California.

Cao, X., Xu, Z., & Fan, Y. (2010). Exploring the Connections Among Residential Location, Self-Selection, and Driving: Propensity Score Matching with Multiple Treatments. *Transportation Research Part* A, 44, 797–805.

Carmona, M., Heath, T., Oc, T., & Tiesdell, S. (2003). *Public Places Urban Spaces* (1st ed., p. 312). Oxford: Architectural Press.

Center for Urban Transportation Research. (2012). *Florida MPOAC Transportation Revenue Study* (p. 123). Tampa, FL. Retrieved from http://www.mpoac.org/revenuestudy/RS_Final_Report.pdf

Cervero, R. (2003). The Built Environment and Travel: Evidence from the United States. *European Journal of Transport and Infrastructure Research, 3*(2), 119–137.

Cervero, R. (2006). Alternative Approaches to Modeling the Travel-Demand Impacts of Smart Growth. *Journal of the American Planning Association, 72*(3), 285–295.

Cervero, R., & Kockelman, K. (1997). Travel Demand and the 3Ds: Density, Diversity and Design. *Transportation Research Part D: Transport and Environment, 2*(3), 199–219. Retrieved from http://www.sciencedirect.com/science/article/pii/S1361920997000096

Cervero, R., & Radisch, C. (1996). Travel choices in pedestrian versus automobile oriented neighborhoods. *Transport Policy, 3*(3), 127–141.

Chatman, D. (2005). *How the Built Environment Influences Non-Work Travel: Theoretical and Empirical Essays*. University of California. Retrieved from http://policy.rutgers.edu/faculty/chatman/Howenvironmenttravel.pdf

Ewing, R., Bartholomeu, K., Winkelman, S., Walters, J., & Chen, D. (2007). *Growing Cooler: The Evidence on Urban Development and Climate Change* (p. 170). Washington, DC: Urban Land Institute. Retrieved from postcarboncities.net/files/SGA_GrowingCooler9-18-07small.pdf

Ewing, R., & Cervero, R. (2001). Travel and the Built Environment: A Synthesis. *Transportation Research Record: Journal of the Transportation Research Board*, *1780*(1), 87–114. Retrieved from http://trb.metapress.com/content/a1w1712rw1225372/

Ewing, R., & Cervero, R. (2010). Travel and the Built Environment. *Journal of the American Planning Association*, *76*(3), 265–294.

Ewing, R., Haliyur, P., & Page, G. (1994). Getting Around a Traditional City, Suburban Planned Unit Development and Everything in Between. *Transportation Research Record*, 1466, 53–62.

Federal Surface Transportation Policy and Planning Act of 2011. (2011), S. 326, 112th Congress.

Federal Transit Administration. (2012). SAFETEA-LU Implementation. *Federal Transit Administration*. Retrieved from http://www.fta.dot.gov/legislation_law/12916_4696.html

Florida Department of Community Affairs. (2009). *Transportation Planning*. Retrieved from http://www.dca.state.fl.us/fdcp/DCP/transportation/CurrentTopics.cfm#Greenhouse

Florida Department of Environmental Protection. (2009). *Executive Orders and Partnership Agreements.* Retrieved from http://www.dep.state.fl.us/climatechange/eo.htm

Florida Department of Transportation. (2010). *2009 National Household Travel Survey User Guide* (pp. 1–21). Tallahassee, Florida.

Frost, M., Linneker, B., & Spence, N. (1998). Excess or Wasteful Commuting in a Selection of British Cities. *Transportation Research Part A*, *32*, 529–538.

Garling, T., Gillholm, R., & Garling, A. (1998). Reintroducing Attitude Theory in Travel Behavior Research. The validity of an Interactive Interview Procedure to Predict Car use. *Transportation*, *25*(2), 129–146. Retrieved from http://link.springer.com/article/10.1023/A:1005004311776?LI=true

Governor's Action Team on Energy and Climate Change. (2008). *Documents*. Retrieved from http://www.flclimatechange.us/documents.cfm

Handy, S. (1993). Regional Versus Local Accessibility: Implications for Nonwork Travel. *Transportation Research Record*, *1400*, 58–66.

Handy, S. (1996). Understanding the Link Between Urban Form and Nonwork Travel Behavior. *Journal of Planning Education and Research*, *15*(3), 183–198.

Handy, S. (2005). *Critical Assessment of the Literature on the Relationships Among Transportation, Land Use, and Physical Activity* (p. 102). Washington, DC. Retrieved from http://onlinepubs.trb.org/onlinepubs/archive/downloads/sr282papers/sr282Handy.pdf

Horner, M. (2007). A Multi-Scale Analysis of Urban and Commuting Chang in a Small Metropolitan Area (1990-200). *The Annals of Regional Science*, *41*, 315–332.

Kockelman, K. (1991). *Travel Behavior as a function of Accessibility, Land Use Mixing, and Land Use Balance: Evidence from the San Francisco Bay Area*. University of California, Berkeley.

Leck, E. (2006). The Impact of Urban Form on Travel Behavior: A Meta-Analysis. *Berkeley Planning Journal*, *19*(1), 37–58. Retrieved from http://escholarship.org/uc/item/20s78772#page-22

Levinson, D., & Kumar, A. (1997). Density and Journey to Work. *Growth and Change*, *28*(2), 147–172. Retrieved from http://nexus.umn.edu/papers/density.pdf

Liu, S., & Zhu, X. (2004). Accessibility Analyst: An Integrated GIS Tool for Accessibility Analysis in Urban Transportation Planning. *Environment and Planning B: Planning and Design*, *31*, 105–124.

Mokhtarian, P., & Chen, C. (2003). TTB or Not TTB, That is the Question: A Review and Analysis of the Empirical Literature on Travel Time (and Money) Budgets. *Transportation Research Part A*, *38*(9), 643–675. Retrieved from http://www.escholarship.org/uc/item/3kr185ts

Mokhtarian, P., & Salomon, I. (2001). How Derived is the Demand for Travel? Some Conceptual and Measurement Considerations. *Transportation Research Part A*, *35*, 695–719. Retrieved from http://escholarship.org/uc/item/1z26n1r8

National Household Travel Survey. (2001). FAQ - What is trip chaining? Retrieved from http://nhts.ornl.gov/2001/pub/tripchaining.pdf

National Research Council. (2009). *Driving and the Built Environment: The Effects of Compact Development on Motorized Travel, Energy Use, and CO2 Emissions -- Special Report 298*. *Transportation Research*. Washington, DC: The National

Academies Press. Retrieved from http://www.nap.edu/catalog.php?record_id=12747#orgs

Oregon Transportation Research and Education Consortium. (2011). *Travel Behavior, Residential Preference, and Urban Design: A Multi-Disciplinary National Analysis* (pp. 1–63). Portland, Oregon.

Puentes, R., & Tomer, A. (2008). *The Road…Less Traveled: An Analysis of Vehicle Miles Traveled Trends in the U.S.* Washington, DC. Retrieved from http://www.brookings.edu/research/reports/2008/12/16-transportation-tomer-puentes

Rutherford, S., McCormack, E., & Wilkinson, M. (1996). Travel impacts of urban form: Implications from an analysis of two Seattle area travel diaries. *TMIP Conference on Urban Design Telecommuting and Travel Behavior*, 95–167.

Schwanen, T., & Mokhtarian, P. (2005). What if You Live in the Wrong Neighborhood? The Impact of Residential Neighborhood Type Dissonance on Distance Traveled. *Transportation Research Part D: Transport and Environment*, *10*, 127–151.

Shaheen, S., Bengamin-Chung, J., Allen, D., & Howe-Steiger, L. (2009). *Achieving California's Land Use and Transportation Greenhouse Gas Emission Targets Under AB 32: An Exploration of Potential Policy Processes and Mechanisms* (p. 95). Retrieved from http://tsrc.berkeley.edu/sites/tsrc.berkeley.edu/files/achieving california's land use.pdf

Shay, E., & Khattak, A. (2005). Auto Ownership and Use in Neo-Traditional and Conventional Neighborhoods. *Transportation Research Record*, *1902*, 18–25.

Shoup, L., & Lang, M. (2011). *Transportation 101:An Introduction to Federal Transportation Policy* (pp. 1–84). Washington, DC.

Steiner, R. L., Srinivasan, S., Provost, R. E., Mackey, J., Arafat, A., Anderson, N., &DeLarco, L. (2010).*VMT-Based Traffic Impact Assessment: Development of a Trip Length Model* (pp. 1–56). Gainesville, Florida.

Sustainable Communities and Climate Protection Act of 2008, Cal. Gov't Code § 65080(b)(2)(A) (2008).

UCLA: Statistical Consulting Group. (2013). *How do I interpret a regression model when some variables are log transformed?* Retrieved February 2, 2013, from http://www.ats.ucla.edu/stat/mult_pkg/faq/general/log_transformed_regression.htm

U.S. Department of Transportation. (2013)[a]. Highway Authorizations: Moving Ahead for Progress in the 21st Century Act (MAP-21). *MAP-21*. Retrieved from http://www.fhwa.dot.gov/map21/ha.cfm

U.S. Department of Transportation. (2013)[b]. MAP-21: Performance Management. *MAP-21*. Retrieved from http://www.fhwa.dot.gov/map21/pm.cfm

United States Environmental Protection Agency (EPA). (2009). Fact Sheet -- Proposed Rule: Prevention of Significant Deterioration and Title V Greenhouse Gas Tailoring Rule. Retrieved from http://www.epa.gov/NSR/fs20090930action.html

Van Acker, V., Van Wee, B., & Witlox, F. (2010). When Transport Geography Meets Social Psychology: Toward a Conceptual Model of Travel Behavior. *Transport Reviews*, *30*(2), 219–240.

Zhou, B., & Kockleman, K. (2008). Self-Selection in Home Choice: Use of Treatment Effects in Evaluating the Relationship Between the Built Environment and Travel Behavior. *Transportation Research Record*, *2077*, 54–61.

BIOGRAPHICAL SKETCH

Russell Provost received his bachelor’s degree from Virginia Tech in Public and Urban Affairs in 2005 where he became accustomed to GIS applications. After graduating, Mr. Provost participated in the AmeriCorps Program coordinating a local effort to develop ecotourism opportunities in rural Oregon. While in Oregon, he also participated in the Ford Family’s Foundation Leadership Program designed to train local leader in the community in various leadership skills. Mr. Provost held two research positions while attending the University of Florida Russell’s has over eight years of experience in GIS analysis in a variety of planning contexts including ecotourism, watershed planning, suitability modeling, and long range planning. His research interests include GIS applications in environmental and sustainability planning.