

Guidelines for Developing Travel Demand Models: Medium Communities and Metropolitan Planning Organizations

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Raleigh, NC 27699-1549

September 2007

Technical Report Documentation Page

1. Report No. FHWA/NC/2006-58 Phase II	2. Government Accession No.	3. Recipient's Catalog No.	
4. Title and Subtitle Guidelines for Developing Travel Demand Models: Medium Communities and Metropolitan Planning Organizations		5. Report Date September 2007	
		6. Performing Organization Code	
7. Author(s) John R. Stone, Asad J. Khattak, and Bing Mei		8. Performing Organization Report No.	
9. Performing Organization Name and Address Department of Civil, Construction and Environmental Engineering, NC State University, Raleigh NC 27695-7908 Triangle Regional Model Service Bureau, ITRE, NC State University, Raleigh NC 27695-8601 Department of City and Regional Planning, University of North Carolina at Chapel Hill, Chapel Hill NC 27599		10. Work Unit No. (TRAIS)	
		11. Contract or Grant No.	
12. Sponsoring Agency Name and Address North Carolina Department of Transportation Transportation Planning Branch 1 South Wilmington Street Raleigh, North Carolina 27601		13. Type of Report and Period Covered Phase II Final Report July 1, 2004 - June 30, 2007	
		14. Sponsoring Agency Code 2005-11	
Supplementary Notes:			
16. Abstract This report is the second of two reports that develop guidelines to simplify and standardize travel demand modeling in terms of a community size, needs and issues. The first report (Phase I) documented simplified methods and guidelines for estimating travel in small communities with populations up to 10,000 people. The focus of this report (Phase II) is on medium size communities with populations of 10,000 to 50,000 people, and on MPOs and cities with 50,000 or more people. Instead of using the typical data intensive, survey based methods for all communities regardless of size, the guidelines recommend appropriately scaled approaches and short cut methods to reduce time and cost, yet provide adequate estimates of traffic volumes and impacts. Methods for medium size communities include synthetic estimation of through trips and external trips and quick response travel models. Of particular interest are simplified submodels for trip generation, trip distribution, and mode choice. Also, proposed are innovative submodels for pedestrian, bicycle and transit trip generation that depend on land use characteristics. Case studies demonstrate the methods.			
17. Key Words Medium urban and MPO transportation planning, travel demand modeling		18. Distribution Statement	
19. Security Classif. (of this report) Unclassified	20. Security Classif. (of this page) Unclassified	21. No. of Pages 187	22. Price

Form DOT F 1700.7 (8-72)

Reproduction of completed page authorized

Preface

This report documents the second phase of a two phase project to develop guidelines for travel demand modeling in North Carolina. The first phase effort addresses transportation modeling concepts for small communities with populations up to 10,000. The second phase documents travel demand model guidelines for communities with populations greater than 10,000 and for Metropolitan Planning Organizations which have populations 50,000 or greater.

Disclaimer

The contents of this report reflect the views of the authors and not necessarily the views of the North Carolina State University and University of North Carolina at Chapel Hill. The authors are responsible for the facts and the accuracy of the data presented herein. The contents do not necessarily reflect the official views or policies of the North Carolina Department of Transportation or the Federal Highway Administration at the time of publication. This report does not constitute a standard, specification, or regulation.

Acknowledgements

The authors are grateful to the members of the NCDOT Research Project Steering Committee (2005-11) and NCDOT staff, who provided valuable advice and data for the project. They are:

- Rhett Fussell, PE, Chair Phase I
- Dan Thomas, PE, Chair Phase II
- Mike Bruff, PE
- Alena R. Cook, PE
- Tim Padgett, PE
- Jonathan H. Parker, PE
- Jeremy Raw
- Joe Stevens
- Scott Walston, PE
- Dennis Pipkin, PE

The authors especially appreciate the contributions and hard work of staff at NCDOT, students at NCSU and UNC-CH, and staff in the Triangle Regional Model Service Bureau.

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EXECUTIVE SUMMARY

Background

Building upon the collaboration among the Triangle Regional Model Service Bureau, NC State University and UNC-Chapel Hill, and upon on-going travel demand modeling research at the two Universities and the Institute for Transportation Research and Education (ITRE), we developed guidelines for best practice for developing travel demand models and sub-models in order to simplify, streamline and standardize the travel demand modeling process.

Most major travel demand models developed and used by the North Carolina Department of Transportation (NCDOT) are long range, urban travel demand models applying the traditional four-step process. In smaller areas, sketch tools or hand allocation models are used. For medium sized communities quick response methods with simplified submodels may be used or full scale computerized models may be used, especially for MPOs. This research describes various levels of analysis and tools that can be used based on an agency's staff constraints and the needs of the study area.

Problem

Transportation professionals must select appropriate methods and tools for analysis in terms of a community's size, needs, features and development, during the course of the analytical and outreach activities. Transportation planning in small and medium urban areas is becoming increasingly important since the popularity of these areas has risen over the past several decades. In addition, while large metropolitan areas are usually able to dedicate significant effort to their transportation modeling and planning, smaller communities often search for ways to streamline transportation planning to reduce their expenditures. Therefore, it is critical for NC communities, especially for smaller ones, to use good guidelines and tools for modeling practices. Defining those guidelines and developing those tools is the subject of this research.

Scope and Objectives

There are two phases in this project. Phase I, which is documented in a separate report, focuses on smaller North Carolina areas with populations less than 10,000. The Phase I project goal is to improve and simplify the on-going conventional planning process while making it a more efficient and less time consuming process for smaller areas with populations less than 10,000. Tools for Phase I rely on U.S. census and North Carolina data, simplified travel demand modeling approaches, and GIS tools that allow integration of multiple factors that affect community travel.

The objectives of the Phase I research were:

- To improve, yet simplify, the transportation modeling process for small NC communities with populations less than 10,000.
- To develop guidelines and tools for best modeling practices for small NC communities consistent with community features, needs and concerns.
- To test the option of developing long term partnerships for research and transportation demand modeling using North Carolina expertise and data sets.

This report addresses the research efforts conducted in Phase II and focuses on larger NC communities and MPOs. The objectives of Phase II are:

- To improve and simplify the on-going conventional planning process for larger North Carolina urban areas with populations greater than 10,000.

- To develop guidelines and tools for best modeling practices for medium sized communities and MPOs in terms of their needs and issues regarding transportation, economic development and environment, and other considerations.
- To continue to test the option of developing long term partnerships for research and transportation demand modeling using North Carolina expertise and data sets.

Approach

The research methodology follows the common travel demand modeling approach: data collection, network development, trip generation, trip distribution, mode choice, trip assignment and deficiency analysis. Professionals apply this methodology with customized methods depending on the scope and size of the study areas.

In Phase I we defined two distinct categories for small urban areas in North Carolina:

- Category A – population < 5,000
- Category B – population between 5,000 and 10,000

In Phase I we developed appropriately scaled approaches that reduce time and cost, yet provide adequate estimates of traffic volumes and impacts resulting from new transportation projects. The different travel forecasting approaches (context sensitive solution, trend line analysis, manual travel allocation, TransCAD Quick Response and GIS display tools) were evaluated and matched to the study area based on its size, issues and transportation needs. We determined available sources for model data including default national or state averages, and determined for the most part eliminated the need for new surveys. Appropriate sub-models for trip generation, distribution, mode choice, traffic assignment, and external trip analysis were developed and tested.

In Phase II we expanded the research to include two more categories for urban areas in North Carolina:

- Category C – population between 10,000 and 50,000
- Category D – population greater than 50,000 (the definition for an MPO)

Category E multi-MPO regions are out of scope for this research. The research team believes, and the NCDOT Research Project Steering Committee concurred, that models for multi-MPO regions are custom developments that depend on unique circumstances and that guidelines for such models are beyond the scope of this research.

Findings and Recommendations

In Phase I, the research developed models, sub-models, tools and guidelines for best practice for the North Carolina communities with populations less than 10,000. There are various planning tools in the “toolbox” that can be applied depending on a community’s on size and needs. Of special note are default NC trip rates and data sources, manual travel allocation techniques, rural transit demand estimation, and land capacity methods for sizing development. Detailed case studies illustrate the use of the methods and databases. The summary travel demand model guidelines for small communities are presented by a matrix and the modeling decision tree in the Phase I report. The guidelines and decision tree are repeated in this Phase II report and expanded to include factors that affect modeling communities with populations greater than 10,000.

Phase II research focused on medium size communities with populations of 10,000 to 50,000 people, and on MPOs and cities with 50,000 or more people. The premise of the research maintains that instead of using the typical data intensive, survey based methods for all communities regardless of size, guidelines

can be developed to recommend appropriately scaled approaches and short cut methods to reduce transportation modeling time and cost while providing adequate estimates of traffic volumes and impacts. Methods developed during Phase II research for medium size communities include synthetic estimation of through trips, synthetic estimation of external trips, and quick response travel models. Of particular interest are simplified submodels for trip generation, trip distribution, and mode choice. Also, the research developed innovative submodels for pedestrian, bicycle and transit trip generation that depend on land use characteristics. Guideline matrices and decision trees, which follow on subsequent pages of this Executive Summary, help the analyst select appropriate models, tools and data bases that are compatible with the community being evaluated. Case studies demonstrate the guidelines, methods, tools and data bases.

Future studies that apply the guidelines and models developed by this research will broaden the experience with the new tools.

Table ES-1, Part I. TDM Guideline Matrix: Data for Travel Demand Models

Categories A and B are documented in the Phase I report. Categories C and D are in this Phase II report. Category E Regional models are custom efforts and are not addressed by these guidelines. Phase I Appendices (I-), Phase II Appendices (II-).

Category	Size	Issues	Community Characteristics	Data, Rates, Parameters	Data Sources	Network Complexity / Zones	Tools () ~ Appendix
A (Phase I)	< 5,000	Economic Development, New Roads, Truck Traffic; Community & Environmental Impacts, Hazard Mgt.	Income Level; Rural, Fringe; Vacation, Retirement; Industry; Attractions; Regional Center; CBD Vitality; Growth Rate; Nearby Interstate or Other TIP Projects Outside Study Area; Size & Type of TIP Improvements; RPO; No MPO	Default NC Rates (I-H); Rates derived from 2001 NHTS (rural part); Rates derived from the rural sub-sample of NC MPO surveys	Census CD 2000 Short Form Blocks; USGS GIS; CTPP; Amer. Fact Finder; Google Earth; FEMA, aerial photos, NC Demographics office	Major Roads; Census Blocks or User Defined TAZs Coarse zones, no more than 5 – 10 and the major roadway system.	CSS (I-A); GIS Land Supply (I-B); Trend Line (I-C); Manual Travel Allocation (I-D)
B (Phase I)	5,000 – 10,000	Cat A +; New Bypass	Cat A	Cat A; NCHRP 365 for fringe area (I-H)	CTPP, Census, GIS, Data Sources Table	Cat A + Streets, Census Tracts or User Defined TAZs Number of zones should range between 10 and 15. Roadway system should reflect major roadway system plus important connector routes.	TransCAD* NC QR (I-E); CSS; GIS
C (Phase II)	10,000 – 50,000	Cat B +; CBD Revitalization;	Cat A + Suburbs; RPO; No MPO	Default NC Rates (II-C,D), NCHRP 365 for fringe area (I-H)	CTPP, Census, NCHRP 365, Data Sources Table (I-E-1)	Cat B + bus transit Guidelines on network selection and zone compatibility.	TransCAD NC CSS (I-A); QR (II-D); GIS (II-C,F,H)
D (Phase II)	> 50,000 (MPO)	Cat B+; Bus Transit, Air Quality + Federal Planning Requirements; TIA of Special Generators	Cat C; MPO	Local Data, Surveys, Default NC Rates, NCHRP 365, 2001 NHTS; Comprehensive Plans, Zoning Maps, Emission Factors.	CTPP, Surveys, Planning Department or Agencies, EPA, Data Sources in Tables I-B-1, I-E-1	Cat C See guidelines	TransCAD (II-D), CSS (I_A); GIS (II-C,F,H); 2-D (II-C); LUC (II-C); Land Use Scenarios (II-H)

E	Regional	Cat B+; CBD & Area Development; Interstate Loops; Rail Transit	Cat D for All Communities in Region; Homogeneous Region; Multi- Nucleated Region; MPO	Local Data, Surveys, Comprehensive Plans, Zoning Maps, Emission Factors.	Surveys, Data Sources Table	Cat C + rail transit See guidelines	TransCAD; CSS; GIS; Custom tools & methods
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* TransCAD or other mainstream commercial four-step package

Table ES-1, Part II TDM Guideline Matrix: Sub-models for Travel Demand Modeling

Categories A and B are documented in the Phase I report. Categories C and D are in this Phase II report. Category E Regional models are custom efforts and are not addressed by these guidelines. Phase I Appendices (I-), Phase II Appendices (II-).

Category	Size	Land Use () ~ Appendix	Trip Generation () ~ Appendix	Trip Distribution () ~ Appendix	Mode Choice () ~ Appendix	Network Assignment () ~ Appendix	External Trips () ~ Appendix	Tools () ~ Appendix
A (Phase I)	< 5,000	Comprehensive Plan; Land Supply Analysis (optional); (I-B)	US or NC Average Rates; If low income use US rates; If high income use NC rates; NCHRP 187 or NCHRP 365; CTPP Rates; Local Survey Rates; Consider 1 or 2 Trip Purposes; Consider NHB2; (I-H)	Distribute manually (spreadsheet) based on total employment; (I-D, I-F)	TCRP B3 for Demand Responsive Transit; (I-J)	Trend Line & Growth Factor Ratio Forecast for Single Routes; Manual Travel Allocation for Simple Nets; (I-D)	Manual Travel Allocation; Synth; (I-G) Consider all external trips are through trips	CSS (I-A); GIS Land Supply (I-B); Trend Line (I-C); Manual Travel Alloc (I-D,I-F); NuSynth (II-A); NC rates (I-H); Distr (I-I); Transit (I-J); Assig (I-E); External Trip Model (II-B)
B (Phase I)	5,000 – 10,000	Cat A; Land Supply Analysis; (I-B)	Cat A; If fringe, use Metro Rates; (I-H, II-D)	Mean travel time from skims and zone-zone travel times; (I-E, II-E)	Cat A, GIS Analysis; (I-J, II-F)	QR Stochastic Method Daily; (I-E)	Synth with local adjustments (I-E) or NuSynth (II-A); External Trip Model (II-B)	Cat A tools or NC QR (I-E)
C (Phase II)	10,000 – 50,000	Cat A + Land Supply (I-B) Analysis; Land Use Scenarios (II-H)	Cat A or Local Rates from Survey; Use 3 Trip Purposes (II-D); Land use & non-auto modes (II-C)	Cat B; Gravity Model (II-E)	Cat B and Mode Split Factor if Fixed-route Transit (II-F)	All-or-nothing; QR Stochastic Method Daily (II-G); QR User Equilibrium; Daily assignment (II-G)	Cat B & (II-B)	Cat B
D (Phase II)	> 50,000 (MPO)	Cat C; Concentric Zone Model; Sector Model	Local Rates from Survey (II-D); Fringe rates (I-H); Land use & non-auto modes (II-C); NCHRP 365 rates; Rates derived from 2001 NHTS; Use 3 trip purposes or more; Apply time-of-day if necessary	Cat C; Destination Choice if local survey data available; Gravity Model (II-E)	Cat C or MNL Model with TransCAD (II-F) if local survey data available	User equilibrium method with 1or 2 hour peak (II-G); Time-of-day assignment (II-G); TD-TA feed back loop (II-G)	Cat C; External Station Survey (II-A; II-B)	Cat C ; 2-D (II-C); LUC (II-C); Land Use Scenarios (II-H)

E	Regional	Cat C + Land Use Models; Metro PIng; Multiple Nuclei & Polycentric Model	Cat D	Cat D; Validated by regional survey data	TransCAD, MNL (II-F) (Nested Logit Model preferred)	User equilibrium method; Time-of-day; Multi-class multi-modal assignment (MMA); Hourly or peaks; TD-TA feedback loop	External station survey; Separate AON or MMA assignment (combined with auto trips) for commercial vehicles	
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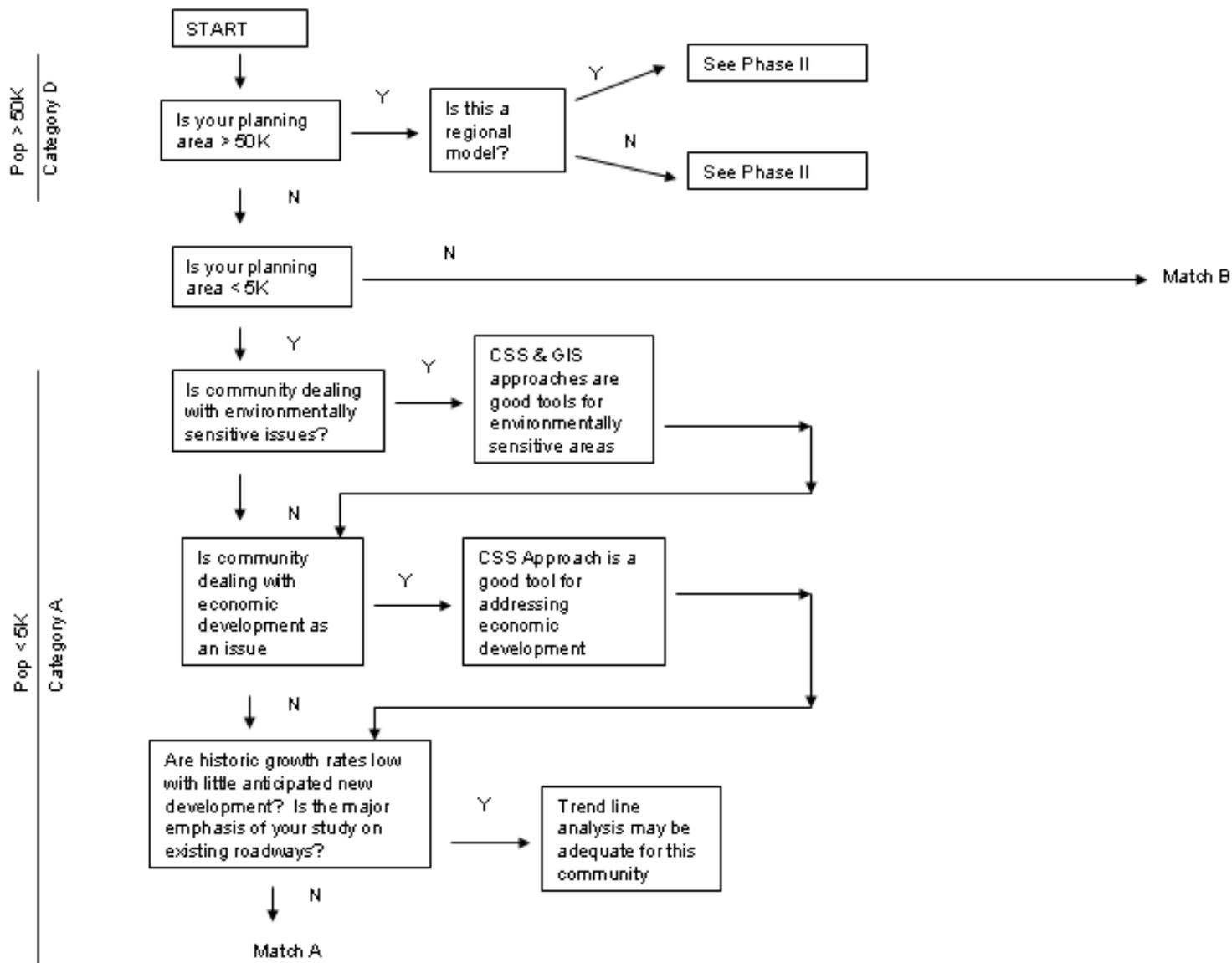
Table ES-1, Part III: TDM Guideline Matrix: Reasonableness Checks in TDMs

Categories A and B are documented in the Phase I report. Categories C and D are in this Phase II report. Category E Regional models are custom efforts and are not addressed by these guidelines. Phase I Appendices (I-), Phase II Appendices (II-).

Category	Size	Land Use Data and Transportation Networks	Trip Generation	Trip Distribution	Mode Choice	Network Assignment	Validation Targets	Tools ()~Appendix
A (Phase I)	< 5,000	Compare Land Use Results for Manual Travel Allocation to Land Supply Analysis	NCHRP 365 rates; NC average rates	Professional judgment; 2001 NHTS or NPTS average trip lengths for rural areas	Professional judgment	Traffic counts/ Professional judgment	NC Guidelines	(I-B) (I-C) (I-D)
B (Phase I)	5,000 – 10,000	Overall visual inspection on speed ranges, capacity ranges, and facility types. Check network connectivity, missing nodes, missing links, one-way links going the wrong direction. Use minimum path checks for coding errors. Review traffic counts using measures such as volume per lane and historic growth rates. Perform land use data checks at the zonal, regional, and aggregate levels. Review land use variables, population / household ratio, population / employment ratio, and plots of densities and density changes for future year data.	Ratio of unbalanced Ps and As should be between 0.9 and 1.0. Review percent of trips by purpose and compare to typical ranges outline in Table I-E-3.	Cat A plus Plot average trip length distribution for each trip purpose and review based on your knowledge of the area. Review average trip length by trip purpose. Review modeled VMT against HPMS data	Compare mode splits to those reported for your county or community from the US Census long form data or CTPP data.	Traffic count data that has been validated and VMT data if available. For recommended data summary checks refer to Validation Targets column for recommended references.	<i>Calibration and Adjustment of System Planning Models</i> , FHWA 1990; <i>Model Validation and Reasonableness Checking Manual</i> , TMIP June 2001	(I-E) (I-H)
C (Phase II)	10,000 – 50,000							(I-E) (II-D) (II-G)
D (Phase II)	> 50,000 (MPO)		Cat C; Validated by local household survey data or compared with NCHRP 365 rates; Compare trip rates estimated from different methods (e.g. 2-D, LUC, NCHRP365, NC QRM, TransCAD QRM).	Cat C; Validate trip length distribution survey derived from 2001 NHTS or local household survey, CTPP trip lengths for work trips, and CTPP work flow data; Compare district-to-district flow survey data	Cat C; Validated by household survey data; Compared with NCHRP 365 national default shares; Check against NHTS mode shares for small MPOs	Cat C; plus screen line, cut lines, and/or cordon line validation; federal % deviation by functional class; and volume group; R ² ; mode congested travel times vs. field surveys.	Cat C	(I-E) (II-D) (II-G)

E	Regional		Cat D	Cat D	Cat D, plus validation by local household survey data & transit on-board survey data (if available)	Cat D	Cat C	
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Figure ES-1. Decision Tree for Category A (0 < Population < 5,000)



Pop < 5K
Category A

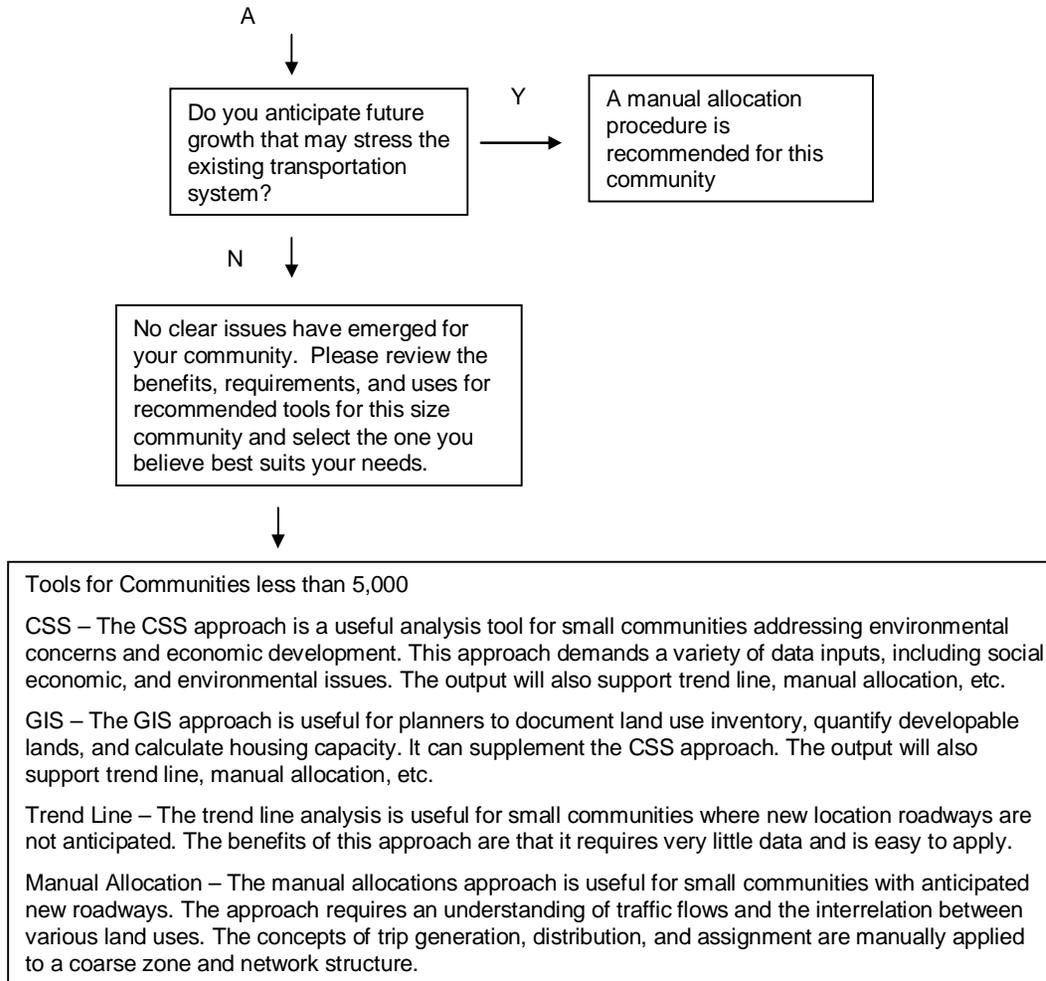


Figure ES-2. Decision Tree for Category B (5,000 < Population < 10,000)

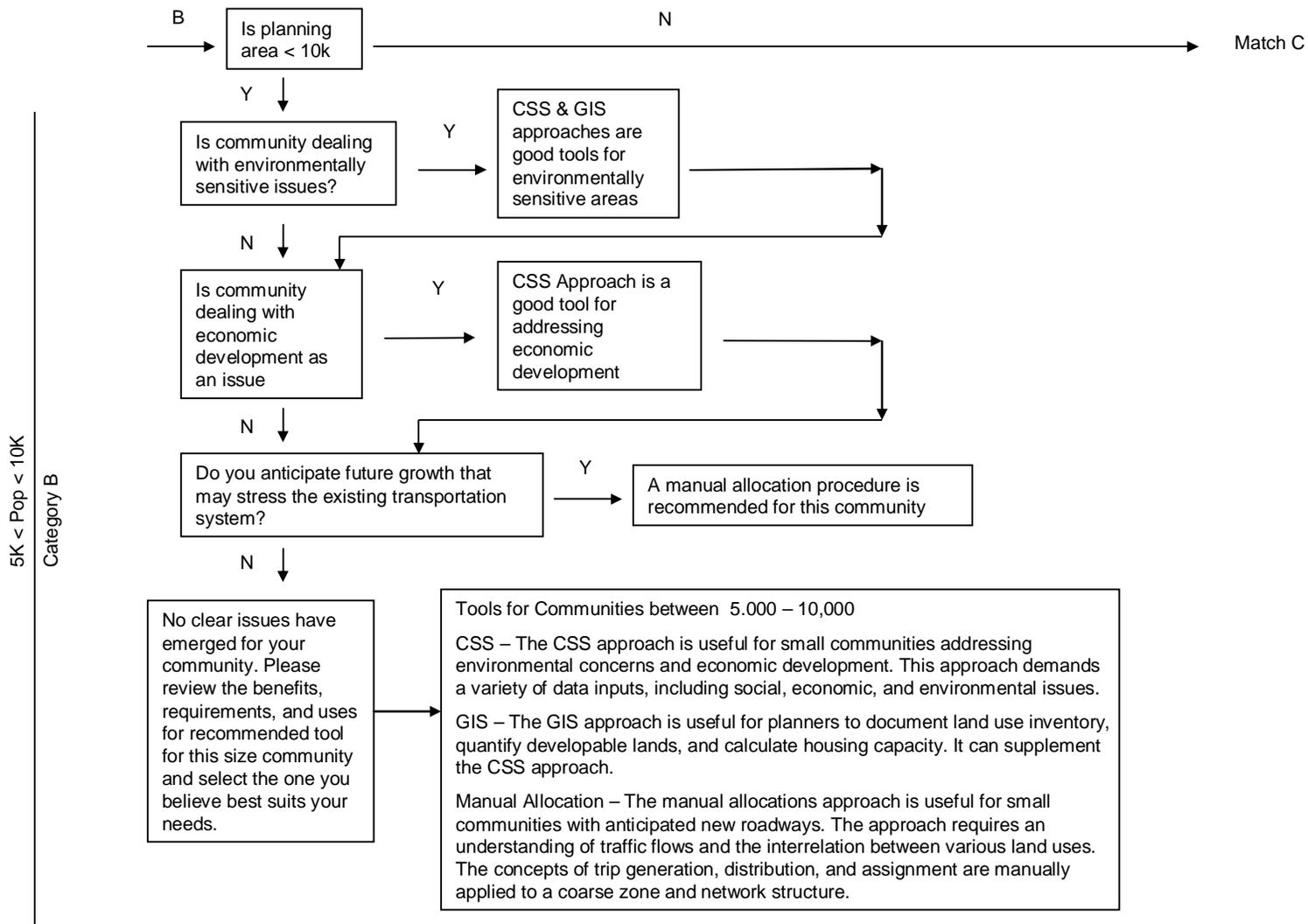


Figure ES-3. Decision Tree for Category C (10,000 < Population <50,000)

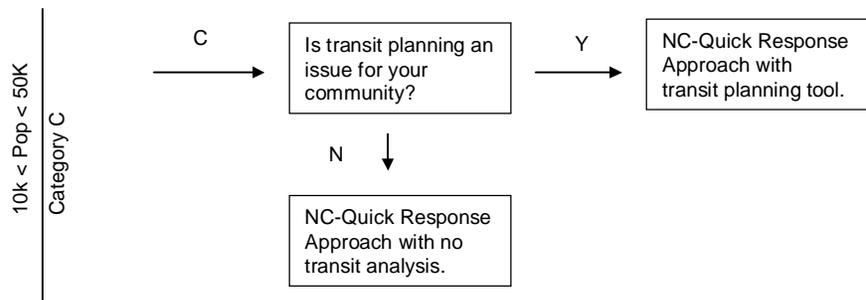
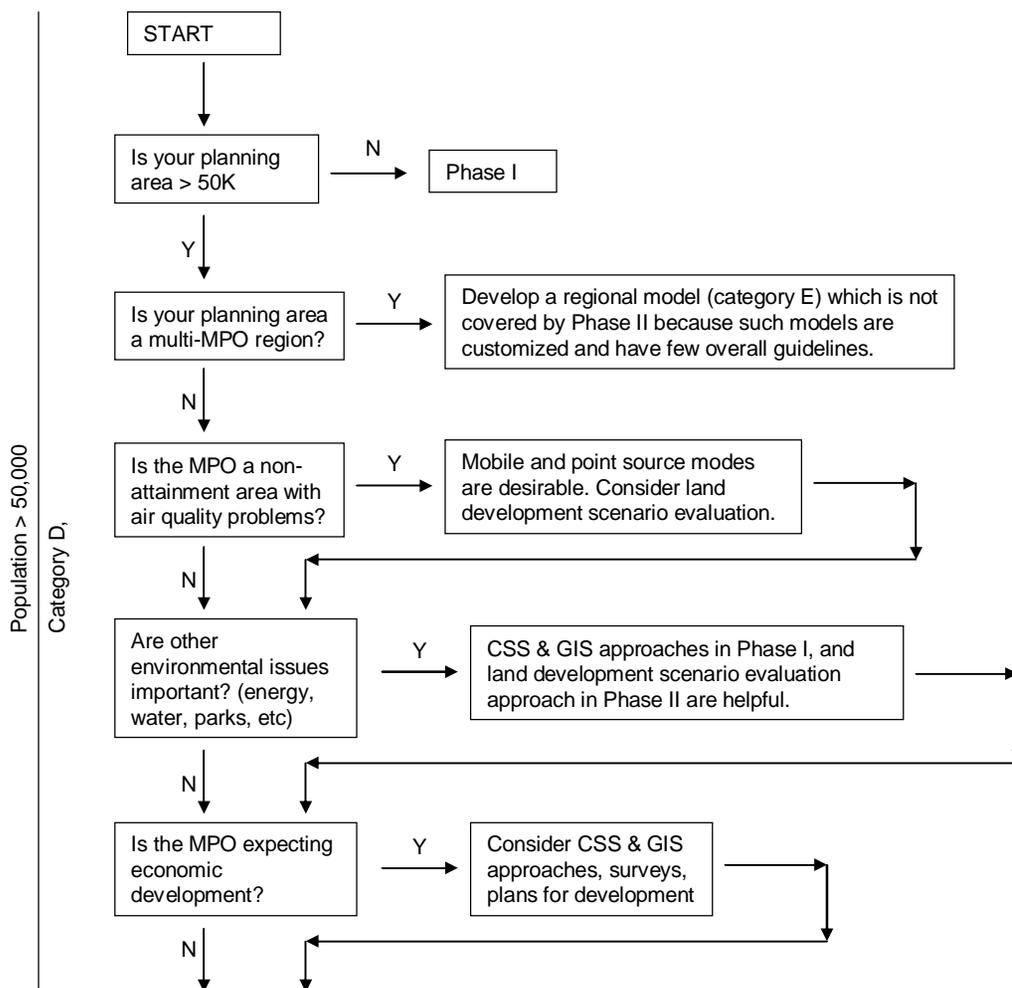
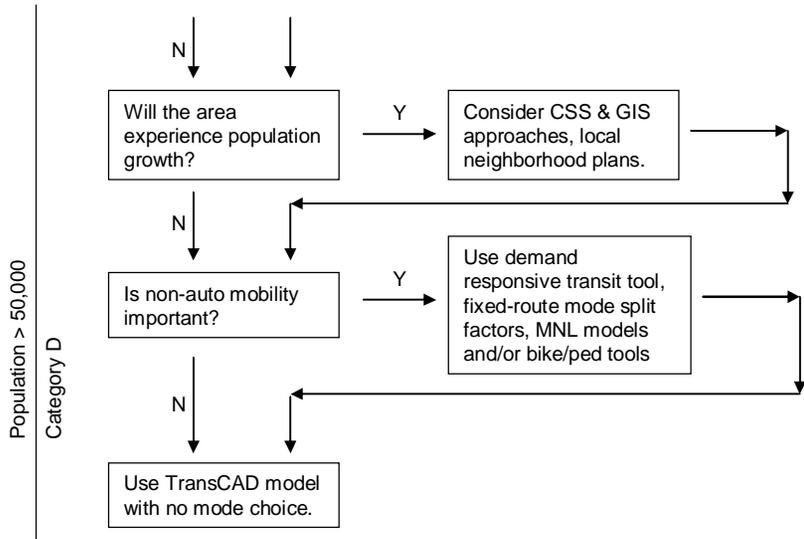


Figure ES-4. Decision Tree for Category D (Population > 50,000)





CHAPTER 1: INTRODUCTION

Background and Relationship to the Phase I Report

The transportation planning process is intended as a rational paradigm to furnish unbiased information about the effects that proposed transportation projects will have on a community and on its expected users. Depending on the complexity of the community and the transportation system, the planning process, especially the modeling aspects, can become expensive and time consuming. The overall goal of this research is to develop guidelines for choosing and using appropriate models – models that are sized to fit the complexity of the transportation-planning problem.

With the accelerating growth of highway and other transportation modes, increasingly complex problems of wide interest to transportation authorities have arisen during recent decades. In recognition of the challenges, the Federal Aid Highway Act required that all transportation projects in urbanized areas with populations of 50,000 or more be based on the 3-C (continuous, comprehensive, and cooperative) planning process [1]. Outlining and consolidating the significant factors and issues which are closely related to travel forecasting, other federal legislation (such as the 1990 Clean Air Act Amendments (CAAA), the 1991 Intermodal Surface Transportation Equity Act (ISTEA) [2] and Transportation Equity Act for the 21st Century (TEA-21) of 1998 [3]) emphasize the need for multi-dimensional transportation planning. According to these acts, local plans, community values, development goals, land uses, environmental issues and regional commitment, as well as multi-modal transportation options, should be incorporated into the transportation planning process. The extent to which these various elements are included in the modeling process depends on the size and complexity of the community.

As noted in the Phase I report [4] of this research project, states follow different policies when developing travel models for transportation plans. Notably, North Carolina develops models and plans for all municipalities regardless of size. Most states, however, develop models only for MPO-size areas (populations 50,000 and greater) and for multi-MPO regions. Such models use a full “four-step” simulation – trip generation, trip distribution, mode choice and travel assignment. For smaller than MPO-size areas, most states rely on corridor level and project level traffic forecasting models which are typically based on simple time series methods.

To address the transportation system needs in various sized communities in North Carolina, the North Carolina Department of Transportation (NCDOT) forecasts future travel including trucks, automobiles and transit vehicles. Some models include pedestrians and bicycles. NCDOT professionals also examine the effects of land use plans and patterns on the transportation system. The largest travel demand models developed and used by NCDOT are multi-MPO regional travel demand models that use the “traditional” four-step planning process. In recognition of the synthesis of travel demand models with GIS tools, NCDOT has developed specialized display tools for transportation planning to make model development more efficient and less costly. Several years ago NCDOT converted their regional models from Tranplan to the more powerful and efficient TransCAD. To meet varied planning needs, concerns and missions in different NC communities, NCDOT professionals develop city and community transportation models, and special sub-models to for the modeling process, especially for larger study areas [4, 5].

By state statute NCDOT must develop transportation plans for all NC communities, not just MPO and regional areas. Thus, many resources are devoted to smaller cities. To improve the results of the planning process for all NC communities while making it a more efficient and less time consuming process, as the Phase I report [4] pointed out, NCDOT professionals must select appropriate methods and tools in terms of a community’s specific size, needs, features, and development throughout the analytical and outreach activities of the transportation process. Since traditional and expensive modeling is generally more suitable to large communities and relatively little national guidance exists for transportation plans for

communities under 50,000 population, NCDOT needs guidelines and simplified travel demand models for small NC towns and cities.

In the first Phase I of this multi-year project, the research team developed NC travel demand modeling guidelines for small towns and cities with populations less than 10,000. Phase I includes two city categories in terms of population: Category A (population less than 5,000) and Category B (population between 5,000 and 10,000). Using the U.S. census and North Carolina database, case cities in the A and B Categories were used to examine the methodology of context sensitive solutions (CSS), trend line analysis, sketch-planning/quick response methods, and GIS tools that allow integration of multiple factors that affect community travel. The Phase I best modeling practices for small communities in Categories A and B include data sources, sub-models and reasonableness checks. They are summarized in the main products of Phase I - the TDM guideline matrix and the decision tree [4]. The matrix and decision tree are repeated in the Executive Summary of this Phase II report. This report expands the matrix and model decision guidelines to include larger cities - Category C (population 10,000 – 50,000) and Category D (MPO, population greater than 50,000). Guidelines for Category E (multi-MPO regions) are not included because models for multi-MPO areas are custom, one-of-a-kind developments that depend on the unique issue of the region, not generalized guidelines related to population size.

Problem

Various issues in urban areas include air quality, economic development, population growth, neighborhood access and identity, mobility, the environment, etc. To address such a variety of issues in communities of varying sizes and complexity, the NCDOT planning process must be flexible and efficient. In the past NCDOT has accomplished virtually all its own community modeling, impact assessments, and plan evaluations in-house with high level tools that require large investments of resources for all communities. As discussed in the Phase I report [4], the current heavy planning responsibilities and the expectation of increasing future responsibilities have forced NCDOT to consider other options to accomplish its mission. NCDOT transportation planning options include:

1. Continue to develop most all transportation models in-house.
2. Sub-contract model development and plan evaluation for some communities to outside agencies and consultants.
3. Develop partnerships to accomplish modeling and transportation system evaluation.
4. Develop and use a variety of appropriate transportation sub-models and tools that fit the size and needs of communities.

Option 1 will continue. Option 2 has not been pursued. Option 3 is viable and practiced for the Triangle Regional Model (TRM) and the Metrolina model. The TRM Service Bureau at NC State University Institute for Transportation Research and Education has successfully operated for four years with contributions from the local MPOs. The Metrolina model is developed and applied by the NCDOT Research Group in collaboration with Charlotte area MPOs.

Option 4 is the subject of this research – develop guidelines, tools and methods to choose and apply efficiently to communities of various sizes and issue complexity.

As mentioned above, different modeling options were examined and evaluated through case studies in Phase I based on the planning guidelines developed for urban category A and B [4]. In addition, modeling guidelines were proposed for larger NC communities. In this Phase II report, the proposed guidelines and tools for larger communities and MPOs are developed applied to case studies. The Phase I travel demand model guidelines matrix will be updated by new results and findings.

Research Scope and Objectives

This multi-year research project has two phases. As proposed at the beginning of the research project, the urban areas were divided into five categories in terms of urban population:

- Category A: population < 5,000
- Category B: 5,000 < population < 10,000
- Category C: 10,000 < population < 50,000
- Category D: population > 50,000 (MPO)
- Category E: multi-MPO region

Phase I focused on smaller areas with population less than 10,000 (Category A and B). Phase II studied Categories C and D which include medium communities as well as MPOs in North Carolina. Category E was not considered in Phase II because regional models are generally custom models. Since Phase I has an independent technical report, this report will only address the research efforts conducted in Phase II.

The objectives of the Phase II travel demand model research are:

- To improve and simplify the on-going conventional planning process for larger urban areas (population greater than 10,000) in North Carolina.
- To develop guidelines and tools for best modeling practices for medium communities and MPOs in terms of their needs and issues regarding transportation, economic development and environment, and other considerations.
- To continue to test the option of developing long term partnerships for research and transportation demand modeling using North Carolina expertise and data sets.

As in Phase I, the Phase II research built upon previously successful project relationships among NCDOT, NC State University, the University of North Carolina-Chapel Hill, and the TRM Service Bureau.

Chapter Summary

The North Carolina Department of Transportation (NCDOT) primarily develops and uses long range, traditional four-step regional travel demand models for most NC communities regardless of their sizes and needs. This approach is complicated, data intensive and time consuming, and it is not the most efficient method in many cases, especially for smaller communities. The goal of this Phase II travel demand model research is to improve and simplify the conventional NCDOT modeling process while making it a more efficient and less time consuming process for medium and larger communities, as well as MPOs. To achieve the objectives, various sub-models and tools are developed to improve trip generation, trip distribution, mode choice and trip assignment. The cost-effective tools in such a “tool box” can be selected by planners based on community size and needs.

Chapter 2 of this report reviews the literature to determine the state of current practice for travel demand modeling in medium communities and MPOs. Chapter 3 presents recommended guidelines in matrix format and in a decision tree. The Chapter 3 decision tree and matrix of guidelines updates those presented in the Phase I report. Chapter 4 develops special tools and sub-models for communities with populations greater than 10,000 people, and Chapter 5 states conclusions and recommendation resulting from the research and case study applications. A set of detailed appendices develop tools and sub-models, and illustrate the recommended guidelines for two medium communities and a MPO region.

CHAPTER 2: LITERATURE REVIEW

Introduction

The NCDOT *Multi-Year Travel Model Research* has two phases: Phase I studies travel estimation methods for small communities with populations less than 10,000, and Phase II focuses on methods for medium communities with populations greater than 10,000 and on MPO areas with populations greater than 50,000. The travel demand models for larger urban areas are mostly based on the conventional planning processes with four major steps including trip generation, trip distribution, mode choice and trip assignment, which have been fully studied for many years. This chapter reviews travel demand modeling principals and methods developed by USDOT and other agencies. The discussion is organized according to the four steps in the conventional travel demand modeling process.

Trip Generation

Research on trip generation estimation usually addresses internal auto trip models for small and medium communities. However, external trips, through trips and internal trips by alternative modes are relatively overlooked. In Phase II of this project, the research team developed or improved special trip generation estimation methods for special trips.

External and Through Trips

The most widely used through trip model was developed by Modlin [6] based on external station surveys conducted in the early 1970s for small communities in North Carolina. The methodology estimates through trip patterns by using highway functional classification, average daily traffic (ADT), percentage of trucks, route continuity, and urban areas population. Based on Modlin's work, *NCHRP Report 365, Travel Estimation Techniques for Urban Planning* [7] selected and reprinted a set of his models to serve as the through trip estimation technique for small urban areas. Subsequently NCDOT developed a computer program based on Modlin's work for efficiently forecasting through trips. The program is known as SYNTH [8]. In recent years, new research has attempted to update the dated through trip models. Anderson [9, 10] found that Huff's probability contour model (1963) is useful for through trip estimation when it met certain specifications. His alternative methodology revealed that the surrounding context of the planning area actually affects through trip patterns. Anderson [11] also developed a through trip methodology based on new survey data and the multiple regression analysis of community characteristics, facility type, and economic factors. Horowitz and Patel [12] improved the method for through trip tables by creating a new approach to account for geographic characteristics of the study area.

Similar to through trips, external trips (internal-external and external-internal trips) were not systemically studied. Due to the complexity and uncertainty of external trips in different regions, external trips are usually determined based on local surveys. The only external trip model appearing in available literature was developed by Modlin [13]. It is a regression model to estimate internal-external and external-internal split based on socioeconomic characteristics of planning area.

The external and through trip models reviewed above were developed for applications in small urban areas with populations less than 10,000. Care must be taken for larger areas, and, indeed, external station surveys are preferred if resources are available.

Internal Trips

A number of existing studies have provided empirical evidence that internal travel demand is influenced by both land use factors and socioeconomic characteristics [14]. Among integrated land use and internal trip models, the most popular model is the 3-D model developed by Cervero and Kockelman [15]. They popularized a concept of the "three D's" measurement—density, diversity, and

design. Density measures typically include both population and employment densities; diversity measures often are indicators of land use mix; and design measures are mostly concerned with the street network.

Besides the continuous efforts in developing new measures within various land use sub-dimensions, recent research has been making progress in applying statistical methods to land use measurements [16]. Examples include factor analysis and cluster analysis. Factor analysis is used to combine all the underlying land use features into composite measures [17, 18]. The idea of using composite measures is to capture the collective effects involving multiple land use indicators, as well as to avoid multi-collinearity problems in model estimation. Cluster analysis aims at reducing the multiple measures into a few neighborhood typologies [19]. This method classifies neighborhoods into different types based on the quantitative measures. The identified neighborhood types can then be used to examine the neighborhood effects on internal travel demand.

Several extensive literature surveys are already available in summarizing the connection between land use and internal trip generation [14, 20, 21, 22]. Shay, Khattak, and Spoon (2003) specifically conducted a synthesis of literature on walkability, which surveyed the literature on walkability (environment) and walking activity (behavior), offered a descriptive hierarchy of walkable environments, and suggested areas for further research.

Trip Distribution

The gravity model is the most commonly used trip distribution method, and it has been fully documented in many references. Its use is satisfactory in many cases ranging from small communities to large multi-MPO areas. Recent studies [23, 24, 25] have found, however, that the gravity model (which is based on relative zone attractions, productions and impedances, and special zone-to-zone adjustment factors like friction factors and K-factors) inadequately describes why travelers make a particular destination choice. This is especially true for special generators destination choices which depend on factors based on employment, shopping and other purposes besides travel impedances and opportunities.

Recent studies show that destination choice methods (DCM) are worthwhile when data are available [26, 27, 28, 29]. While the gravity method is aggregate, the destination choice method is disaggregate in nature. Compared to the gravity model, the destination choice model accounts for more explanatory variables including traveler behavior, personal characteristics, and zonal measures; and it does not require friction factors or special adjustment factors. The family of destination choice models includes probit, general extreme value, logit, and mixed logit models. In the 1960's discrete choice models concentrated on mode choice travel choices using simple binary logit models [30, 31]. It was not until the 1970's that other travel choices were analyzed using enhanced closed form logit models such as the multinomial logit (MNL) model [32, 33, 34]. Recently, much attention has focused on mixing logit models over an observed distribution. One such model is the mixed multinomial logit (MMNL) model, and this model has shown to be advantageous in several studies [35, 36, 37, 38, 39]. The MMNL model is the same as the MNL model except that the parameters are randomly distributed over the observed data. Since the MNL model has multiple explanatory variables used to describe the choice of destination and it estimates the conditional probability of a trip maker choosing a destination, it is more behavioral than the gravity model and is able to account for additional factors such as individual characteristics and destination characteristics that affect travel decisions. This is especially true for unique land uses such as shopping centers, universities, and airports.

Guidelines for applying distribution models and examples are presented later in this report.

Mode Choice

Mode choice analysis is the most complex of the modeling steps and in the last decade much of the research and advancement in travel demand models has related to this step [7]. Depending on the level of detail required, four types of transit estimating procedures are used:

- 1) Sketch planning;
- 2) Direct generation of transit trips;
- 3) Use of trip end models;
- 4) Trip interchange modal split model.

For those areas with relatively low transit use and good land use characteristics that are highly correlated to transit ridership, Geographic Information Systems (GIS) models and multiple linear regression models can be efficiently used for sketch planning and direct generation of transit trips. The trips may not be loaded to the network because they are few in number, and transit may primarily represent mobility for social service clients.

Trip end models follow trip generation and precede trip distribution. While not often used, they may be found in some small community models for primarily social service transit. Since they are custom models depending primarily on local socio-economic characteristics, they cannot predict future demand changes as service level changes. They cannot be transferred to other communities.

Most mode choice models are trip interchange mode split models that use the logit formulation. The formulation commonly includes the simple multinomial logit (MNL), incremental logit (pivot point), and nested logit models. The multinomial logit and nested logit formulations are used to estimate mode shares for transit strategies, and they require a comparative description of all modes of available or proposed including highway, HOV, and transit. Mode choice models are data-intensive. The incremental logit formulation allows for analysis of transit improvement strategies or policies without the complete simulation of the entire transit system and its alternatives [7], thus it is the most transferable mode choice model. A limitation of this approach is that it cannot be used to estimate transit use in an area that does not have existing transit service and patronage.

Alternative choices for mode choice models are discussed and demonstrated in subsequent sections of this report.

Trip Assignment

Basically, trip assignment includes both highway and transit assignment of vehicles or person trips. According to the level of analysis, the assignment can be to a regional highway and transit network or to a detailed network for a sub-area or corridor study. The commonly used network assignment algorithms for travel demand modeling include:

- 1) All-or-nothing (AON)
- 2) Capacity restraint
- 3) Equilibrium
- 4) Stochastic

The Phase I report presented the details of these assignment algorithms.

In recent years, specific attention has been given to how speeds are estimated and subsequently used in the travel forecasting and emissions estimation process since vehicle emission rates are affected by vehicle speed. For advanced and complicated regional travel demand modeling practices in many areas, especially non-attainment areas, the Clean Air Act Amendments of 1999 (CAAA) and subsequently issued guidelines require that speeds used in travel demand forecasting process must reflect real conditions observed on the road and be reasonably consistent throughout the modeling process. However, it has not been unusual to find different models for speeds (and travel times) used in different parts of the process.

COMSIS Corporation developed a methodology for introducing feedback into the traditional four-step process by using an iterative process through all of the steps until the process converged to a stable set of link speeds [40]. By using the feedback loop the initial minimum path travel times and impedance factors between zones are replaced by more typical loaded path travel times and factors developed after traffic assignment. TRB recently conducted a nation-wide survey of the state-of-the-practice in travel demand forecasting in metropolitan areas [41]. This assessment showed that over 80% of large MPOs and about 40% of medium MPOs feed back congested travel times to distribution and mode choice steps. For some advanced and complicated regional travel demand models, a feedback loop between trip distribution and trip assignment is usually carried out to achieve a more satisfactory assignment result [42, 43]., that is, the feedback process results in higher network speeds, shorter travel times, and lower volume-to-capacity ratios. However, modeling experience in Florida [44] indicates that there is not sufficient evidence to support a significant benefit from the feedback process to model accuracy.

Subsequent sections of this report provide guidelines for applying alternative assignment models, document the common concerns for introducing feedback, and present examples in the appendices.

Chapter Summary

This chapter reviews travel demand models in terms of the four steps: trip generation, trip distribution, mode choice and trip assignment. Characteristics of the models for the steps are discussed to provide a direction for discussion in the subsequent chapters. Specific four-step model application guidelines and examples are provided in the appendices.

CHAPTER 3: TDM GUIDELINES FOR MEDIUM COMMUNITIES AND MPOS

Introduction

The primary goal of this research project is to develop guidelines and tools for best travel demand modeling (TDM) practices for different sized NC communities consistent with their features, needs and concerns [4]. During the study, we defined five distinct categories for urban areas in North Carolina:

- Category A – population < 5,000
- Category B – population between 5,000 and 10,000
- Category C – population between 10,000 and 50,000
- Category D – MPOs with population > 50,000
- Category E – Multi-MPO regions

In Phase I of this project, small communities (Category A and B) were studied. A variety of sources and project research developed sub-models, tools, and reasonableness checks for small communities. Summary guidelines for the best practice of these methods were summarized by using two displays: a travel demand model (TDM) guideline matrix and a TDM Decision Tree. The details of the TDM guidelines for small communities given in the Phase I final report [4].

In Phase II we expended the research to include two more categories for urban areas in North Carolina: medium communities (Category C) and MPOs (Category D). Multi-MPO regions (Category E) were not studied because they represent specific custom models that must be tailored to a specific area.

The Phase II research methodology follows the common travel demand modeling steps: data collection, network development, trip generation, trip distribution, mode choice, trip assignment and impact analysis. TDM Guidelines for NC medium communities and MPOs are developed by integrating research findings for each modeling step in these areas in terms of their scope of needs and population sizes. This chapter will repeat the results of the Phase I matrices and decision trees of guidelines for best practice for smaller communities (Category A and B), and it will update the matrices and decision trees for medium size and MPO communities (Categories C and D).

It is noted that Category E multi-MPO regions are out of scope of this research since the research team believes, and the NCDOT Research Project Steering Committee concurred, that models for multi-MPO regions are custom models that depend on unique study area circumstances and that guidelines for such models are beyond the scope of this research.

In this chapter, the **TDM Guideline Matrix** includes three parts described as below:

- TDM Matrix Part I summarizes community characteristics, data and parameters, data sources, network complexity and zones, and TDM approaches;
- TDM Matrix Part II presents sub-models for travel demand modeling, including land use, trip generation, trip distribution, mode choice, network assignment, and external trips;
- TDM matrix Part III introduces reasonableness checks for the TDM four-step approach. The matrix summarizes various methods and techniques for validating and calibrating the land use model, trip generation, trip distribution, mode choice, and network assignment.

Columns in the three TDM matrices refer transportation engineers and planners to appendices in this report for detailed case study applications of the various TDM analysis tools.

The **TDM Decision Tree** recommends sequences and choices for model the five urban categories according to their populations, needs and issues related to transportation.

The TDM guideline matrix and the decision tree are shown in Table 3-1 and Figure 3-1, respectively.

Matrices for TDM Guidelines

Category A: Small Community Guidelines (Population < 5,000)

See the Phase I report for details.

Category B: Small Community Guidelines (5,000 - 10,000 population)

See the Phase I report for details.

Category C: Medium Community Guidelines (10,000 – 50,000 population)

Typically, communities in this category are Rural Planning Organizations (RPO) and non-MPO areas that potentially have economic and population growth. They may anticipate congestion on their community network of streets and thoroughfares. Congestions may be evident in the central business district (CBD) especially if “Main Street” is a highway through town. A new bypass is usually foreseen to as the solution to main street traffic problems.

In medium communities with populations between 10,000 and 50,000, local transportation survey data is desirable, but not necessary, for the travel demand forecasting. **Working data** for developing a travel demand model in these medium sized communities may come from the U.S. Census Bureau, Census Transportation Planning Package (CTPP), NCHRP Report 365, Highway Performance Monitoring System (HPMS), Travel Model Improvement Program (TMIP), Federal Emergency Management Agency (FEMA), the NCDOT Traffic Engineering Accident Analysis System (TEAAS), and the NC Demographics Office. In addition, Table B-1 and B-2 in the Phase I report have additional summary tables for data sources for land use and GIS analysis.

Since transit ridership is low in most medium size communities, a traditional three-step travel demand model is an accepted and efficient approach. In advance of the tradition trip generation, distribution and assignment steps, a new **through trip model** (Appendix A) and a new **external trip model** (Appendix B) help start this TDM approach for medium sized communities. The through trip and external trip models replace the usual cordon surveys. Accurate estimates of through and external trips are important because they account for a considerable portion of the total trips in small and medium urban areas – up to 30% or more.

For **trip generation** estimation, a quick response approach with default North Carolina trip rates (Appendix D) produces acceptable results. This cost-effective approach does not require local survey data.

The gravity model (Appendix E) is recommended for **trip distribution** step. Assuming that trips distribute according to travel time, it is acceptable to use average travel times from the zone-to-zone minimum path matrix to estimate initial friction factors. This simplification avoids iterative calibration procedure and expensive travel surveys.

Mode choice is an optional step for medium communities. Usually there is a low ridership demand responsive system for seniors and people with disabilities. And a low ridership fixed-route system may operate, but transit demand is too low to affect roadway traffic volumes. If necessary, the GIS planning tool (Appendix F) can be used for small and medium communities to identify areas that have a relatively high propensity for transit ridership.

The stochastic **assignment** algorithm (Appendix G) is appropriate for the trip assignment step in a medium city travel demand model. The daily traffic assignment yields acceptable results, and it is easy to use.

Model **validation and reasonableness checking** should occur at each step of the TDM process – definition of zonal land use data, development of the highway network and TAZ structure, estimating through and external trips, generating internal trip, distributing trips, and assigning trips. Model validation and calibration are iterative processes and each TDM step may need to be revisited several times until validation or calibration targets are met and a robust model is achieved.

Category D: MPO Guidelines (population > 50,000)

With more than 50,000 people MPOs generally have more transportation-related issues (e.g., air quality, public transportation) than small and medium communities. Federal legislation requires all transportation projects in urbanized areas with populations of 50,000 or more to be based on a process that is continuous, comprehensive, and coordinated to address long term issues, land use development, and multiple modes.

MPOs generally require local **survey data** to calibrate and validate travel demand models. The various data sources introduced for smaller Category C communities can be used for an MPO TDM model development when local survey data are not available.

As the study area becomes larger including one or more MPO's or RPO's with multiple modes, **TransCAD software** is the recommended tool for current NCDOT practice. Traditional travel demand approaches using TransCAD or other software account for transportation and demographic factors.

However, they do not fully capture **contemporary land use design** that promotes choices for travel modes – walking, bicycling, and ridesharing, including transit. Modern development and redevelopment often create neighborhoods and districts with a mix of homes, condominiums, apartments, shops, offices and even light industry to promote higher density land use, internal trip capture, and the traditional charm of a vibrant small town or village. Different land uses can create substantial variation in travel behavior among neighborhoods. To yield more accurate travel demand estimates, appropriate TDM approaches are identified for MPO communities to account for a finer-grained categorization of land uses as well as travel options. Such land use related approaches include integrated land use and pedestrian trip generation and the land use scenario evaluation.

Integrated land use and pedestrian trip generation (Appendix C) is particularly valuable in testing the effect of density and accessibility-related measures on alternative modes, and in exploring how elastic the travel demand is with regard to changes in land development patterns. There are two methods that integrate land use dimensions into predicting pedestrian trip productions. One method, named the density and diversity (2-D) method, is a simple technique that can be easily used by practitioners with limited land use data available to them. The 2-D method only takes into account a small number of land use variables (e.g. residential density, employment density, service employment share) in predicting pedestrian trip generation. The other method, named the land use characterization (LUC) method, is a theoretically appealing technique that comprehensively takes into account multiple land use dimensions. Appendix C details the two methods, demonstrates each of them using the Jacksonville, NC case, compares the estimation results from the two methods for validation, and discusses their advantages and drawbacks.

Land development scenario evaluation (Appendix H) is useful at the post-estimation stage of trip generation to further predict vehicular traffic, air quality, environmental impacts and a variety of other

related impacts. Data inputs include the trip production equations or rates estimated for North Carolina (Appendices A, C, D), the community's existing land use and zoning GIS maps, growth scenarios described in the community's most recent comprehensive plan, and EPA standard emission factors. The collected data can be further used to describe and visualize various land development scenarios, to identify areas transformable from the baseline scenario to alternative growth scenarios, and to assess the potential traffic reduction effect and the associated environmental impacts of the growth alternatives. Appendix H presents a detailed description about the evaluation process of two different land development scenarios: status quo development versus traditional neighborhood development. The demonstration case for this approach is Jacksonville, NC.

A full four-step travel demand forecasting process is recommended for MPO study areas. In MPOs through trip and external trip estimates are generally accomplished based on external station surveys. The trip estimates built upon external surveys best capture the trip patterns of through and external trips. Comparatively, the new through trip model (Appendix A) and external trip model (Appendix B) developed in Phase II can efficiently provide a good starting point for external trip estimates, but survey data should be used if affordable.

From a cost-effective point of view, this research suggests that an acceptable trip generation estimate can be produced based on three basic trip purposes (HBW, HBO and NHB) and North Carolina regional rates (Appendix D). The gravity model with survey data for calibration is the common approach for trip distribution (Appendix E). However, a destination choice model is suggested when special generators exist within the MPO region and local data are available. For the mode choice step, the multinomial logit model (MNL), perhaps in combination with the GIS screening tool, can be used to evaluate various transit routes and forecast ridership (Appendix F). Depending on the community characteristics and size trip assignment may be accomplished by all-or-nothing, stochastic or user equilibrium methods. Daily assignments are typical for medium sized communities and time of day assignments with optional travel time feedback may be useful for MPO study areas.

Model validation and reasonableness checking employ guidelines similar to those used for Category C study areas and travel demand models. More survey data are required to check the modeling results in trip distribution and mode choice steps.

Decision Tree for TDM Guidelines

The decision tree (Figure 3-1) attempts to formalize a systematic procedure for selecting TDM tools that are appropriately scaled for the complexity of the study area. For simplicity of illustration, the decision tree recognizes population as the first consideration because the larger the study area, the more likely it will require a more complicated tool or set of sub-models and databases. This chapter repeats the Phase I decision tree developed for Categories A and B, and expands it to include Categories C and D. Category E (regional model) is not included in the decision tree.

After the urban category is determined in terms of population, primary study area issues guide the selection of the appropriate tool or tools. It is important to note that the evaluations of Context Sensitive Solutions (CSS) and GIS analysis are often good starting points for any community's consideration of transportation problems. It should be noted that the issues considered by the decision tree are not singular considerations that lead to one analysis method. That is, if the decision tree recommends CSS analysis does not mean to exclude other subsequent approaches that may be helpful. Communities have multiple needs involving transportation, land use and related issues, so multiple tools should be considered and used according to the complexity of the study area.

Summary

This chapter presented and discussed guidelines for developing travel demand models for medium communities with populations between 10,000 and 50,000 and MPO study areas with populations greater than 50,000. Depending on the population, community characteristics, and the variety of local issues, a matrix of guidelines and a decision tree of sequential TDM steps suggest sources for data, steps for developing the network and TAZ structures, sub-models, validation approaches and overall methodologies. To support the guidelines, Appendices A through H describe detailed methods and case studies for each modeling step: through trip estimation, external trip estimation, land use assessment, trip generation, trip distribution, mode choice and trip assignment.

Table 3-1, Part I. TDM Guideline Matrix: Data for Travel Demand Models

Categories A and B are documented in the Phase I report. Categories C and D are in this Phase II report. Category E Regional models are custom efforts and are not addressed by these guidelines. Phase I Appendices (I-), Phase II Appendices (II-).

Category	Size	Issues	Community Characteristics	Data, Rates, Parameters	Data Sources	Network Complexity / Zones	Tools () ~ Appendix
A (Phase I)	< 5,000	Economic Development, New Roads, Truck Traffic; Community & Environmental Impacts, Hazard Mgt.	Income Level; Rural, Fringe; Vacation, Retirement; Industry; Attractions; Regional Center; CBD Vitality; Growth Rate; Nearby Interstate or Other TIP Projects Outside Study Area; Size & Type of TIP Improvements; RPO; No MPO	Default NC Rates (I-H); Rates derived from 2001 NHTS (rural part); Rates derived from the rural sub-sample of NC MPO surveys	Census CD 2000 Short Form Blocks; USGS GIS; CTPP; Amer. Fact Finder; Google Earth; FEMA, aerial photos, NC Demographics office	Major Roads; Census Blocks or User Defined TAZs Coarse zones, no more than 5 – 10 and the major roadway system.	CSS (I-A); GIS Land Supply (I-B); Trend Line (I-C); Manual Travel Allocation (I-D)
B (Phase I)	5,000 – 10,000	Cat A +; New Bypass	Cat A	Cat A; NCHRP 365 for fringe area (I-H)	CTPP, Census, GIS, Data Sources Table	Cat A + Streets, Census Tracts or User Defined TAZs Number of zones should range between 10 and 15. Roadway system should reflect major roadways plus important connector routes.	TransCAD* NC QR (I-E); CSS; GIS
C (Phase II)	10,000 – 50,000	Cat B +; CBD Revitalization;	Cat A + Suburbs; RPO; No MPO	Default NC Rates (II-C,D), NCHRP 365 for fringe area (I-H)	CTPP, Census, NCHRP 365, Data Sources Table (I-E-1)	Cat B + bus transit Guidelines on network selection and zone compatibility.	TransCAD NC QR (II-D); GIS (II-C,F,H); CSS (I-A);
D (Phase II)	> 50,000 (MPO)	Cat B+; Air Quality + Federal Planning Requirements; TIA of Special Generators	Cat C; MPO	Local Data, Surveys, Default NC Rates, NCHRP 365, 2001 NHTS; Comprehensive Plans, Zoning Maps, Emission Factors.	CTPP, Surveys, Planning Department or Agencies, EPA, Data Sources in Tables I-B-1, I-E-1	Cat C See guidelines	TransCAD (II-D), CSS (I-A); GIS (II-C,F,H); 2-D (II-C); LUC (II-C); Land Use Scenarios (II-H)

E	Regional	Cat B+; CBD & Area Development; Interstate Loops; Rail Transit	Cat D for All Communities in Region; Homogeneous Region; Multi- Nucleated Region; MPO	Local Data, Surveys, Comprehensive Plans, Zoning Maps, Emission Factors.	Surveys, Data Sources Table	Cat C + rail transit See guidelines	TransCAD; CSS; GIS; Custom tools & methods.
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* TransCAD or other mainstream commercial four-step package

Table 3-1, Part II TDM Guideline Matrix: Sub-models for Travel Demand Modeling

Categories A and B are documented in the Phase I report. Categories C and D are in this Phase II report. Category E Regional models are custom efforts and are not addressed by these guidelines. Phase I Appendices (I-), Phase II Appendices (II-).

Category	Size	Land Use () ~ Appendix	Trip Generation () ~ Appendix	Trip Distribution () ~ Appendix	Mode Choice () ~ Appendix	Network Assignment () ~ Appendix	External Trips () ~ Appendix	Tools () ~ Appendix
A (Phase I)	< 5,000	Comprehensive Plan; Land Supply Analysis (optional); (I-B)	US or NC Average Rates; If low income use US rates; If high income use NC rates; NCHRP 187 or NCHRP 365; CTPP Rates; Local Survey Rates; Consider 1 or 2 Trip Purposes; Consider NHB2; (I-H)	Distribute manually (spreadsheet) based on total employment; (I-D, I-F)	TCRP B3 for Demand Responsive Transit; (I-J)	Trend Line & Growth Factor Ratio Forecast for Single Routes; Manual Travel Allocation for Simple Nets; (I-D)	Manual Travel Allocation; Synth; (I-G) Consider all external trips are through trips	CSS (I-A); GIS Land Supply (I-B); Trend Line (I-C); Manual Travel Alloc. (I-D,I-F); NuSynth (II-A); NC rates (I-H); Distr (I-I); Transit (I-J); Assig (I-E); External Trip Model (II-B)
B (Phase I)	5,000 – 10,000	Cat A; Land Supply Analysis; (I-B)	Cat A; If fringe, use Metro Rates; (I-H; II-D)	Mean travel time from skims and zone-zone travel times; (I-E; II-E)	Cat A, GIS Analysis; (I-J; II-F)	QR Stochastic Method Daily; (I-E)	Synth with local adjustments (I-E) or NuSynth (II-A); External Trip Model (II-B)	Cat A tools or NC QR (I-E)
C (Phase II)	10,000 – 50,000	Cat A + Land Supply (I-B) Analysis; Land Use Scenarios (II-H)	Cat A or Local Rates from Survey; Use 3 Trip Purposes (II-D); Land use & non-auto modes (II-A)	Cat B; Gravity Model (II-E)	Cat B; and Mode Split Factor if Fixed-route Transit (II-F)	AON; QR Stoch Method Daily (II-G); QR User Equil; Daily assignment (II-G)	Cat B & (II-B)	Cat B
D (Phase II)	> 50,000 (MPO)	Cat C; Concentric Zone Model; Sector Model	Local Rates from Survey (II-D); Land use & non-auto modes (II-C); NCHRP 365 rates; rates derived from 2001 NHTS; Use 3 trip purposes or more; Consider TOD	Cat C; Destination Choice if local survey data available; Gravity Model (II-E)	Cat C or MNL Model with TransCAD (II-F) if local survey data available	User equilibrium method with 1 or 2 hour peak (II-G); Time-of-day assignment (II-G); TD-TA feed back loop (II-G)	Cat C; External Station Survey (II-A, II-B)	Cat C; 2-D (II-C); LUC (II-C); Land Use Scenarios (II-H)

E	Regional	Cat C + Land Use Models; Metro PIng; Multiple Nuclei & Polycentric Model	Cat D	Cat D; Validated by regional survey data	TransCAD, MNL (II-F) (Nested Logit Model preferred)	User equilibrium method; Time-of-day; Multi-class multi-modal assignment (MMA); Hourly or peaks; TD-TA feedback loop	External station survey; Separate AON or MMA assignment (combined with auto trips) for commercial vehicles	
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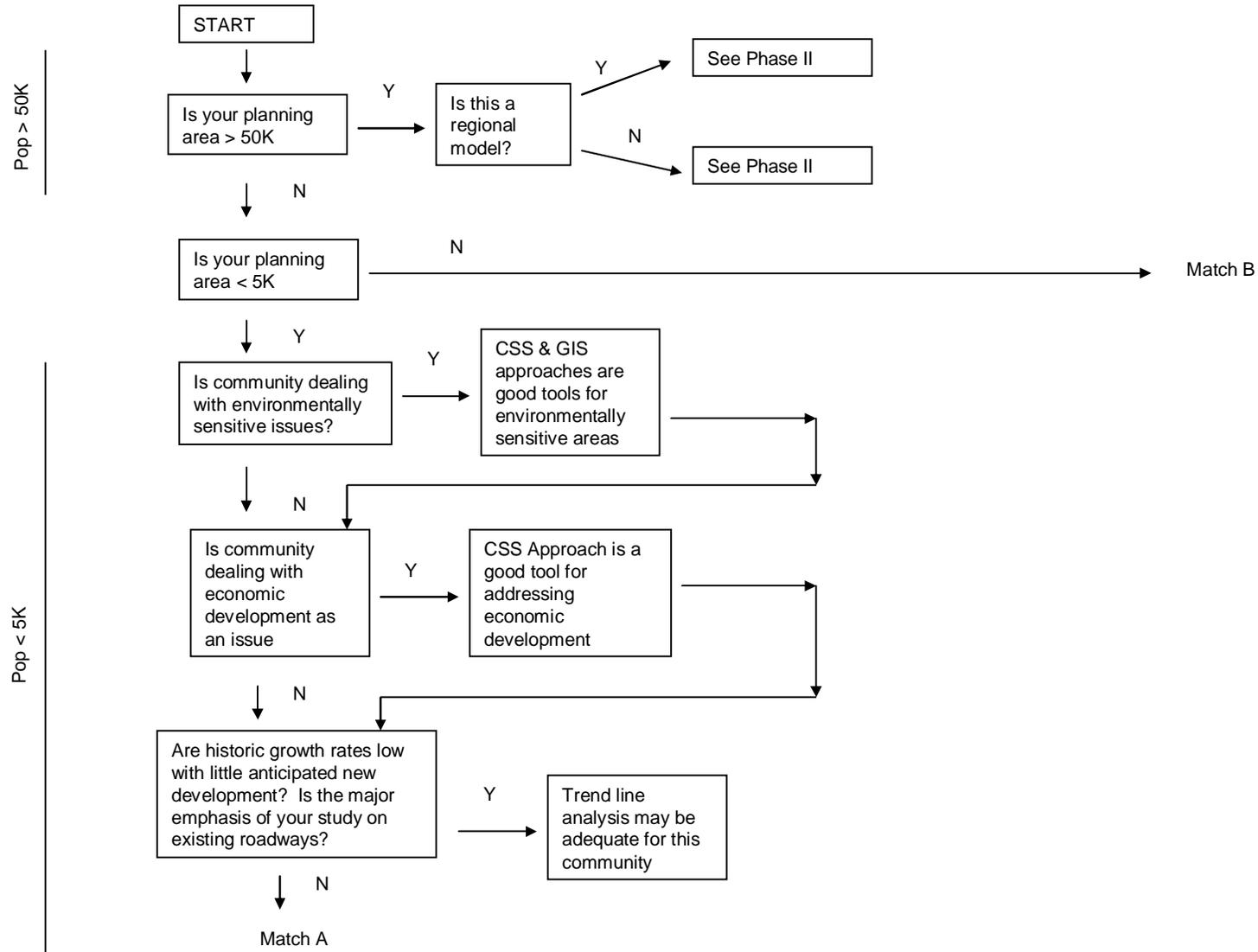
Table 3-1, Part III: TDM Guideline Matrix: Reasonableness Checks in TDMs

Categories A and B are documented in the Phase I report. Categories C and D are in this Phase II report. Category E Regional models are custom efforts and are not addressed by these guidelines. Phase I Appendices (I-), Phase II Appendices (II-).

Category	Size	Land Use Data and Transportation Networks	Trip Generation	Trip Distribution	Mode Choice	Network Assignment	Validation Targets	Tools ()~Appendix
A (Phase I)	< 5,000	Compare Land Use Results for Manual Travel Allocation to Land Supply Analysis	NCHRP 365 rates; NC average rates	Professional judgment; 2001 NHTS or NPTS average trip lengths for rural areas	Professional judgment	Traffic counts/ Professional judgment	NC Guidelines	(I-B) (I-C) (I-D)
B (Phase I)	5,000 – 10,000	Overall visual inspection on speed ranges, capacity ranges, and facility types. Check network connectivity, missing nodes, missing links, one-way links going the wrong direction. Use minimum path checks for coding errors. Review traffic counts using measures such as volume per lane and historic growth rates. Perform land use data checks at the zonal, regional, and aggregate levels. Review land use variables, population / household ratio, population / employment ratio, and plots of densities and density changes for future year data.	Ratio of unbalanced Ps and As should be between 0.9 and 1.0. Review percent of trips by purpose and compare to typical ranges outline in Table I-E-3.	Cat A plus Plot average trip length distribution for each trip purpose and review based on your knowledge of the area. Review average trip length by trip purpose. Review modeled VMT against HPMS data	Compare mode splits to those reported for your county or community from the US Census long form data or CTPP data.	Traffic count data that has been validated and VMT data if available. For recommended data summary checks refer to Validation Targets column for recommended references.	<i>Calibration and Adjustment of System Planning Models, FHWA 1990; Model Validation and Reasonableness Checking Manual, TMIP June 2001</i>	(I-E) (I-H)
C (Phase II)	10,000 – 50,000							(I-E) (II-D) (II-G)
D (Phase II)	> 50,000 (MPO)		Cat C; Validated by local household survey data or compared with NCHRP 365 rates; Compare trip rates estimated from different methods (e.g. 2-D, LUC, NCHRP365, NC QRM, TransCAD QRM).	Cat C; Validate trip length distribution survey derived from 2001 NHTS or local household survey, CTPP trip lengths for work trips, and CTPP work flow data; Compare district-to-district flow survey data	Cat C; Validated by household survey data; Compared with NCHRP 365 national default shares; Check against NHTS mode shares for small MPOs	Cat C; plus screen line, cut lines, and/or cordon line validation; federal % deviation by functional class; and volume group; R ² ; mode congested travel times vs. surveys	Cat C	(I-E) (II-D) (II-G)

E	Regional		Cat D	Cat D	Cat D, plus validation by local household survey data & transit on-board survey data (if available)	Cat D	Cat C	
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Figure 3-1. Decision Tree for Category A (0 < Population < 5,000)



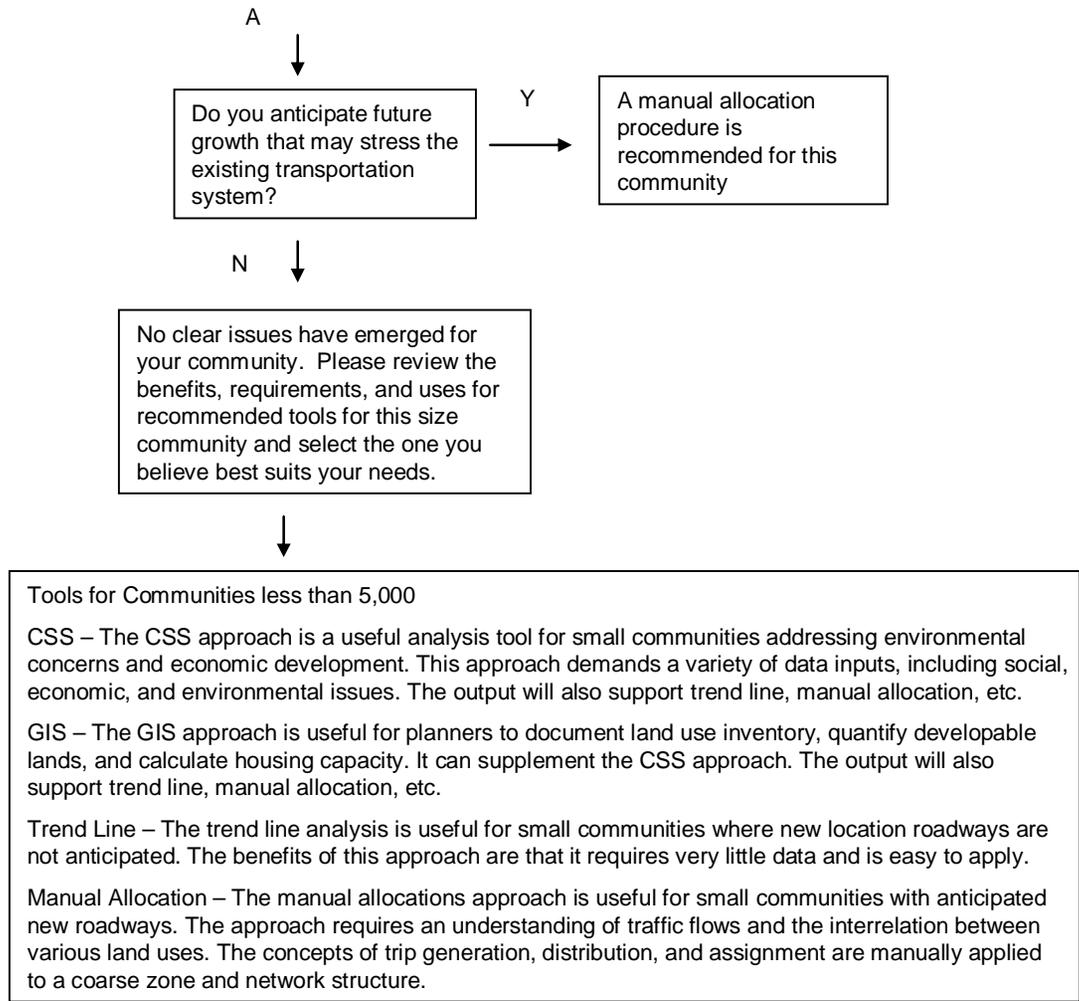


Figure 3-2. Decision Tree for Category B (5,000 < Population < 10,000)

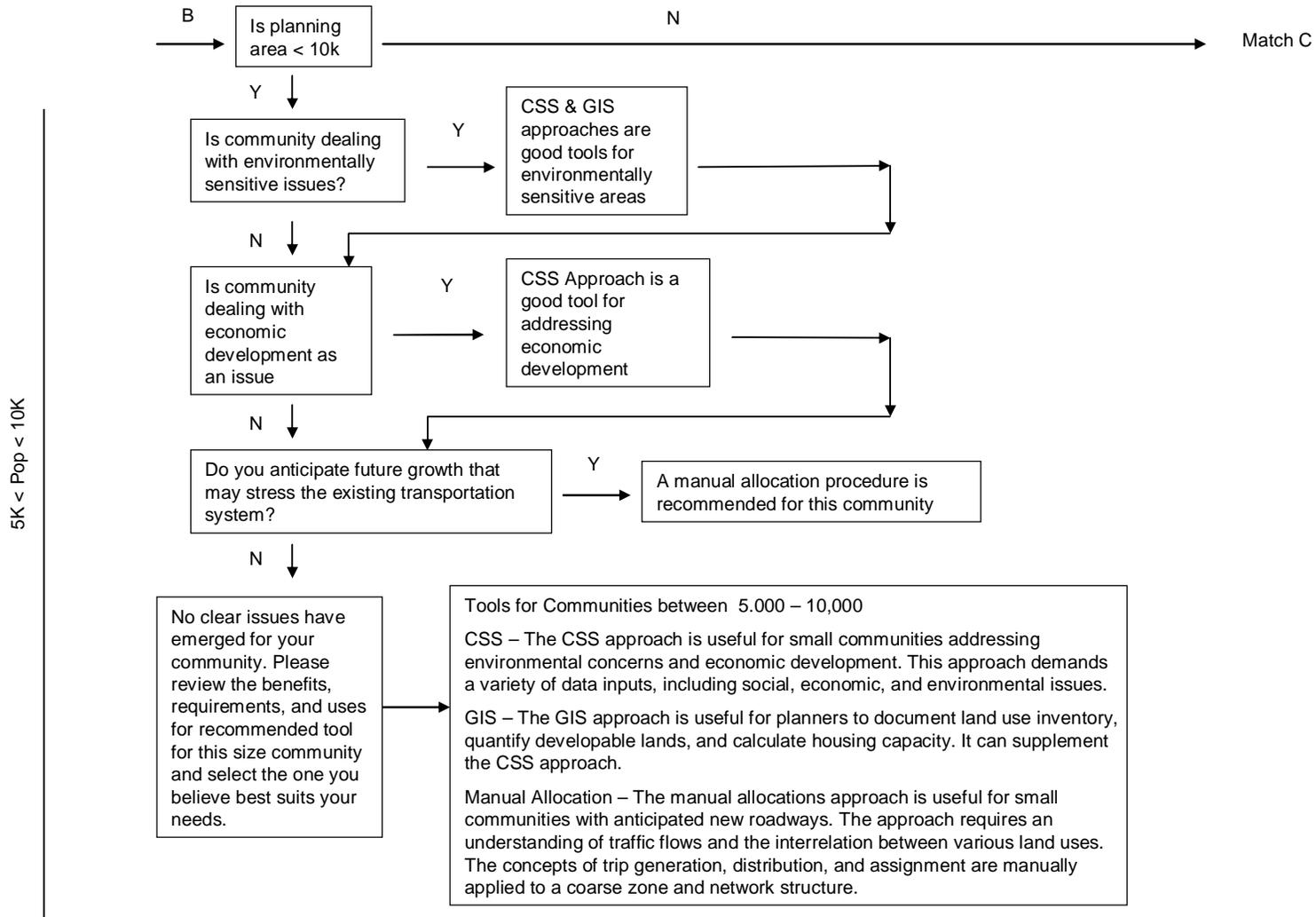


Figure 3-3. Decision Tree for Category C (10,000 < Population <50,000)

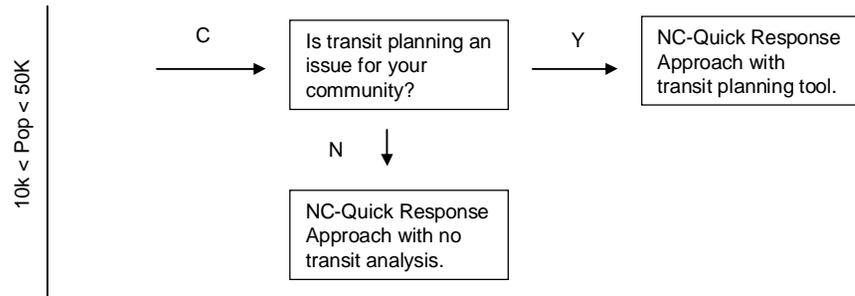
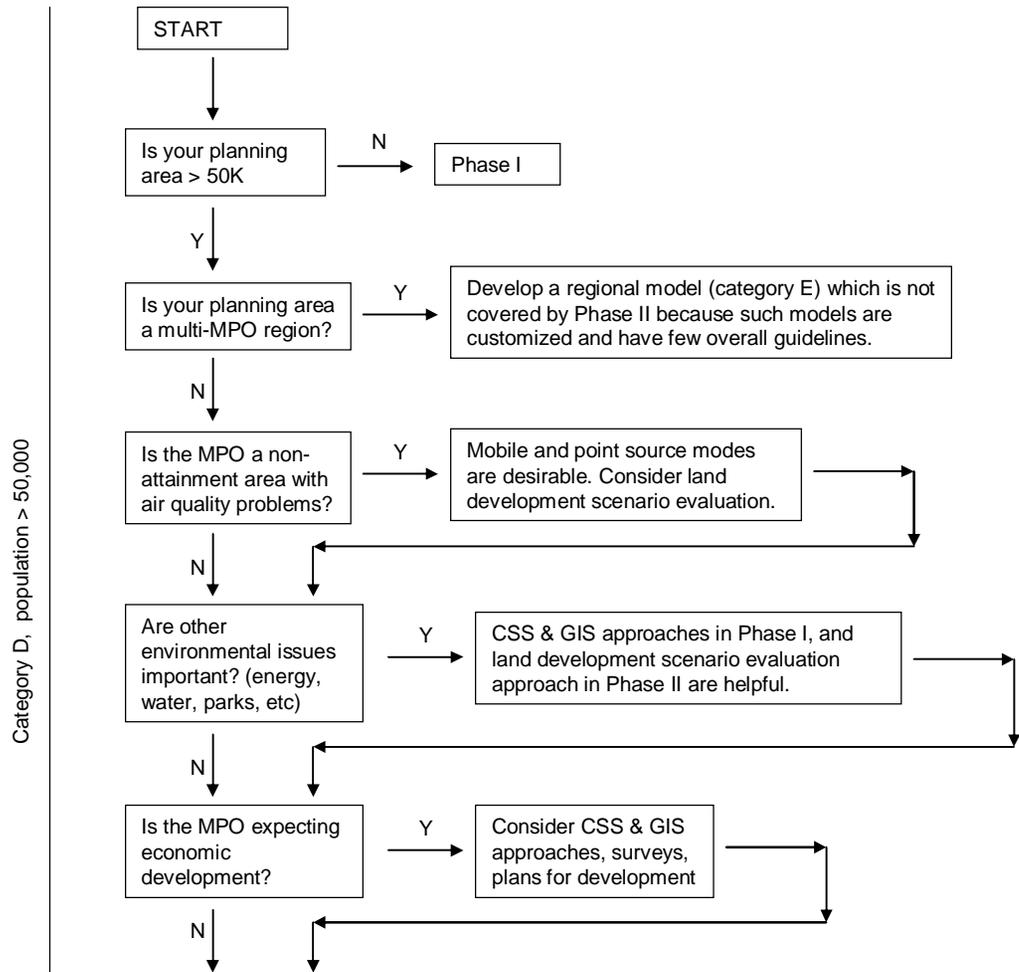
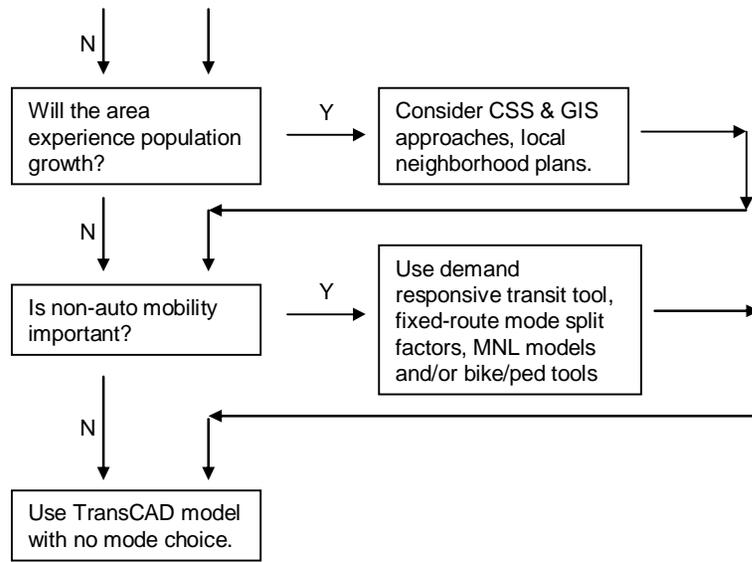


Figure 3-4. Decision Tree for Category D (Population > 50,000)



Category D, population > 50,000



CHAPTER 4: SPECIAL TOOLS AND SUB-MODELS

Introduction

In Phase I of the research project, multiple systematic approaches were promoted for the transportation planning in small urban areas with populations less than 10,000. Each of these methodologies, such as context sensitive solutions (CSS), trend line travel forecasting, and manual travel allocation, is able to address the small communities in terms of their size, needs and concerns. In addition, various sub-models were developed to simplify the estimates of trip generation, trip distribution, and trip assignment in small communities where a traditional three-step quick response travel demand forecasting approach is warranted.

Compared to Phase I, Phase II focuses on medium communities (Category C, population between 10,000 and 50,000) and MPOs (Category D, population > 50,000) where a three-step or a full four-step travel demand modeling (TDM) should be used. Therefore, the Phase II special tools and sub-models aim at improving each step of the traditional TDM process. In summary, these new Phase II sub-models include:

- Synthetic through trip model
- Economic based external trip model
- Trip generation: internal trips
 - a) Quick response approach
 - b) Integrated land use and pedestrian trip generation
- Trip distribution
 - a) Simplified gravity models
 - b) Destination choice models
- Mode choice
 - a) GIS sketch planning
 - b) Regression
 - c) Multinomial logit model
 - d) Mode split factor
- Trip assignment
 - a) Feedback loop
 - b) Time-of-day (TOD) assignment
- Land development scenario evaluation

These new sub-models can be selected and easily used by transportation professionals to facilitate transportation modeling in larger study areas according to their varied needs. Two case cities, Fuquay-Varina (Category C) and Jacksonville (Category D) are used to demonstrate the sub-models. The details of the sub-model applications are discussed in Appendices A through H.

Synthetic Through Trip Model

Building on previous studies of through trip behavior, we developed a systematic two-phase methodology to estimate through trip generation and through trip distribution in small and medium urban areas. One of the features of the new through trip model is its use of geographic economy theory and other functions to account for economic and geographic factors which usually represent the unique characteristics of a planning area besides the conventional explanatory factors used in previous through trip models such as urban population, average daily traffic (ADT), trucks and highway classifications. The new through trip model uses recent external survey data and is able to capture current through trip patterns. Furthermore, a systematic methodology is used through the entire model development, including variable analysis, scenario design, variable selection, validation of model assumption, model transformation and model performance evaluation. The methodology insures a robust model that is validated statistically. Since the

new through trip model is applicable in both small and medium urban areas, it offers a reliable approach for through trip estimation in place of a traditional expensive external survey. It may also be used to plan a survey if one is needed.

In the framework of the new through trip model, one regression model estimates the percentage of through trip ends at each external station (through trip generation rate) and two regression models estimate the distribution of the through trip ends among external stations for small (population < 50,000) and medium (population between 50,000 and 200,000) urban areas. Appendix A provides the details of data collection, the model development process, and a case study.

Appendix A describes the synthetic through trip model, its development and application.

Economic Based External Trip Model

According to current travel demand modeling practice, the control total of external (internal-external and external-internal) trips for a given external station is usually the daily traffic volume after through traffic has been subtracted out [45]. The accuracy of the external trip estimation heavily relies on the through trip estimates. However, in many metropolitan areas, limited data are available on the percentage of cordon traffic that are through trips and the origin-destination movements of external trips [45]. To solve this problem, a new economic based external trip model was developed to estimate the percentage of total external trips in the study area (Appendix B). The new model is called “economic based” because employment data are required to apply the new approach. Two reasons motivate such a model. First, the employment types and magnitudes of a study area represent its unique regional economic attractions which significantly impact external trips coming in and going out for different trip purposes. Second, the employment data is generally readily available, thereby making the new model easy to use and not data intensive.

The new external trip model builds upon recent external survey data in a variety of study areas with different urban sizes. The employment data are categorized by the North American Industry Classification System (NAICS). According to a systemic modeling methodology, two different regression equations result for external trip estimation in small study areas (population < 50,000) and medium sized study areas (population between 50,000 and 200,000). Each of the two forecasting equations includes different explanatory factors of the “economic index” (EI), which represents the regional economy relative to the statewide economy.

The new external trip model is cost-effective and validated to provide acceptable accuracy by testing a few case cities. The model results that give the estimated split between through trips and external trips can serve as an acceptable approach to control through/external trip totals. Appendix B illustrates the external trip model development and validation.

Trip Generation: Internal Trips

Integrated Land Use and Pedestrian Trip Generation

In reality trip generation rates can vary with accessibility and density, yet trip generation models in practice do not reflect these factors. Thus, it is important to examine how elastic travel-activity demand is with regard to changes in accessibility and land use development densities. Such a study can result in more accurate forecasts and stronger linkages with land use.

Appendix C outlines an integrated land use and pedestrian trip generation study of the relationship between land use patterns and pedestrian trip generation rates. This study uses two datasets: the Triangle

Region dataset for estimating pedestrian trip models and the Jacksonville dataset for applying the estimated models. The Triangle dataset includes both travel behavior data from the 2006 Triangle Travel Survey and land use data from local and regional GIS agencies that are integrated with the behavioral data. The key findings are:

- ê Walking trips are positively related to housing density, employment density, road density, bus stop density, sidewalk coverage, and accessibility to retail stores at the residential location.
- ê More industrial land uses at residential locations are associated with decreased walking trips.
- ê Households in the downtown area have the highest pedestrian trip rates. When residential neighborhoods are relatively sprawled, households have fewer walking trips.
- ê Daily driving trips and walking trips relate differently to land use variables, which indicates the importance of considering trip generation separately for modes.

Two methods for predicting pedestrian trip generation (productions) are developed: the 2-D method and the LUC method. The 2-D method estimates trip production equations by regressing the number of household pedestrian trips on three simple land use measures; a method which has a low data demand and is relatively simple to conduct. The LUC method uses factor and cluster analyses to identify an appropriate neighborhood typology based on a comprehensive list of land use variables. It further estimates pedestrian trip rates for each identified neighborhood cluster. The LUC method requires detailed GIS data and statistical and spatial analyses.

The two methods are demonstrated in a case study of Jacksonville, NC (Appendix C). The outcomes are compared for validation and calibration purposes. Results show that the LUC method generates significantly higher pedestrian trip rates than the 2-D method. However, the LUC method shows more consistency on the spatial dimension. The correlation between the forecast outcomes from the two methods is relatively high, at 0.8, indicating good reliability of the two methods.

Quick Response Approach

TransCAD tests two quick response approaches with two default national trip generation rates (NCHRP 187 and NCHRP 365) and two North Carolina regional rates (Metrolina rates and Triangle region rates). The validity of the approaches and ease of use were examined.

For medium communities with populations between 10,000 and 50,000 (Category C), the Fuquay-Varina case study (Appendix D) indicates that the national default trip rates provided by NCHRP 187 and NCHRP 365 cannot be reliably used due to significantly different unbalanced productions and attractions. The two types of NC average rates (Appendix D), especially the values from Metrolina household survey, result in acceptable trip generation estimates with production-attraction ratios closer to 1. For more accurate trip generation estimation, adjustments need to be made to the NC average rates based on local surveys or local knowledge of the planning area. Three basic trip purposes (HBW, HBO and NHB) are sufficient for estimating trip generation in medium communities.

In most MPO areas (Category D) trip generation is a complicated and data intensive process. MPO travel demand models often account for additional trip purposes (e.g., home-based school) besides the basic HBW, HBO and NHB trip purposes. Thus, MPOs generally conduct household surveys to determine local trip rate values. Furthermore, special generators are likely in MPO areas and are usually modeled separately. Such considerations complicate MPO models and increase their cost.

Simplified trip generation using the three basic trip purposes (HBW, HBO and NHB) works well, however, according to the results in the Jacksonville case study (Appendix D). Besides the simplification of using three basic trip purposes, other simplifications were helpful including: using a reduced number of

employment types in trip attraction model, and aggregating some special generators into the usual employment types if land use has common characteristics. Different default trip rates were also tested. The trip rates from the Metrolina household survey seem to duplicate local Jacksonville rates and appear to have transferability to other MPO areas.

Trip Distribution

Simplified Gravity Model

As demonstrated in Phase I, a simplified trip distribution approach uses mean travel time from the zone to zone minimum path matrix to estimate initial friction factors. The performance of this approach is tested in Phase II for larger urban areas, and compared with the NCHRP 365 model and a population based method (Appendix E). For a medium community with population between 10,000 and 50,000 (Category C) which is an “isolated” community and may not need a calibrated trip distribution model, the simplified gravity model still produces acceptable result. If the city is a fringe area city near a larger metropolitan area, then the NCHRP 365 model appears reasonable. For most MPOs (Category D) where the population is more than 50,000 and a calibrated process is required by trip distribution to duplicate the observed trip length distribution or average trip length, the gamma function with calibrated parameters provides desired modeling results. Although the network skims can be simply used for estimating average travel time with less data collection, they seem to provide less satisfactory estimation results for larger cities.

Destination Choice Model

Although the gravity model is the most common trip distribution model in MPO and regional travel demand forecasts, the destination choice model is still a beneficial supplement for trip distribution estimation in larger urban areas where special traffic generators such as airports, amusement parks, shopping centers, or schools are likely. Special generators usually have unique land uses with unique trip lengths and trip distribution patterns compared to other TAZs in the study area. The destination choice model, such as the widely used multinomial logit model (MNL) or mixed multinomial logit model (MMNL), has multiple explanatory variables used to describe the choice of destination. It estimates the conditional probability of a trip maker choosing a destination from several choices, it is more behavioral than the gravity model, and it is able to account for additional factors such as individual traveler characteristics and destination characteristics that affect travel decisions. However, to apply the destination choice model for trip distribution, activity-based and travel behavior surveys specific to the special land use are required. Such surveys are expensive, time consuming, and usually unavailable.

Mode Choice

GIS Sketch Planning

Analysis with Geographic Information System (GIS) tools is useful for highlighting areas or corridors within a planning region where there are land use characteristics that are highly correlated to transit ridership. A GIS sketch planning procedure (Appendix F) can be performed in two different ways to measure transit propensity that represents the relative demand for transit. The first approach, referred to as the threshold method, identifies zones that have developed a sufficient population and employment densities to support fixed route transit. GIS is used to map household and employment densities that are considered to be transit supportive. The second approach uses statistical analysis to identify transit propensity by considering race, gender, income, and auto ownership in a weighted index. The factors and weights are based on TCRP Report 28: *Transit Markets of the Future: The Challenge for Change* [46], and TCRP Report 27: *Building Transit Ridership* [47]. This approach produces useful output for evaluating transit planning options and seems to be a cost-effective tool for small urban areas.

Regression

In this research, multiple linear regression models were also investigated to develop a cost-effective mode choice estimating approach for a proposed route. Ridership data and socioeconomic variables probably correlated with transit ridership were extracted from Triangle Region and examined. To determine the reasonable combination of variables with high goodness-of-fit with survey data, a multiple linear regression analysis was conducted at two levels: the route level and the zone level. Overall the results of the regression analysis approach were unsatisfactory yielding very low R-squared values (Appendix F).

Multinomial Logic Model

A common approach to forecasting transit ridership is with multinomial or nested logit models. The most basic form of mode choice analysis is the multinomial logit (MNL) model with specific utility equations reflecting various service parameters such as travel time, walk time, fare, and number of transfers. It is acceptable to borrow coefficients from reliable mode choice models rather than to estimate them from surveys if the sample size of transit users is very small or survey data is not available in a region that currently has no transit service. The *TMIP Manual on Model Validation and Reasonableness Checking* [45] provides a table with coefficient values used for various cities. Additionally, the mode choice coefficients used in the Triangle Regional Model have undergone FTA review and therefore provide a good resource for selecting model coefficients.

Appendix F provides a case study to address the MNL model by using default Triangle region model's coefficients. The results show that the MNL model with recommended coefficients can be employed as a cost-effective means to evaluate transit options for small MPO areas.

Mode Split Factor Model

Since multinomial logit models are usually data intensive and time-consuming, a simple mode split factor model may be an efficient approach for mode choice estimation in MPO areas. The mode split factors can be developed based on trip purpose and travel distance to estimate shares of auto trips and non-auto trips (e.g., walk, bike, transit, etc). By using the simple mode split factoring approach, intensive modeling efforts may be avoided or reduced, such as the coding of a complete transit network, development of transit ridership data required for model validation, and extensive household surveys.

The mode split factoring approach was used for the MPO model in Jacksonville, North Carolina [48].

Travel Assignment

The Phase II research evaluated the following network assignment algorithms Category C and Category D study areas: all-or-nothing, stochastic with different parameters, capacity constraint, and user equilibrium (Appendix G). For MPO areas, a special analysis of a feedback loop process and a time of day assignment were performed (Appendix G).

In medium communities with population between 10,000 and 50,000 (Category C), all-or-nothing, capacity constraint and user equilibrium daily assignments do not produce satisfactory results compared to link traffic counts. The stochastic daily assignment with user defined parameters is verified to more robust and easier to apply.

In MPO areas with populations larger than 50,000 (Category D), the user equilibrium assignment algorithm results in more accurate estimated link volumes than those from other assignment algorithms.

A feedback loop between trip distribution and trip assignment was also evaluated. This iterative process estimates congested travel times after an initial assignment, re-calculates highway network skims with updated travel times, and re-develops the origin-destination matrix. For the Jacksonville MPO case study conducted in Appendix G, the feedback loop seems to improve the trip assignment and tends to achieve stable results that lead to lower system-wide VMT which implies reduced system-wide congestion.

These results indicate that the feedback loop has potential to help the trip assignment process reflect realistic congested travel speed and travel time. However, a fairly low convergence speed of the iterative modeling results is observed in the case study. Furthermore, the feedback loop may cause a fluctuation of traffic loading accuracy during interim iterations, which degrades the reliability of the feedback loop if it is solely used. These mixed results reflect the current debate in practice. The performance of feedback loop is not always satisfactory according to reports by some MPO regions and states [42, 43, 44].

Time of day (TOD) assignment simulates peaking and congestion characteristics of traffic in a 24 hour period. The practice is a reasonable and robust approach for loading traffic on the networks of MPOs and larger urban areas. The reason is that a high portion of daily trips are generally made during peak periods and the resulting peak-period traffic conditions are critical for assessing the level of service provided by the transportation system. To conduct TOD assignments in MPO areas, it is usually sufficient to divide a 24-hour period into AM peak period, PM peak period and off-peak period. More detailed periods or hours of the day may be defined according to local needs and traffic patterns. Utilization of the transportation system in peak periods is higher than that in off-peak periods, which results in more severe traffic congestion and lower travel speeds.

Land Development Scenario Evaluation

While the fundamental NCDOT problem is estimating future traffic for land use and transportation options, NCDOT must also examine the contributions of pedestrians and bicycles to traffic and the direct effects of land use choices and patterns. Of particular concern are air quality impacts because of health issues, federal mandates for clean air, and linkages to federal transportation funds.

Appendix H demonstrates a land development scenario evaluation exercise with Jacksonville, NC. This exercise first depicts two land development scenarios: Current Jacksonville Development vs. Traditional Neighborhood Development (TND). The TND scenario is characterized by high-density, mixed use, and alternative-mode friendly design. The exercise identifies areas in Jacksonville that are readily transformable to a TND, and it assesses the potential impact of the TND growth alternative on vehicular traffic, mode choice, and air pollution.

This example shows that consideration of the TND growth alternative can be helpful in terms of reducing traffic congestion, improving air quality, and saving energy resources. The key findings about possible daily impacts of Jacksonville's TND scenario include fewer morning peak period auto trips and fewer afternoon peak period auto trips, reduced vehicle miles traveled (VMT), reduced vehicle emissions (i.e., fewer pounds of hydrocarbons, carbon monoxide, nitrogen oxides, and carbon dioxide), and reduced fuel consumption, measured in terms of fewer gallons of gasoline per day. Of course, implementation of TND scenarios can also be made difficult by existing land use regulations, preferences of the population for larger lots and the desire to live away from other land uses.

Chapter Summary

This chapter develops Phase II sub-models to improve travel demand forecasting in medium communities (population between 10,000 and 50,000) and MPO areas (population > 50,000). Such research efforts aim at reducing data collection efforts and improving forecasting accuracy for each of the traditional travel demand modeling process: through/external trip estimation, internal trip generation, trip distribution, mode choice, trip assignment, and evaluation of interaction between transportation planning and land use. Iterative feedback from travel assignment to trip distribution and time-of-day assignment are explored. Appendices give detailed examples.

CHAPTER 5: FINDINGS AND RECOMMENDATIONS

Medium Communities with Populations from 10,000 to 50,000

North Carolina communities with populations from 10,000 to 50,000 usually require computer-based travel demand models. However, a quick response method (QRM) with national or statewide default parameters can provide acceptable results. A three-step travel demand modeling process without mode choice analysis is also sufficient for planning purposes in such medium sized communities. Such a cost-effective travel demand model can be simplified by employing the following approaches: synthetic through and external trip estimates, state average trip generation rates, mean travel time for trip distribution, optional GIS approach for mode choice estimation, and stochastic trip assignment.

Through Trip Forecasting

The NCDOT SYNTH program is an effective procedure for forecasting through trips for communities that fall within the urban population range of 4,000 to 50,000, under which the original model was specified. However, even when used for a community falling within this range, caution should be applied to the through trip percentages estimated as they may not reflect the economic and geographic factors of the community being studied, especially so since SYNTH is based on 1970's data.

A new through trip model (Appendix A) is developed to capture through traffic patterns based on analysis of external survey data collected mostly between 2001 and 2004 in a variety of small and medium urban areas. Since the new model accounts for the unique economic and geographic characteristics of the study area, it suggests transferability for other U.S. small and medium urban areas. The new model has proven to be easy to use, not data intensive and can be seamlessly embedded into the standard travel demand forecasting process. More applications of the new model in other places are recommended to fully demonstrate the new approach.

External Trip Forecasting

In small and medium communities, a usual way for external trip estimation is to calculate the difference between given ADT counts and estimated through trip ends at external stations. This approach heavily relies on the through trip estimates and requires classified traffic counts.

Serving as an alternative approach, an economic based model is developed to forecast external trip control totals in small and medium urban areas. The input employment data are generally available from online sources (e.g., U.S. economic census), and they are the only required model input, thus reducing data collection efforts and modeling cost. This model explains external trip generation from an economic point of view, and therefore it provides another reasonable starting point for external trip estimates. The small city model needs more data for complete validation, while the medium city model seems to be transferable to other communities, especially NC communities.

Trip Generation

The benefits of applying the TransCAD QRM approach are clearly its ease of use and straight forward application. It is efficient to apply transferable average NC trip rates for trip generation estimates in various NC medium communities. Default U.S. trip rates (NCHRP 187 and 365) are not suitable for medium communities. In addition, it seems that only internal trips can be reasonably estimated based on the QRM approach. Caution is necessary for borrowed EI/IE trip rates.

Trip Distribution

The gravity model is sufficient for trip distribution forecasting for a medium community with population between 10,000 and 50,000. As for its performance in small communities with populations less than 10,000, the mean travel time from the zone to zone minimum path matrix still works as a robust approach to estimating (or at least providing a good starting point for) initial friction factors. The assumption behind this approach is that trips distribute according the travel time, a common simplification. The characteristics of trip length in medium or smaller urban areas are relatively easy to capture by a simplified method. The network skim-based mean travel time is an applicable and promising approach, especially when household survey data are not available for model calibration.

Mode Choice

Mode choice can often be omitted in the travel demand forecasting process for a medium community. However, a GIS screening tool is a cost-effective means to evaluate transit scenarios in an urban area which currently has little or no fixed route service. It can be used to forecast the propensity for future transit ridership. In addition, it has an easy-to-apply analysis process and easy-to-understand output maps. The GIS screening tool can be used by smaller urban areas to identify areas within their community that have a high propensity for transit ridership. This information can aid the development of the transportation plan for a community. In summary, medium communities (population between 10,000 and 50,000) might best be served by a GIS mapping procedure that identifies potential transit corridors based on various predictive variables.

While regression analysis shows promise with limited data, the transferability of the approach is not reliable enough to recommend without more analysis against a larger data set.

Trip Assignment

The all-or-nothing assignment algorithm does not allow the user to adjust assignment parameters to achieve assignment results that better reflect traffic count measurements, assuming that parameters for all previous sub-models have been adjusted. Instead the user must modify link attributes directly in order to change a link assignment. There is an inherent risk in making link level adjustments as the adjustments may be masking a system relationship problem or error that may bias the future year forecast.

For equilibrium assignment, a usual approach is to conduct time of day (TOD) assignment based on hourly or peak period trip tables. However, for a community with a population between 10,000 and 50,000 the TOD assignment can be burdensome to the analyst unless automated procedures are developed for the assignment step.

As in Phase I [4], the stochastic assignment is fairly straightforward to apply and comes closer to replicating “real world” path finding where several optimum paths may exist between a given origin and a given destination. The value of θ can be adjusted to reflect a more conservative assignment where fewer optimum paths are allowed versus an assignment where many optimum paths are utilized. Since the stochastic assignment has such advantages over, it is recommended to be used in a community with a population between 10,000 and 50,000. A case study demonstrates the superior of stochastic assignment in a medium community (Appendix G).

MPOs with Populations Greater than 50,000

For MPOs with populations greater than 50,000, a variety of planning approaches are available. These are discussed below.

Through Trip Forecasting

For MPOs or larger regional areas, the NCDOT SYNTH model produces unreasonable through trip estimation results. According to current modeling practices in MPO areas, external station surveys are usually conducted to capture local through trip patterns. Some MPOs use the SYNTH model output as a starting point for through trip estimation, although it was developed and assumed to be used for small urban areas. Professional knowledge of local traffic patterns is required for this approach to adjust the estimates.

To provide a cost-effective alternative method for through trip estimation in larger urban areas, this research proposes the new through trip model which is suitable for MPO areas. The utilization of extensive recent survey data, adoption of a systematic analysis methodology and integration of economic and geographic factors make the model robust and transferable for other U.S. urban areas. The model is not data intensive so that the expensive external surveys can be avoided for through trip estimation in larger urban areas.

External Trip Forecasting

MPOs generally estimate external trips based on external surveys. The Phase II research develops an efficient model for external trip estimation only requiring employment information. Such a model is not very data intensive which implies saving time and money instead of conducting an expensive external survey. This model is transferable for other MPOs according to available data.

Trip Generation: Internal Trips

Integrated Land Use and Pedestrian Trip Generation Approach

The integrated land use and pedestrian trip generation approach aims at developing models to predict alternative travel demand in metropolitan areas as well as to address the spatial variation in travel behavior. In general, there are three improvements to the transportation demand model structure:

- ê Considering trips separately for different modes (such as walking versus driving) to avoid obscuring important factors associated with trip-making.
- ê Including land use factors (densities, mix of uses, design, availability of sidewalks, etc.) as one set of the travel demand predictors to generate better estimation of trip generation rates.
- ê Comparing trip generation rates from different methods to examine the spatial generalizability of the new model structure.

The integrated land use and pedestrian trip generation approach has proposed two methods: the 2-D method and the LUC method. The proposed 2-D method demonstrates a simple tool for transportation planners with limited land use data to incorporate a small number of but important land use variables into predicting pedestrian trip generation. The other proposed method, LUC, demonstrates an approach that is able to address the multi-dimensional nature of land use patterns and incorporate a comprehensive list of land use variables into predicting walking trips. A limitation of this approach is data unavailability in certain regions, e.g., in Jacksonville, NC, which makes it difficult to validate estimation results in this research. Thus, this report cannot determine whether the 2-D method or the LUC method produces more accurate results.

Overall, the 2-D and LUC method come with different advantages and drawbacks. The 2-D method is characterized by its simplicity and high levels of spatial generalizability. The LUC method is theoretically appealing due to its full consideration of land use dimensions. The LUC method is recommended when practitioners are acquainted with GIS analysis and have good access to land use data. Comparison of the

results from two methods has indicated good reliability of both methods. Practitioners may select the appropriate method to use based on the characteristics of the communities, available GIS information and software packages, and their local knowledge of the land use environments.

Quick Response Approach

To simplify relatively complicated MPO travel demand models, this research attempted to simplify data requirement and modeling structures while ensuring sufficient accuracy of estimates. The major conclusions are summarized below:

- ê For MPOs, using three basic trip purposes (HWB, HBO and NHB) is a legitimate method to simplify the trip generation process.
- ê A reduced number of employment types can be used for acceptable trip attraction estimation.
- ê Within an acceptable range of deviation, some special generators can be aggregated into the typical employment types if land use has common characteristics, e.g., aggregating a shopping mall with retail employment and aggregating a hospital into service employment.
- ê NC average trip rates (e.g., Metrolina rates) appear to transfer to other MPO areas.

Trip Distribution

For a MPO region which usually has a large area size, the previously mentioned simplified gravity model cannot offer satisfactory results. Therefore a traditional gravity model with an iterative calibration process is desirable for MPO regions. Furthermore, a destination choice model is suggested for use if there are special generators (e.g., airport) in the study area and adequate survey data are available.

Mode Choice

Mode choice should be a necessary component in MPO travel demand models; however, relatively simple analysis tools might be employed as a means to evaluate transit options. These simplified approaches may include a multinomial logit model (MNL) with default or borrowed parameters, MNL in combination with the GIS screening tool, and mode split factors based on travel distance. The primary advantage of these simplified approaches is that they do not require the collection of specialized behavior data but can be applied using existing data set. These tools can be used by MPO areas to evaluate various transit routes and forecasted ridership in the development of a multimodal transportation plan.

Assignment

For MPO areas, the user equilibrium assignment produces more reasonable results than other algorithms which replicate traffic counts. This might be because the equilibrium algorithm looks at several equally good paths through the network in MPOs when assigning trips so as to buffer sensitivities by allowing the assignment to run through several iterations, thereby allowing a small change in speed to equal a small change in volume.

The feedback loop was not shown to be a robust and efficient approach for trip assignment in the travel demand modeling process. This research finds the application of a feedback loop between trip distribution and trip assignment seems to improve the assignment results and results in lower system-wide VMT indicating an overall less congested traffic condition on highway network. However, the feedback loop caused a slow convergence with unreasonable traffic loadings in interim iterations. To improve the feedback loop performance with faster convergence and more accuracy, the method of successive averaging (MSA) [49, 50, 51] or method of successive weighted averaging (MSWA) [52] should be considered with respect to increased modeling effort and cost.

The time-of-day (TOD) assignment is shown to reflect the variation of highway utilization and true traffic congestion levels in terms of different time periods. For MPO areas compared to a daily traffic assignment, TOD assignment is a reasonable approach to assess transportation system performance and forecast future link loadings. The peak periods (usually AM and PM periods) generally result in higher V/C ratios and lower travel speeds in the transportation system compared to off-peak periods. The traffic congestion on those roads with lower functional classifications seems to be more sensitive to time of day. If a feedback loop were used with TOD assignment, it is recommended to estimate congested travel time by using TOD trip tables and the corresponding link capacities rather than using values from daily assignments. In addition, the default TOD factors of daily vehicle trips should be used with caution. TOD default factors should be adjusted based on local knowledge.

Land Development Scenario Evaluation Approach

The land development scenario evaluation approach proposed here is a quick and useful method to assess and compare the potential traffic and environmental impacts of alternative land development patterns.

Jacksonville, NC is the demonstration case. It shows that TND designs can bring significant transportation and environment benefits including reduced traffic congestion, reduced fuel consumption, and reduced vehicular emissions to growing communities. However, the transportation and environmental benefits of TND designs may come at a price. In reality, implementing TND designs is difficult and has to be a process that involves many stages and many stakeholders.

Overall, planners should consider higher density, mixed use, and alternative mode designs as growth alternatives, with the caveat that there may be several challenges in planning for and implementing such designs.

Future Research

To improve the confidence in applying the TDM guidelines described by this report, more data and case studies are desirable to test three major components of the guidelines: data, sub-models and tools and reasonableness checks. Newly developed sub-models should be given higher attention for validation or further improvements since they constitute the framework of a travel demand model in an urban area.

Products and Implementation and Technology Transfer Plan – Phase 2

Primary Products

Guidelines for best practice for travel demand modeling in medium-sized communities and metropolitan planning organizations. Summary travel demand model guidelines for medium-sized communities and MPOs are presented by an extensive matrix and a multi-level decision tree. The matrix and decision tree include information for small communities with populations less than 10,000. (Phase 1 report). The information can help transportation planners and engineers apply appropriate methods, data sources and sub-models to develop best practice models for medium-sized communities with populations between 5,000 and 50,000 and MPOs with populations greater than 50,000. Regional models with multiple MPOs and custom implementations are not covered.

Models, sub-models, and tools. There are many planning tools in the “toolbox” that can be applied to the medium-sized communities and MPOs based on their size and needs. The tools address trip generation, trip distribution, mode choice and network assignment. Of particular interest are models for synthetic through trip estimation and distribution; an external trip model based on economic factors; mode choice models including a sketch planning model for transit, a regression model for transit propensity or latent

demand, and the standard multinomial logit model; and several implementations for travel assignment including: all-or-nothing assignment, stochastic assignment with different parameters, capacity constraint assignment, user equilibrium assignment with and without a feedback loop from assignment to trip distribution, and a time of day assignment. To round out the research three land use models examined the relationship between land use patterns and pedestrian trip generation rates. All models, sub-models and tools were demonstrated with case study communities.

Executive Summary. The Executive Summary presents the guidelines for best practice, the decision tree, and suggestions for model use and data sources.

Case Studies. The guidelines, models and tools are demonstrated by case study applications. Complete data, spreadsheets, and TransCAD input files are available.

Technical Documentation. A technical report presents the background for the research, literature review, and justification for using the various guidelines, tools, and methods.

Secondary Products

Input Data and Default Parameters. Baseline values, project data and parameters are given for the case studies.

Recommendations. Suggestions for implementing the guidelines for medium-sized communities and MPOs for travel demand modeling at NCDOT and for future research are presented.

Implementation and Technology Transfer Plan

The implementation and technology transfer of the products of this research have already begun.

During the first phase of the implementation, the NCSU-UNC project team held two workshops for NCDOT personnel who will use the guidelines and methods. During the first workshop the team discussed the guidelines, tools and methods. During the second workshop the team presented the manual allocation spreadsheet and discussed other methods. Additional workshops outside the scope of this project may be necessary for other personnel and for complete demonstration of all the tools and small community cases. For example, the NCDOT Transportation Planning Branch has a tradition of in-house training sessions for which the results of this research can be applied.

Implementation of the Phase 2 results has similarly begun. The updated guidelines, decision tree, and models for medium-sized communities and MPOs have been delivered to NCDOT. The information can easily be accommodated in existing NCDOT on-the-job training programs that already exist. Occasionally NCDOT holds MPO workshops and the results of this research can be included.

NCDOT should distribute the final technical reports for Phase 1 and Phase 2 to project engineers and planners in North Carolina and other states.

CHAPTER 6: REFERENCES

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APPENDIX A: SYNTHETIC THROUGH TRIP ESTIMATION

Introduction

According to the US Census, about 52% of all residents live in small communities with populations less than 50,000, and 22% live in medium urban areas with populations between 50,000 and 200,000. Such small and medium communities have sizable through (external-external) traffic but may have insufficient staff or funding to conduct expensive surveys for developing good through trip tables for good transportation plans. Yet, Federal legislation requires local plans if the population is 50,000 or more, and some states like North Carolina require all municipalities to have transportation plans.

The application of Synth [1, 2], the current principal through trip model, has outdated data and limited city samples. The model heavily relies on traffic characteristics and ignores economic and geographic factors, which weaken its transferability between urban areas. Plus, ignoring economic and geographic factors ignores important impacts on through trip patterns. Anecdotal evidence shows that professionals apply the Synth, which is calibrated to small towns, to medium sized cities even though there is no validated medium city model. This appendix presents a new medium city model, as well as an updated small city model. They are validated with new traffic survey data and have optional economic and geographic variables.

Building on previous studies of through trip behavior, this appendix presents a systematic two-phase methodology to estimate at external stations in small and medium urban areas:

- (1) through trip generation rates (percentage of through trip ends at a station measured as percent average daily traffic, ADT%); and
- (2) through trip distribution rates (percentage distribution of through trip ends from an origin station to a destination station) among stations.

By using multiple regression analysis and selected variables, the synthesized through trip models achieve high goodness-of-fit with survey data and validated model assumptions.

Literature Review

Compared to the extensive research efforts made to develop or improve other components of travel demand models, there is limited research on through trip estimation. Such research is difficult because of the varied locations and sizes of urban areas and the paucity of information about the destination characteristics of through trips [3]. Previous through trip models were designed for small urban areas with populations less than 50,000. The most widely used through trip model, which was published in 1982 [1], is based on research accomplished in the 1970's by Modlin [4] and Pigman [5]. This model was built upon external survey data collected in small communities of North Carolina and had a phase to estimate through trip generation at each external station and a phase to determine through trip distribution among stations. The model correlated through trip patterns with the effects of highway functional classification, average daily traffic (ADT), percentage of trucks, route continuity, and urban area population. Modlin pointed out that his models must be updated to remain valid as relationships among the independent parameters change. Based on Modlin's work, NCHRP 365 [3] selected and reprinted a set of regression models to serve as the through trip estimation techniques in small urban areas. The predicting equations suggested by NCHRP 365 have the same deficiencies as Modlin's TRR model: they were calibrated for small communities with populations less than 50,000, and they represent through trip patterns based on data collected 30 to 40 years ago. In addition, they heavily depend on traffic characteristics and do not account for unique study area economic and geographic factors which may significantly affect through trip patterns.

In recent years, new research has attempted to update through trip models with geographic and economic characteristics of small urban areas. Anderson [6, 7, 8] determined an interaction between small communities, nearby major cities (NMC), and highway facilities. Although the factor NMC was not clarified, his study shows that the economic context of a study area contributes to through trip patterns and that a study area is not an isolated island. Horowitz and Patel [9] improved the method for developing through trip tables in the *Quick Response Freight Manual* [10] by accounting for geographic characteristics of the study area, such as barrier effects and the location relations between external stations. Their study provides the geographic simulation approach which this paper uses.

Data Collection and Variable Analysis

Four major types of available data were assembled for this research: external origin-destination (O-D) survey data, transportation network data, socioeconomic data, and geographic data. The observed through trip generation and distribution rates were calculated based on external O-D survey data, while candidate independent variables which may affect through trips were developed by analyzing other data.

External O-D Survey Data

From July to October in 2005, the authors contacted US city and state agencies for recent external survey studies. In addition, the members and friends of TRB Committee ADA30, Transportation Planning for Small and Medium Sized Communities, were asked for data. Twenty-three agencies in five states responded and afforded their survey reports. Data cleaning eliminated study areas that were significantly larger than 200,000, located on the US border, or excluded key variables. The resulting dataset used for this research had external surveys for 17 communities and 253 external stations (Table A-1). The research methodology split the dataset into communities to develop the new models and into communities to evaluate the models.

Table A-1. Summary of Used External O-D Surveys

Urban Category	State	Community	Population (in 2000)	Study Year	# of Stations	Survey
Small	Alabama	Alexander City	15,008	2004	6	Inbound
		Arab	7,174	2004	4	Inbound
		Hartselle	12,019	2004	4	Inbound
		Roanoke	6,563	2004	4	Inbound
		Russellville	8,971	2004	4	Inbound
		Sylacauga	12,616	2004	5	Inbound
		Troy	13,935	2004	5	Inbound
	North Carolina	Pilot Mountain	2,912 *	1995	7	Two-way
Medium	North Carolina	Goldsboro	86,752	2003	32	Two-way
		Jacksonville	95,179	2002	9	Two-way
		Wilmington	172,322	2003	8	Outbound
	Texas	Brazos County	152,415	2001	15	Two-way
		Longview	256,152	2004	60	Two-way
		Midland/Ector County	237,132	2002	19	Two-way
		San Angelo	88,439	2004	23	Two-way
		Texarkana	129,749	2003	16	Two-way
Tyler	174,706	2004	32	Two-way		

* Population in 1995

Some study areas conducted one-way (inbound or outbound) external surveys to save money. With the assumption that an external station generally has equal inbound and outbound traffic over a day, the one-way through trip rates of a one-way external survey can be doubled for two-way rates where two-way rates are not available. A Nash-Sutcliffe statistical analysis [11] and the resulting high values of the model efficiency statistic for Jacksonville, NC, data validated the assumption of replacing two-way rates with doubled one-way rates (for through trip generation rates, inbound vs. two-way is 0.93, outbound vs. two-way is 0.88; for through trip distribution rates, inbound vs. two-way is 0.96, outbound vs. two-way is 0.98).

$$Test\ Statistic = 1 - \frac{\sum_i (X_i - Y_i)^2}{\sum_i (X_i - \bar{X}_i)^2} \quad (1)$$

where,

X_i = two-way through trip rate for observation i ;

Y_i = one-way through trip rate for observation i ;

\bar{X}_i = mean value for all observed two-way through trip rates.

Transportation Network Data

In this research, the necessary transportation network data at external stations included ADT, percentage heavy trucks, highway functional classification and the number of roadway lanes. The information for ADT and trucks was readily available in the external survey reports. To determine the highway facility types and the number of roadway lanes at external stations, an extensive library of geographic, demographic, and transportation data provided on the TransCAD 4.0 package CD-ROM was used. Local roadway maps available on State DOT websites and Google maps helped validate highway information.

Socioeconomic Data

The year 2000 U.S. Census provided socioeconomic data including population, employment, and income level (medium annual household income) for each study area. The small gaps of up to five years between survey year and census year for the study areas were ignored.

As discussed above, the spatial economic context of the study area may have significant effects on through trip generation and distribution rates because through trips are likely to be attracted to larger trip generators with greater populations. To quantitatively account for the influences of nearby major cities on through trip patterns at an external station, Zipf's and Huff's probability factors were developed based on Zipf's law of special interaction [12], Huff's probability contours [13] and guidelines by which appropriate surrounding cities were selected and studied [14]. The factors represent the weighted measurement of one city's attractiveness over the summation of the attractiveness of all surrounding cities.

$$Zipf_i = \frac{P_i / D_i^2}{\sum_i (P_i / D_i^2)} \quad (2)$$

$$Huff_i = \frac{P_i / D_i}{\sum_i (P_i / D_i)} \quad (3)$$

where,

$Zipf_i$ = Zipf's probability factor of external station i ;

$Huff_i$ = Huff's probability factor of external station i ;

P_i = population of the nearby major city towards external station i ;

D_i = distance between external station i and its corresponding nearby major city;

i = total number of external stations in the study area.

As previous studies [6, 7] have suggested, if a major highway facility (Interstate and US route) was nearby, the roadway, ADT, and distance from the study area to the facility were used instead of a community (NMC) in order to improve the model. This special case occurred at only three external stations in this research.

Geographic Data

This study used TransCAD and its integrated library of geographic data to collect and analyze the geographic characteristics of external stations, highway facilities and study areas to reveal their potential relation with through trip patterns. The resulting geographic variables include study area size, location of highway routes, the topology of external stations, and effects of barriers to the through trip interchange between external stations.

Especially in medium urban areas it was found that some highway facilities are “marginal” routes just cutting the edges of the study area. Basically such highway routes result in a pair of “marginal” external stations at the study area boundary. They are likely to have higher through trip generation rates than “non-marginal” routes that traverse the “core” region of the study area intersected by other highways. A dummy variable (MR) was used to account for the effects of marginal routes.

Based on a simulation approach which was suggested by Horowitz and Patel [9] to approximate the study area, external stations, catchment area and barrier, this research developed appropriate variables to account for the topology of external stations and barriers to the through trip distribution. The simulation process is illustrated in Figure A-1. The study area can be approximated by a circle which covers all the external stations and has a minimum radius (r_1). The through trips at each external station (E_i) are assumed to originate from the centroid of the corresponding catchment area (S_i). If there is a barrier between two catchment areas (i.e., an uninhabited area such as lake, mountain, etc.), two adjacent fictitious external stations are introduced such that the union of their catchment areas approximately covers the barrier. The probability of trips that pass through the study area between any pair of external stations can be summarized by a dummy variable as:

$$P_{ij} = I(C_i, C_j) \vee B(C_i, C_j) \quad (4)$$

where,

P_{ij} = probability of trips that pass through the study area between each pair of external stations;

C_i = the Cartesian coordinates of the centroid of catchment i ;

C_j = the Cartesian coordinates of the centroid of catchment j ;

$I(C_i, C_j)$ = an indicator function, equal to one if the line segment joining points C_i and C_j passes through the study area, and otherwise equal to zero;

$B(C_i, C_j)$ = an indicator function, equal to one if the line segment joining points C_i and C_j passes through a barrier, and otherwise equal to zero.

Since the catchment area can be simulated by an arbitrary width W , four scenarios of the catchment area with different widths ($W = \frac{1}{4} r_i, i = 1, 2, 3, 4$), were tested. Four dummy variables, - *Prob1*, *Prob2*, *Prob3* and *Prob4* - were introduced to represent the resulting P_{ij} under the four different scenarios. In addition, the resulting angles Φ between external stations were also studied because they represented how the relationship between the stations' locations may affect through trip distribution.

In this research, new external O-D survey data from different sized urban areas were collected to provide a basis for studying current through trip patterns. Although fewer agencies than desired sent external survey data, and cleaning the data further reduced the dataset, the dataset still provides a sufficient sample (254 stations). Besides the basic set of independent variables identified by previous models, this research developed efficient economic and geographic factors for transportation planning based on spatial economy theory and topology analysis. The new uses of such optional tools add complexity the new through trip models.

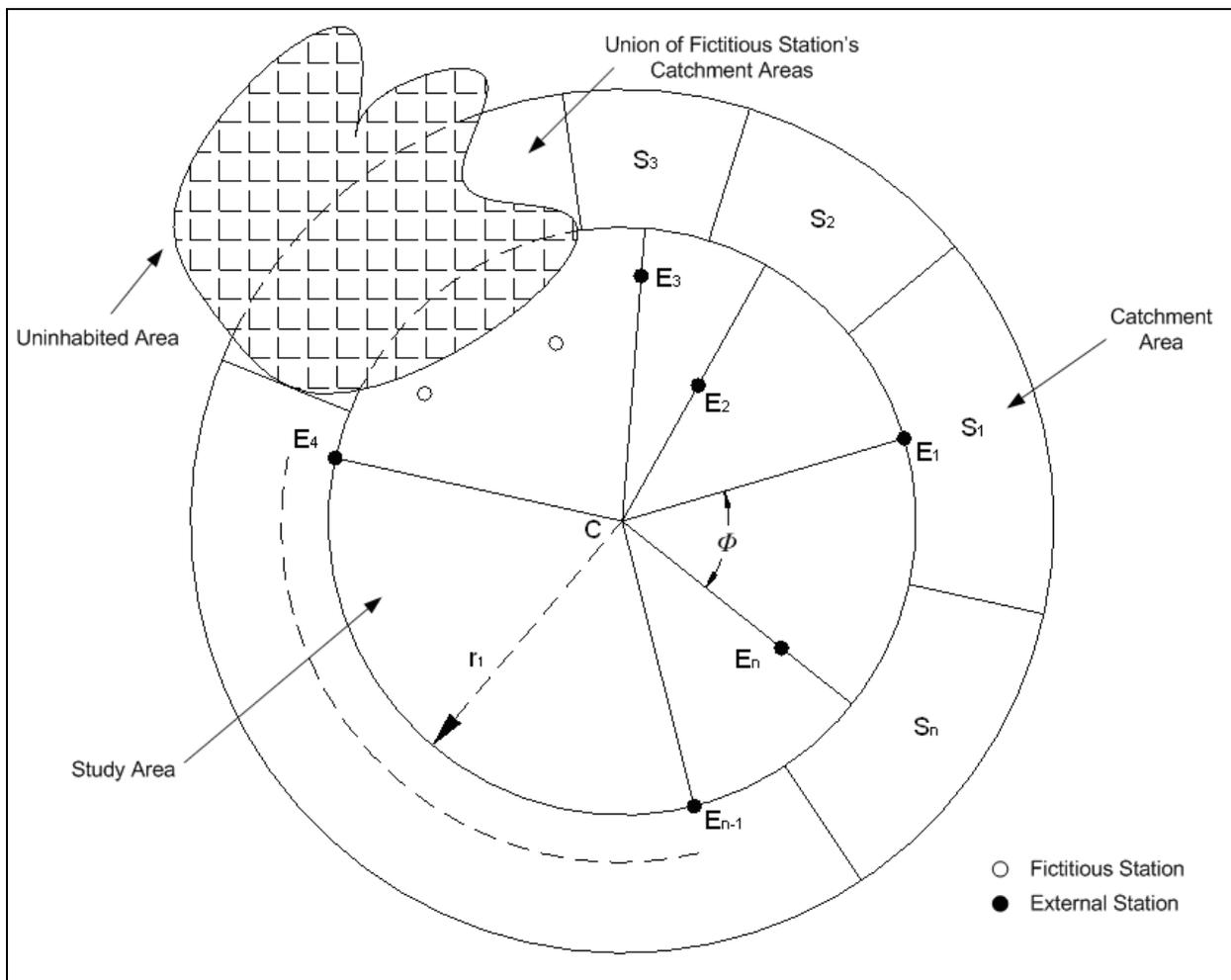


Figure A-1. Simulation of Study Area, External Stations, Catchment Area and Barrier

Methodology

The new through trip methodology (Figure A-2) includes two phases: Phase 1 through trip generation estimation and Phase 2 through trip distribution estimation. There are similar components in the modeling procedure for each phase, which are listed as below:

- 1) Comparison of through trip rates between city categories
- 2) Regression model development
- 3) Validation of model assumptions
- 4) Model transformations
- 5) Model adjustments (for Phase 2)
- 6) Model performance evaluation

The main objective of this research is to develop through trip models for use in small and medium urban areas. The models could be separate ones for small and medium areas or a combined single model which works for both city categories (Figure A-2). The research methodology includes an analysis to compare through trip rates between small and medium urban areas which leads to a scenario design for model development. The motivation to conduct this analysis is to determine if it is necessary to develop two individual models for small and medium urban areas using separate datasets or whether one model is sufficient.

A stepwise selection procedure was employed for multiple regression model development under different scenarios. The significant variables were selected at a 95% confidence level. The candidate models were evaluated and the best one chosen based on the goodness-of-fit with the data. Next, the model residual plots were examined to validate model assumptions and the possible need for model transformation. For the through trip distribution model development in Phase 2, an adjustment procedure was additionally introduced to improve model output. Finally, based on the observed data, the predictive power of the resulting final model was evaluated by comparison to previous models.

The non-transformed models produced fan shapes residual plots indicating that the model assumption of the constant variance of residuals was violated and that a model transformation was required. The square root transformation of dependent variables (i.e., through trip generation and distribution rates) was conducted so as to maintain the sample size since a portion of the observations have values of zero. (About 8% of observed through trip generation rates and about 14% of observed through trip distribution rates have zero values.) The resulting transformed dependent variable more closely satisfied model assumptions. For efficiency of model development in this paper, only transformed model results are discussed in detail.

Model Development

As Table A-1 shows, the external O-D surveys of 17 small and medium sized urban areas were the sources data giving 186 observed through trip generation rates and 473 observed through trip distribution rates for analysis. The observed through trip rates were transformed by the square root and used as dependent variables. To develop through trip models, nine communities were randomly selected and used. The remainder were used for model evaluation. Table A-2 summarizes how the data were used in the methodology.

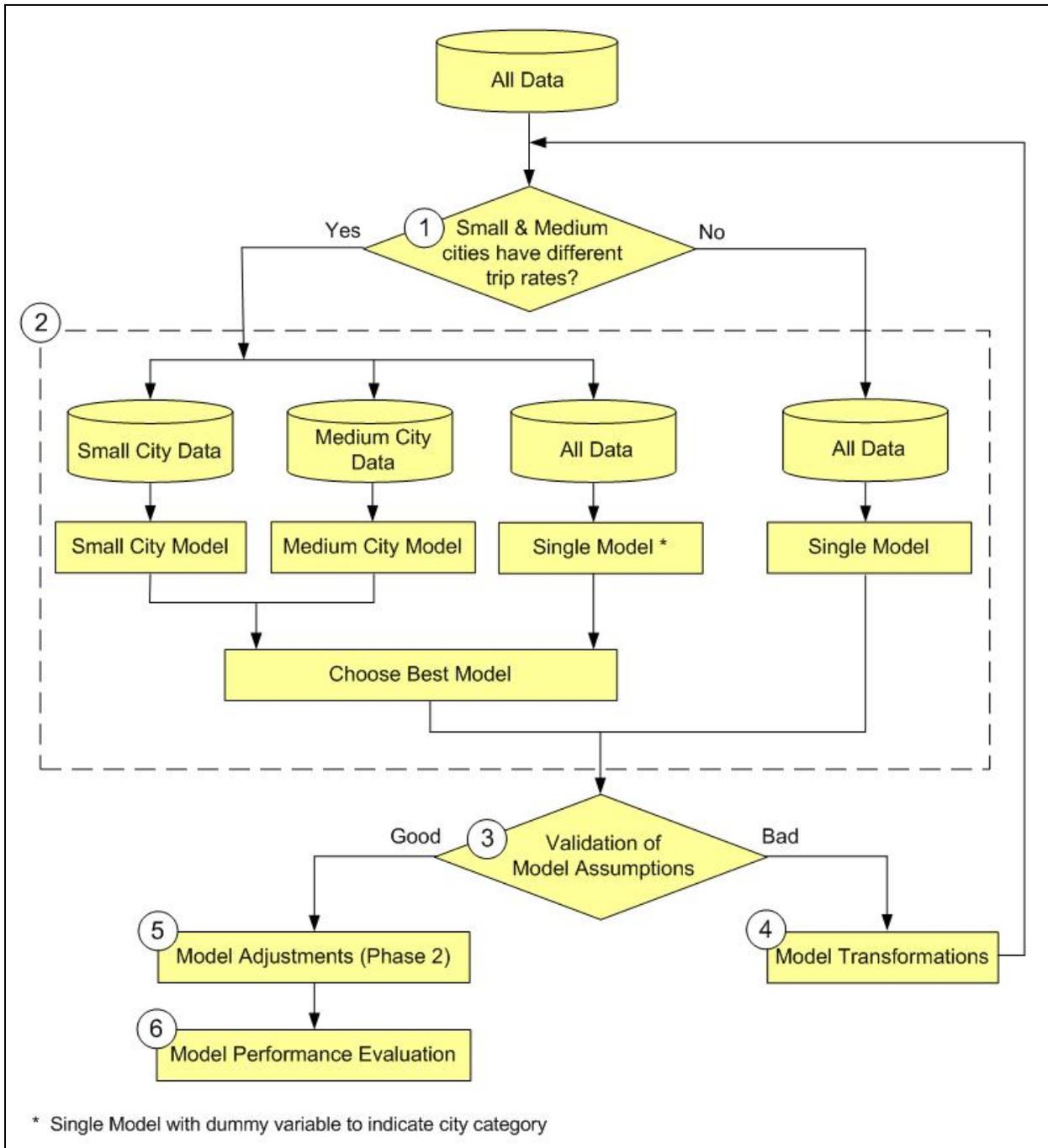


Figure A-2. Methodology Flow Chart

Table A-2. Summary of Data Use in Methodology

Urban Category	State	Community	Through Trip Generation Estimation			Through Trip Distribution Estimation		
			# of Observations	Model Development	Model Evaluation	# of Observations	Model Development	Model Evaluation
Small	Alabama	Alexander City	6	√		30	√	
		Arab	4		√	12		√
		Hartselle	4	√		12	√	
		Roanoke	4	√		12	√	
		Russellville	4		√	12		√
		Sylacauga	4	√		12	√	
	Troy	5	√		18	√		
North Carolina	Pilot Mountain	7		√				
Medium	North Carolina	Goldsboro	32	√		279		√
		Jacksonville	9	√		72	√	
		Wilmington	8		√			
	Texas	Brazos County	8		√			
		Longview	32	√		2	√	
		Midland/Ector County	13	√				
		San Angelo	11	√				
		Texarkana	14	√		6	√	
Tyler	21	√		6	√			

Through Trip Generation Model

The through trip generation model estimates the through trip generation rate (i.e., the percentage of ADT through trip ends) at each external station. Because the ADT is usually known at each external station, the through trip ends at each station can be determined given the estimated through trip generation rate.

To compare through trip generation rates between small and medium urban areas, a two-step hypothesis test procedure was conducted: 1) test the equality of two sample variances, and 2) test the equality of two sample means. The hypothesis test for the equality of two sample variances resulted in an F -value = 1.60 and p -value = 0.2020 (> 0.05), which indicated the transformed through trip generation rates of small and medium urban areas have the same variances at a 95% confidence level. Then a hypothesis test was conducted to compare sample means assuming equal population variances. This hypothesis test produced a t -value of -7.75 associated with a p -value less than 0.0001. It strongly indicated that the through trip generation rates of small urban areas are significantly less than those of medium urban areas, which is consistent with the findings of previous through trip studies [1, 3]. The validation of the significant difference between through trip generation rates observed in small and medium urban areas led to an intuitive modeling framework of two separate models for small and medium urban areas. However, a single model building upon combined data may be more appealing because of an enlarged sample size for analysis. Therefore, two scenarios were designed for through trip generation model development:

Scenario 1 (Separate Models)

- use small urban area data for a small city model development
- use medium urban area data for a medium city model development

Scenario 2 (Single Model)

- use both small and medium urban area data as well as a dummy variable *Small* (equal to 1 if urban population less than 50,000; equal to 0 otherwise) indicating urban category for a single model development

For 15 candidate independent variables, a stepwise selection procedure with a cutoff value of 0.05 (95% confidence level) was used to select significant variables under the different scenarios. Table A-3 summarizes the resulting regression models for through trip generation.

Table A-3. Through Trip Generation Models

Scenario	Urban Category	Sample Size	R ²	Adjusted R ²	Through Trip Generation Model
1	Small	23	0.21	0.18	$Y_i = (5.149 + 0.000133ADT)^2$
	Medium	132	0.71	0.69	$Y_i = (3.404 - 0.872Other + 2.685MR + 0.000101ADT - 0.000027Pop + 0.046TRK + 0.0011Area + 0.000023Emp)^2$
2	Small & Medium	155	0.76	0.75	$Y_i = (3.353 - 0.850Other + 1.671Small + 2.682MR + 0.000104ADT - 0.000029Pop + 0.046TRK + 0.0012Area + 0.000026Emp)^2$

Y_i = percentage of through trip ends of ADT at external station i (%);
 ADT = average daily traffic at external station i ;
 $Other$ = collector/local roads (0 or 1);
 MR = marginal highway route (0 or 1);
 Pop = population in study area;
 TRK = percentage of trucks at external station i (%);
 $Small$ = small urban area (0 or 1);
 $Area$ = area size of study area (mile²);
 Emp = employment in study area.

The three transformed regression models in Table A-3 include different significant variables because the socioeconomic characteristics and traffic patterns change in the three urban categories. It is obvious that the small city model (Scenario 1) has a very poor R^2 (0.21) while the single model developed under Scenario 2 has the highest R^2 (0.76), which means it fits the data best. Although the single model includes more variables than other two models, its highest adjusted R^2 (0.75) still validates its best predictive power after accounting for the number of independent variables. The single model's best goodness-of-fit resulted from a combined dataset with a larger sample size from both small and medium urban areas. The larger sample size better explains the variation of the through trip generation rates caused by related socioeconomic, geographic and traffic factors in different sized urban areas. Compared to the separate models which were only developed for either small or medium study areas, the single model can be used as a comprehensive model for through trip generation estimation in both small and medium cities. Overall, the single model was superior to the separate models and is recommended for through trip generation estimation.

Through Trip Distribution Model

The through trip distribution model estimates a through trip distribution rate between each pair of origin-to-destination stations. The through trip distributions among stations determine the through trip O-D table.

The previous hypothesis test procedures were repeated to compare through trip distribution rates between small and medium urban areas. The transformed through trip distribution rates were proven significantly different between small and medium urban areas (F -value = 2.13 and p -value = 0.0007). In the situation in which the sample variances suggest different population variances, the Satterthwaite's approximate t test [14] was conducted to compare sample means. The resulting t -value of -4.71 (p -value < 0.0001) strongly indicated that small and medium urban areas have significantly different through trip distribution rates. Therefore, as before, two scenarios were designed to develop two separate models for small and medium urban areas and a combined single model with a dummy variable $Small$ indicating urban category.

Due to the deficiencies of data for several specific highway functional classifications, the new distribution models were developed without distinguishing facility types so as to achieve more robust results based on a larger sample size. The new models actually account for highway types by studying some key variables (e.g., ADT, percent through trips, and number of lanes, etc) which are all indicators of highway functional classifications. Furthermore, the resulting model without highway functional class is easier to use and to some extent more accurate than previous models which require correctly identifying stations' functional classifications.

Twenty five candidate variables were studied in the stepwise selection procedure with a 95% confidence level. Table A-4 summarizes the resulting trip distribution regression models.

Table A-4. Through Trip Distribution Models

Scenario	Urban Category	Sample Size	R ²	Adjusted R ²	Through Trip Distribution Model
1	Small	84	0.49	0.45	$Y_{ij} = (1.42 + 1.29RTECON + 0.73D_LANE - 0.03D_PTT + 2.00Prob1 + 1.64D_Zipf)^2$
	Medium	86	0.74	0.73	$Y_{ij} = (0.20 + 5.04RTECON + 0.19D_ADT_CD + 1.13Prob3 - 0.04O_PTT)^2$
2	Small & Medium	170	0.56	0.54	$Y_{ij} = (-0.25 + 2.74RTECON + 1.65Prob1 - 1.64O_MR + 3.18D_Zipf + 0.72D_LANE - 1.53D_MR)^2$

Y_{ij} = percentage distribution of through trip ends from origin station i to destination station j ;
RTECON = route continuity between origin and destination station (0 or 1);
D_LANE = number of highway lanes at destination station;
O_PTT = percentage through trip ends at origin station;
D_PTT = percentage through trip ends at destination station;
D_ADT_CD = ratio of ADT at destination station to the sum of ADT at all stations;
D_Zipf = Zipf's probability factor of destination station;
O_MR = marginal highway route at origin station (0 or 1);
D_MR = marginal highway route at destination station (0 or 1);
Prob1 = likelihood of through trip exchange between origin and destination stations when the width of catchment area equals to one-quarter of the simulated study area radius;
Prob3 = likelihood of through trip exchange between origin and destination stations when the width of catchment area equals to three-quarters of the simulated study area radius.

According to the three prediction equations listed in Table A-4, the medium city model developed under scenario 1 has the highest R^2 (0.74). The small city model's R^2 (0.49) is slightly smaller than that of the single model (0.53). Similar results are found by checking the adjusted R^2 of each model. It is also noticed that the single model does not include the urban category (*Small*) which was validated to be a significant variable during the scenario design for model development. The urban category *Small* was significant when it was tested alone for the scenario design; however, it seemed insignificant after accounting for other variables in the stepwise selection procedure. From a viewpoint of overall goodness of fitting data, the separate models were considered superior to the single model since the medium city model has the largest R^2 and the small city model has almost the same power of goodness-of-fit with the single model.

By using the new models, through trip interchanges among external stations can be predicted. A simple factoring process is suggested to scale estimated percent distributions so that their resulting sum is 100 percent for a specific origin station. The Fratar method can then be applied to control total through trip ends at each station.

Model Performance Evaluation

As Table A-2 shows, a few small and medium case cities were used to evaluate the recommended new through trip models by comparing the results with previously published models [1, 3, 8].

Through Trip Generation Model Evaluation

Three small communities (15 observations) and two medium communities (16 observations) were tested for the performance evaluation of the new single through trip generation model. Table A-5 shows the root mean square error (*RMSE*) of different model estimates.

Table A- 5. Comparison of *RMSE* of Through Trip Generation Models

Urban Category	Community	<i>RMSE</i>			
		New Single Model	TRR 842	NCHRP 365	Anderson's Model
Small	Arab	11.92	13.09	21.25	22.39
	Russellville	9.35	15.99	6.70	26.42
	Pilot Mountain	6.47	11.62	29.80	14.76
Medium	Brazos County	10.11	16.31	17.93	49.53
	Wilmington	6.41	14.75	7.62	78.42

Table A-5 clearly shows that the new single model has a smaller *RMSE* than other small urban area models except Russellville (6.70). The new model's good performance and smaller *RMSE* is also observed in medium urban areas. The comparative analysis supports the conclusion that the new model provides better estimation accuracy than previous models. (The Russellville anomaly and possible data deficiency are in the trip distribution section below.)

The new single model's predictive power in both small and medium urban areas was further evaluated by a scatter plot of estimations for all case cities (Figure A-3). The scatter plot shows that all points approximately fall on a 1:1 line of predictions versus observations. Furthermore, the scatter plot results in a Nash-Sutcliffe model efficiency statistic (Equation 1) with a high value of 0.81. The overall analysis indicates that the new model works well as a single prediction equation in both small and medium urban areas, and it strengthens the conclusion that the calibrated small/medium through trip generation model transfer to other small and medium sized areas.

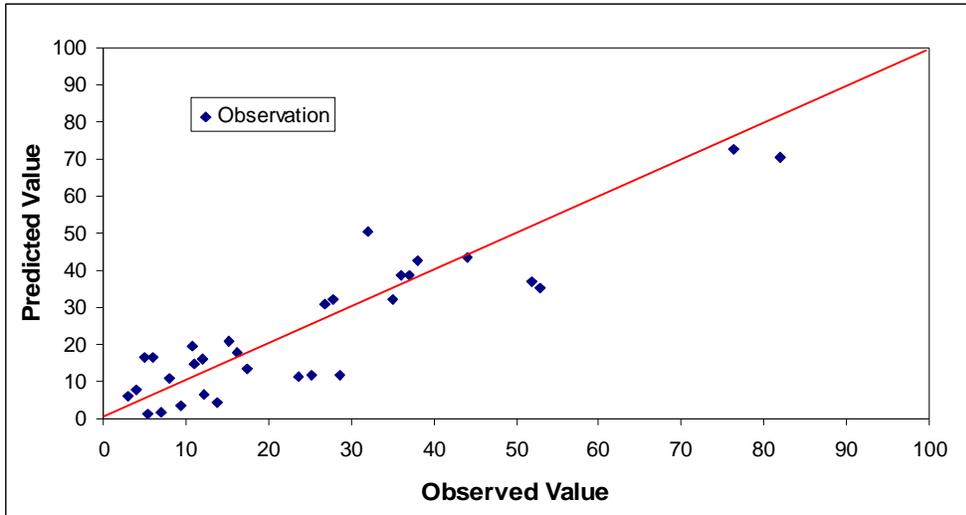


Figure A-3. Performance of New Through Trip Generation Model in All Case Cities

Through Trip Distribution Model Evaluation

Two small communities (12 observations) and one medium community (279 observations) were used to evaluate the recommended separate trip distribution models. The factored through trip distribution rates were also compared with non-factored rates. Table A-6 summarizes the *RMSE* of different models for small and medium urban areas.

It is noted that all models gave relatively large *RMSE* in Russellville. Further data examination found a major highway was not included in the Russellville external survey, which caused deficient survey results assuming all through trips are distributed among surveyed stations. Based on *RMSE* comparisons, the new separate models have an obvious advantage over previous models. Furthermore, the factoring process helps improve estimation results. As a whole, the new through trip distribution model is superior to previous models according to both non-factored and factored estimates. The good performance of the new model in the case communities also suggests transferability to other small or medium urban areas.

Table A-6 Comparison of *RMSE* of Through Trip Distribution Models

Urban Category	Community	<i>RMSE</i> of None-Factored Estimation			<i>RMSE</i> of Factored Estimation		
		New Separate Models	TRR 842 / NCHRP 365	Anderson's Model	New Separate Models	TRR 842 / NCHRP 365	Anderson's Model
Small	Arab	5.57	11.03	20.63	4.64	9.91	18.24
	Russellville	28.13	29.31	30.47	27.95	30.09	27.70
Medium	Goldsboro	5.24	5.27	10.22	4.79	5.36	9.69

Case Study

The new through trip models were applied to Pilot Mountain, a small town of about 1,300 residents in North Carolina (figure with routes/streets mentioned below). A new spreadsheet model [17] implements a manual travel allocation method for small urban areas to accomplish trip generation and trip distribution. Based on the new single through trip generation model and the small city through trip distribution model, the through trip table was separately developed and then integrated into the total Pilot Mountain OD matrix. The traffic assignment was accomplished by a TransCAD equilibrium assignment algorithm.

Accomplishing the Pilot Mountain case using spreadsheet tools required about one day to develop through trip OD table which includes about 33% of the total 57,503 average daily trips in base year 1995. Five days were necessary to complete the entire travel demand forecasting process based on the manual travel allocation spreadsheet model [17]. According to the TransCAD assignment results for Pilot Mountain, the major through route is US 52 and carries most of the area traffic (12,000 ADT) as expected. NC 268 carries about 6,000 ADT in the downtown area and 6,000 ADT near the interchange with US 52. US 52 matches counts within $\pm 12\%$, and the lower volume streets (Shoals Road, Westfield Road and NC 1855) agree within $\pm 20\%$. All the assigned links resulted in a R^2 with high value of 0.82. These results are consistent with FHWA validation guidelines [17].

Findings and Recommendations

The major purpose of this research was to improve the current through trip models for small urban areas and to develop a new methodology for through trip estimation in medium urban areas. Based on newly collected data, a systematic methodology developed robust through trip models which achieved a high goodness-of-fit with data and did not violate model assumptions. Spatial economy theory and topology analysis were used to simulate the economic and geographic contexts of the study area. The recommended through trip generation and distribution models were validated to provide better accuracy than previous models. Furthermore, new economic and geographic variables improve the models' predictive power by accounting for the unique characteristics of different study areas.

The recommended through trip models are not data intensive and are easy to use. In small urban areas where 30% or more of the trips may be through trips, the new models will improve the travel forecasting process and reduce costs. In medium urban area where external surveys may be supported, the new models can help guide survey design, indicate critical survey areas, and help reduce survey cost.

The systematic research methodology is applicable and transferable to additional datasets for small and medium sized areas in other states. By thoroughly performing the methodology, the resulting through trip generation and distribution models are expected to be reliable and the calibrating database will be increased. Such future research will also develop more efficient methods for accounting for the influences of barriers and the relations between external stations and perhaps further simplify the models.

In conclusion the new models are easy to use and their good case study performance suggests that they are transferable to other small and medium urban areas. The models show promise for estimating through trips in a fast and cost-effective manner, and they can, thus, improve the travel demand forecasting process in small and medium study areas. Automating the procedures in a spreadsheet like the manual travel allocation spreadsheet [17] will further enhance cost-effectiveness.

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APPENDIX B: EXTERNAL TRIPS

Introduction

In this research project, external trips are defined as trips which have one end, either origin or destination, within the planning area. External trips can be classified further into external-internal or internal-external trips, depending on the origin of a trip outside the planning area or not. The point on the roadway where the planning cordon is crossed is referred to as an external station.

The estimation of external trip productions and attractions is needed as part of the trip generation process. In the transportation planning process, the external trips and through (external-external) trips need to be split at each external station where the average daily traffic (ADT) count is generally available, because different OD tables need to be developed for external and through trips respectively. Historically, the most popular method for collecting external trip data is to conduct a roadside intercept survey at the regional cordon. However, very few roadside surveys have been conducted in recent years, primarily because of costs and the concern that stopping vehicles on the highway would be perceived as an unacceptable intrusion on the motorist [1]. This appendix aims at developing a cost-effective method to estimate total external (external-internal and internal-external) trips at external stations based on communities' economic characteristics.

Literature Review

The effort on measuring and modeling external trips has been less intensive than for internal trips. One of the reasons is that very little is known about the socioeconomic characteristics at the end of the trip that is outside the planning area. NCHRP Report 365 [1] represents an indirect approach to estimate external trips generated in small communities where an external survey is not available or possible. The first step of this methodology is to use a through (external-external) trip model [2] to summarize the through trip matrix by direction and stations and subtract these totals from the average daily traffic (ADT) counts at stations. The remainders represent the overall control totals by station for external trips. The directional differences of external trips are usually ignored by assuming that the total trips entering the planning area equals the total trips leaving the study area in a typical daily period. The next step may include separating the external trips by purpose and resident status based on an external survey or knowledge of local traffic patterns.

In recently completed research, a new methodology [3] was developed to estimate through trip generation and distribution in both small and medium urban areas based on traffic patterns, economic factors, and geographic factors of planning areas. This model provides accurate results and shows transferability between communities with different sizes and locations. Given the estimated through trip percentages at external stations, the external trips can be calculated by subtracting through trip ends from available ADTs. This new through trip estimation methodology is introduced in Appendix A.

Very few references were found to directly study external trips. Modlin [4] provided a multiple regression equation to estimate the split between external-internal and internal-external trips based on the characteristics of different employment types of communities. Although this model was not widely used it motivated an external trip estimation approach from an economic point of view, which will be used in this research.

Data Collection

Two major types of data were collected for the external trip modeling process. They are external survey data and employment data.

External Survey Data

Recent external survey reports for a variety of study areas were collected and used for the research. In each study area, a one-way or two-way survey was conducted to capture through trip ends, external-internal trip ends and internal-external trip ends at each external station. Therefore, the percentage of total external trips of all trips that enter or leave the study area can be obtained so as to develop a new external trip estimating methodology. Related analysis validated that one-way surveys and two-way surveys produce consistent percents of external trips [3]. The resulting dataset includes 16 different sized study areas in three states. To develop the model, some areas were randomly selected and used. Others were used for model validation. Table B-1 summarizes these communities by different urban sizes: small urban areas (populations < 50,000) and medium urban areas (populations > 50,000).

Table B-1. Summary of External Survey Data

Urban Size	State	City	Population (in 2000)	External Trips (%)	Model Development	Model Validation
Small	Alabama	Alexander City	15,008	43.85	√	
		Arab	7,174	56.78	√	
		Hartselle	12,019	49.38	√	
		Roanoke	6,563	64.39	√	
		Russellville	8,971	63.61	√	
		Troy	13,935	55.29	√	
	North Carolina	Pilot Mountain	2,912*	34.66		√
Medium	North Carolina	Jacksonville	95,179	80.80		√
		Goldsboro	86,752	74.22		√
		Wilmington	172,322	92.76		√
	Texas	Brazos	152,415	83.74	√	
		Longview	256,152	77.34	√	
		Midland/Ector	237,132	92.93	√	
		San Angelo	88,439	90.02	√	
		Texarkana	129,749	72.75	√	
Tyler	174,706	81.90	√			

* Population in 1995

Employment Data

Employment is a critical criterion of the economic profile of a study area. The employment complexion is a key factor representing the “attraction” of a study area, which, therefore, directly affects external trip patterns. Furthermore, employment data is easy to obtain from the U.S. economic census [5] and provides a cost-effective basis for model development.

Profiling American businesses every five years from the national to the local level, the U.S. economic census organizes employment data by different types which are defined by North American Industry Classification System (NAICS) [6]. NAICS is a unique, all-new system for classifying business establishments and it replaces the Standard Industrial Classification (SIC). Table B-2 lists the NAICS employment types according to NAICS.

Table B-2. NAICS Employment Type

NAICS Code	Sector Title	Sector Abbreviation
21	Mining	MIN
22	Utilities	UTIL
23	Construction	CONS
31-33	Manufacturing	MANU
42	Wholesale Trade	WHOLESALE
44-45	Retail Trade	RETAIL
48-49	Transportation and Warehousing	TRANS
51	Information	INFO
52	Finance and Insurance	FINANCE
53	Real Estate and Rental and Leasing	ESTATE
54	Professional, Scientific, and Technical Services	PSTS
55	Management of Companies and Enterprises	MANA
56	Administrative and Support and Waste Management and Remediation Services	ASWMRS
61	Educational Services	EDU
62	Health Care and Social Assistance	HCSA
71	Arts, Entertainment, and Recreation	AER
72	Accommodation and Food Services	AFS
81	Other Services (except Public Administration)	OS

As Table B-2 shows, different employment types have their own industrial characteristics and should have different contributions to external trip generation in communities. In this research, the NAICS employment data were collected for each study area to get the percentage of each type of employment at the local level. Then, local employment characteristics were compared to corresponding statewide employment data so as to develop a set of ratios for all employment types. These developed indexes summarize the unique economic complexion in each community and are considered as explanatory variables to external trip patterns.

Model Development

A multiple regression analysis was conducted to build the relationship between the percentage of external trips in the study area and the regional employment characteristics. The stepwise selection procedure with a cutoff value of 0.05 was used to select the most significant variables at a 95% confidence level. Since the study areas have different urban sizes, the analysis was performed under two different scenarios.

- I. Scenario 1 (Separate Models)
 - use small urban area data for small city model development
 - use medium urban area data for medium city model development
- II. Scenario 2 (Single Model)
 - combine small and medium urban area data
 - use a dummy variable to distinguish urban size

Table B-3 shows the multiple regression models developed under the two scenarios.

Table B-3. External Trip Models

Scenario 1	Small City Model	$Y = 59.64 + 12.01MIN - 1.56WHOLESALE - 1.38ESTATE - 2.16ASWMRS$	$R^2 = 1.00$
	Medium City Model	$Y = 58.66 + 31.76AER$	$R^2 = 0.82$
Scenario 2	Single Model	$Y = 83.11 - 27.56Small$	$R^2 = 0.79$

where,

Y = percent external trips in study area (%);

MIN = ratio of local value to statewide value, for percent employment type of NAICS code 21;

$WHOLESALE$ = ratio of local value to statewide value, for percentage employment type of NAICS code 42;

$ESTATE$ = ratio of local value to statewide value, for percent employment type of NAICS code 53;

$ASWMRS$ = ratio of local value to statewide value, for percent employment type of NAICS code 56;

AER = ratio of local value to statewide value, for percent employment type of NAICS code 71;

$Small$ = small urban area (0 or 1).

According to the two separate models developed under Scenario 1, the percentage of total external trips for a study area is sensitive to the share of local employment types. However, the economic factors are not suggested by the single model. It is also clear that the two separate models developed under Scenario 1 have better goodness-of-fit with data ($R^2 = 1.00$ and 0.82 for small and medium city model respectively) than the single model ($R^2 = 0.79$). Therefore, the separate models are considered superior to the single model.

As Table B-1 shows, one small urban area and three medium urban areas that were not used for model development were used to validate the developed separate models. Table B-4 compares estimates and observed results in these four case cities.

Table B-4. Model Validation

Model	Case City	Observed External Trips (%)	Predicated External Trips (%)	R^2
Small City Model	Pilot Mountain	34.66	56.05	~
Medium City Model	Jacksonville	80.80	82.93	0.67
	Goldsboro	74.22	75.34	
	Wilmington	92.76	100.00	

The comparisons show that the medium city model provides satisfactory estimation of percent external trips for medium case cities ($R^2 = 0.67$). The small city model seems to produce acceptable external trip estimation for Pilot Mountain, North Carolina, although there are insufficient samples of small cities to strengthen this conclusion.

Findings and Conclusions

This study finds that online state and city NAICS economic data can be used to develop reasonable, statistically valid external trip models for small and medium urban areas. The separate regression models are both efficient sketch planning tools and have two major uses:

- 1) The model result can be used as control totals to proportionally adjust external trips estimated by other models;

- 2) The total external trips estimated by this methodology can be assigned to each external station according to the knowledge of local traffic patterns.

The models are easy to use and they are not data intensive. No traffic counts are required to apply the model because economic data is readily available from online sources.

The small city model needs more data for complete validation. Based on three case cities, the medium city model seems to be transferable to other communities, especially NC communities.

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APPENDIX C: INTEGRATED LAND USE AND PEDESTRIAN TRIP GENERATION STUDY

Introduction

Approaches to MPO and regional models tend to focus on developing appropriate model structures and identifying critical travel demand factors. Traditional travel demand modeling has accounted for transportation and demographic factors. However, they do not fully capture some of the emerging emphasis on integration with land use factors and the use of alternative modes. Especially, large regions often have various mixes of residential, commercial, and even light industrial land uses, which can create substantial variation in travel behavior among neighborhoods. To yield more accurate travel demand estimates, a regional approach that estimates trip generation for a finer-grained categorization of land uses and accounts for modal options is needed.

The research described by this appendix aims at developing integrated land use and pedestrian trip generation models. The analysis will confirm our expectation that trip generation rates can vary with land use factors including density, diversity and design. More specifically, the research objectives are:

- ê To examine and estimate the connection between land use and pedestrian trip generation using the 2006 Triangle Travel Survey dataset.
- ê To predict the number of pedestrian trips at the TAZ level in Jacksonville, NC based on the estimated Triangle models.

This research uses two datasets: the Triangle dataset for estimating pedestrian trip models; and the Jacksonville dataset for applying the estimated models. The final Triangle dataset used in this research includes both travel behavior data from the 2006 Triangle Travel Survey and land use data obtained from local and regional GIS agencies that were integrated with the behavioral data.

This report documents two methods for predicting pedestrian trip generation (productions). One method, named the density and diversity (2-D) method, is a simple technique that can be easily used by practitioners with limited land use detail. The other method, named the land use characterization (LUC) method, is an advanced technique that can be used when practitioners are acquainted with GIS analysis and have good access to land use data.

The 2-D method first generates simple density and diversity measures for land use. Examples include population density and employment density. Then, regression analysis was applied to model the association between the simple spatial measures and the number of daily pedestrian trips per household. As the trip generation rates vary by household type, this method estimates OLS, log-transformed, and negative binomial regression models for each household type. Five sets of regression models were estimated, respectively representing 1-person households, 2-person households, 3-person households, 4+-person households, and all households. The household type-specific models were developed to match the Jacksonville TAZ database, since it contains information on household size. The estimated models were applied to the Jacksonville case to demonstrate how the 2-D method can be used to predict pedestrian trip generation in other geographic regions.

The LUC method generates a comprehensive list of land use measures on all of the density, diversity, and design dimensions at both the neighborhood level and the household location level. The method further uses factor analysis to address the issue of high correlations among land use measures, and to derive several land use indices. Based on the derived land use indices, cluster analysis was applied to identify an appropriate neighborhood typology for the Triangle region. The average rates of pedestrian trip generation were then produced for each neighborhood type. To apply the LUC method to the Jacksonville

case, this research assigns neighborhood types to the 143 TAZs in Jacksonville, and then predicts the number of pedestrian trips in each Jacksonville's TAZ based on their assigned neighborhood types.

The report structure is as follows. The second section briefly reviews the relevant literature on land use and travel behavior. The third section describes relevant data sources and data manipulation, followed by the fourth section that summarizes the demographics and travel behavior characteristics of the surveyed households. The fifth section introduces the 2-D method of predicting pedestrian trip generation, followed by the sixth section that details the LUC method. Finally, the forecast outcomes from the 2-D method and the LUC method were compared for validation and calibration purposes. The conclusion section documents the main findings of this study and discusses the advantages and disadvantages of the two methods offered here. In addition, Appendix C-1 reports the detailed prediction results in the Jacksonville case. Appendix C-2 shows how the relationship between land use and trip generation varies by modes (walking versus driving) and points out the important of considering pedestrian trips separately from auto trips.

Literature Review

Land use forms the physical environment setting for urban dwellers and their daily behavior. It plays a key role in travel behavior. Several extensive literature surveys are already available in summarizing the connection between land use and travel behavior [1-3]. A number of existing studies have provided empirical evidence that travel behavior is influenced by both land use factors and socioeconomic characteristics [1]. In the following text, we will provide a brief summary of land use measures that have been used to predict travel behavior.

The land use measures used in travel behavior research vary from simple dichotomies (e.g. contemporary vs. traditional, automobile-oriented vs. pedestrian-oriented, suburban vs. urban) to sophisticated statistical techniques such as indices and latent variables (e.g. land use mix, accessibility, connectivity, etc). The geographic scales of those measures range from regional to local.

Although simple categorization can involve a huge loss of information, this method has its strength because land use factors are difficult to isolate, and the isolation may result in methodological problems such as multi-collinearity [1]. Studies involving simple categorization often identify two extreme neighborhood types, and then compare the residents' travel behavior to learn about the land use effects. The comparisons are typically based on land development characteristics such as transit-oriented [4], mixed-use[5], traditional [6-8], urban[9], new urbanist [10, 11].

As more researchers and practitioners have become skilled in spatial analysis and more spatial data are available, considerable effort and progress have been made in creating multi-dimensional land use measures. Those studies are intended to isolate the effects of different land-use features on travel behavior, and to identify the features that are most important in travel decision making. For example, Cervero and Kockelman [12] popularized a concept of the "three D's" measurement – density, diversity, and design. Density measures typically include both population and employment densities; diversity measures often are indicators of land use mix; and design measures are mostly concerned with the street network.

Street design measures include street connectivity (number of intersections, number of cul-de-sacs, grid layout etc.) and the availability of transportation facilities (sidewalks, bike lanes, transit stop, etc.). Density can be measured in terms of the population (people or households per acre or square mile), employment (jobs per acre or square mile), or building (floor-area ratio, parcel size, etc.) [13]. The proximity of different land uses can be represented by the distance from home to employment or shopping

centers [14] or by the indicators of mixed land use such as dissimilarity indices [12, 15] and entropy variables [15, 16].

Besides the continuous efforts in developing new measures within various land use sub-dimensions, recent research has been making progress in applying statistical methods to land use measurements [17]. Examples include factor analysis and cluster analysis. Factor analysis is used to combine all the underlying land use features into composite measures [18, 19]. The idea of using composite measures is to capture the collective effects involving multiple land use indicators. And they can also avoid multicollinearity problems in model estimation. For example, the grid-like street pattern is often associated with higher density. Certain urban design features such as benches are more likely to appear in transit-oriented and pedestrian-oriented neighborhoods.

Unlike factor analysis which aims at combining various land use indicators into composite measures, the purpose of cluster analysis is to reduce the multiple and often highly correlated measures (such as measures of land use mix) into a few neighborhood typologies [20]. This method classifies neighborhoods into different types based on the quantitative measures. The identified neighborhood types can then be used to examine the neighborhood effects on daily travel.

In order to better understand the connection between land use and pedestrian trip generation, this research will use multiple existing means in the literature to measure land use. The 2-D method examines the land use-travel connection using direct land use measures. The LUC method estimate average pedestrian trip rates based on a neighborhood typology developed by factor and cluster analyses.

Data

Behavioral data used in this research come from the 2006 Triangle Travel Survey (N = 5,107 households). The survey used computer-assisted telephone interviewing to gather household- and personal-level travel data from all members of the sample households during a specified non-holiday non-weekend 24-hour travel day beginning January 31 and ending May 26. Detailed land use data were acquired from local and regional GIS agencies including the Capital Area Metropolitan Planning Organization, the Durham-Chapel Hill-Carrboro Metropolitan Planning Organization, and the Triangle J Council, and were integrated with the behavioral survey data.

Out of the 12 counties in the greater Triangle region, only Durham, Wake and Orange Counties were able to provide parcel-level land use data. Those three counties comprise the study area for this research. An advantage of the Triangle survey is that the sample design included minimum sample sizes for the following population subgroups: low-income households, transit-using households, college students, and households with members who walk or bike to work/school. This ensures statistical power in studying travel behavior of alternative modes such as walking.

A total of 3,480 households in Durham, Orange and Wake Counties were surveyed, comprising the final dataset for model estimation. Figure C-1 shows the spatial distribution of the 3,480 surveyed households.

The attributes describing the surveyed households include personal/household information and georeferenced activity/travel data. We aggregated data for 35,036 trips to the person and then to household level to provide additional information about travelers and household characteristics. Using ArcGIS, land use measures were added to the household-level data to enrich the pedestrian trip generation models.

Descriptive Analysis

The purpose of this section is to summarize the demographics and travel behavior characteristics of the surveyed households and to provide details highlighting how demographic variations in the households across the study area are reflected in the travel behavior data. All results are weighted, unless otherwise noted.

The 3,480 households in Orange, Durham, and Wake Counties reported an average household size of 2.46 persons. On average, 26.5% of the households in the Triangle area are 1-person households; 32.7% are 2-person households; and about 40% are households with 3 or more persons. Wake County contains more large-size households than Orange and Durham County. The distribution of households by size is shown in Table C-1.

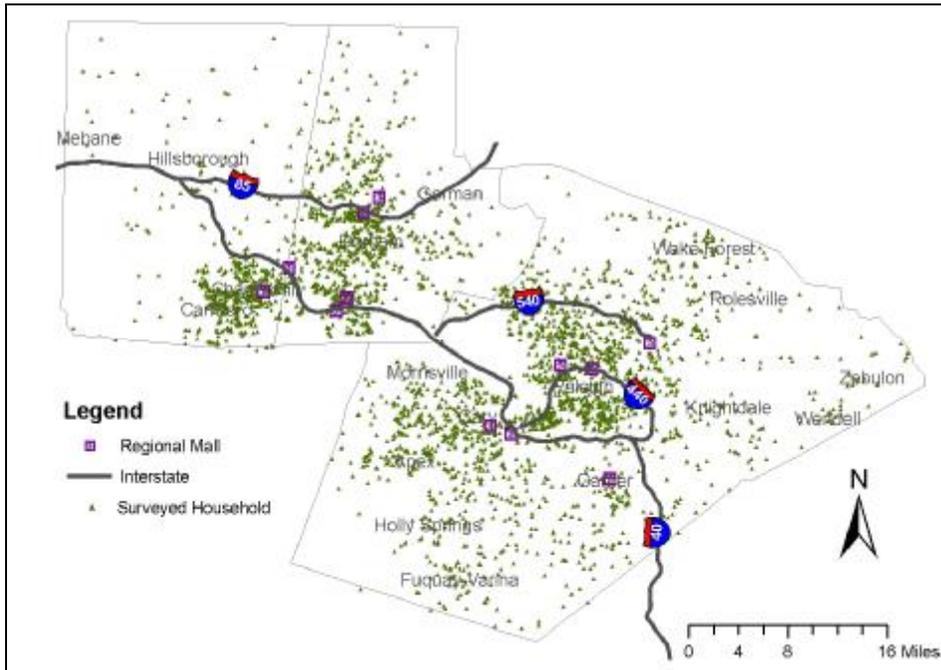


Figure C-1. Locations of the Respondent Residences in Orange, Durham, and Wake Counties

Table C-1. Household size in Orange, Durham, and Wake Counties

	N	Household Size				Total	Mean	Std. Dev.
		1	2	3	4+			
Orange County	565	31.1%	30.2%	16.4%	22.2%	100.0%	2.34	1.21
Durham County	927	31.6%	33.6%	16.7%	18.1%	100.0%	2.28	1.22
Wake County	1,988	23.8%	32.8%	17.1%	26.3%	100.0%	2.55	1.29
Total	3,480	26.5%	32.7%	16.9%	23.9%	100.0%	2.46	1.27

Source: Greater Triangle Household Travel Survey, weighted.

Table C-2 summarizes the average trip generation rates by mode in Orange, Durham, and Wake Counties. Results show that households in Orange County are more likely to use non-automobile alternatives in their daily trips than households in Durham and Wake Counties. Triangle households made 0.83 pedestrian trips per day, on average. There is substantial variation in walking trips, as indicated by the

standard deviation and a wide range from 0 trips to as many as 24 trips per household per day. These descriptive statistics are in line with our expectation for the three counties.

Interestingly, the total trips per household made in Orange and Wake Counties are the same. However, the share of walking trips is nearly 2.7 ($2.7 = 1.73/0.65$) times greater in Orange County, showing evidence of trip substitution between auto and walking trips. This makes analysis of walking trips particular important, as they seem to substitute for driving trips. Note that there are spatial differences between counties, which show that the ratio of walking trips to driving trips in Orange County is 0.28 whereas for Wake County it is 0.1.

Figure C-2 displays the geographic variation in average household size at the census block group level. As shown in Figure 2, the average household size in the urban area is relatively small, while the average household size in suburban area is relatively large.

Table C-2: Household Trips by Mode

		Walk	Bicycle	Transit	Passenger	Drive	Total
Orange	Mean	1.73	0.20	0.32	2.13	6.20	10.95
	Std. Dev.	2.81	0.94	0.87	3.28	4.55	7.37
Durham	Mean	0.84	0.03	0.28	2.30	5.65	9.54
	Std. Dev.	1.95	0.29	1.06	3.58	4.20	6.78
Wake	Mean	0.65	0.05	0.12	2.66	6.65	10.58
	Std. Dev.	2.81	0.94	0.87	3.28	4.55	7.28
Total	Mean	0.83	0.07	0.18	2.51	6.36	10.37
	Std. Dev.	1.96	0.49	0.83	3.70	4.35	7.19
	Range	0-24	0-9	0-11	0-29	0-25	0-49

Source: Greater Triangle Household Travel Survey, weighted.

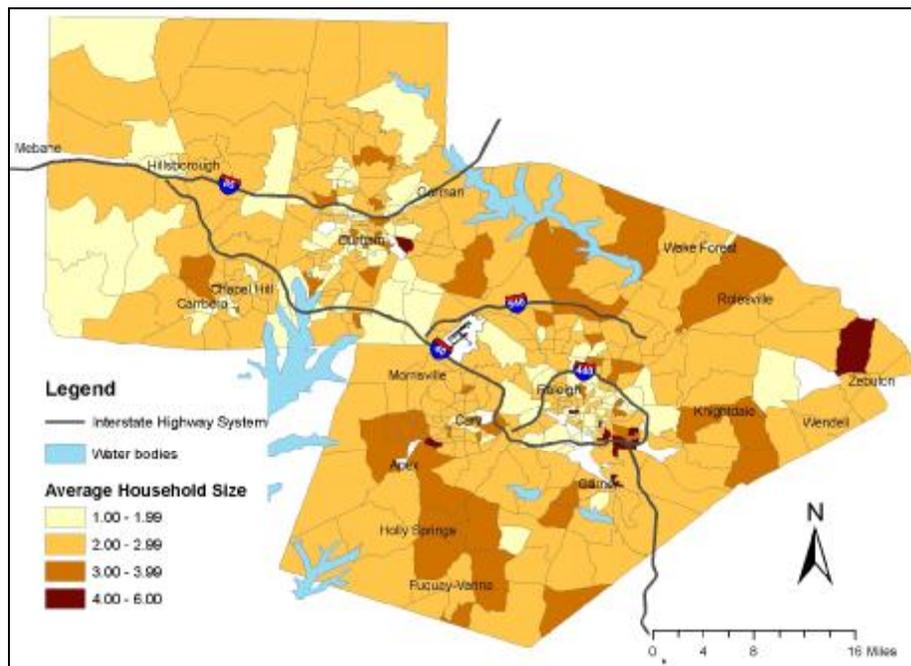


Figure C-2. Average Household Size by Census Block Group in the Triangle Area

Figure C-3 shows the spatial variation in number of walking trips per household at the census block group level. The households located in the urban area tend to have higher pedestrian trip productions. Furthermore, Chapel Hill and Carrboro have very high pedestrian trip rates, compared to other cities in the region.

Results from the descriptive analysis indicate that there is spatial variation in walking trips, pointing to the importance of addressing land use factors in predicting pedestrian trip generation.

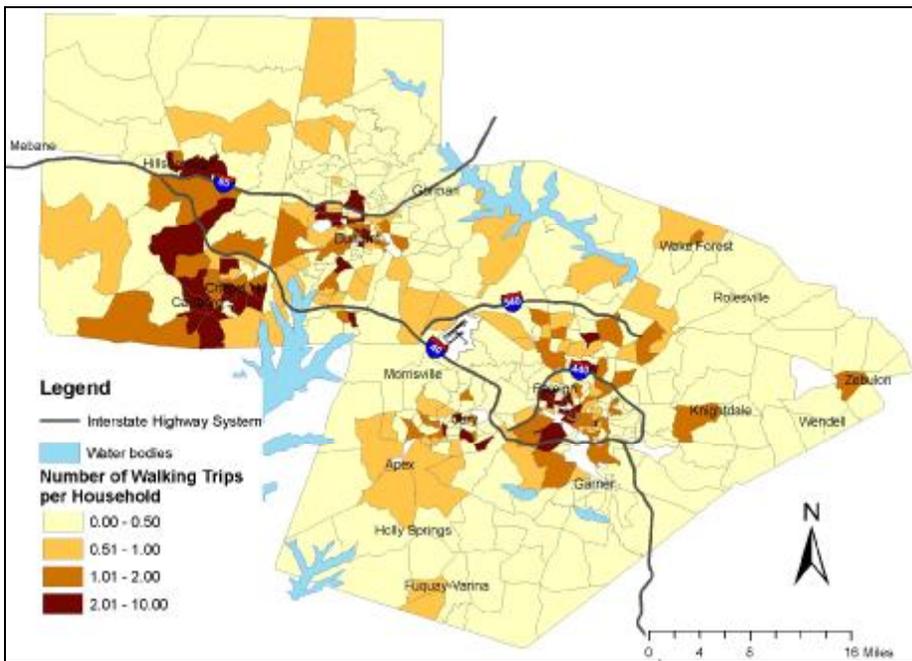


Figure C-3. Average Number of Walking Trips by Census Block Group in the Triangle Area

THE DENSITY AND DIVERSITY (2-D) METHOD

Transportation planners and engineers may have limited GIS data on land use patterns and inadequate access to spatial analysis packages. Given the situation, it is important to develop a simple tool to predict pedestrian trip generation. This section introduces a method using simple land use measures and regression analysis, which has relatively low data requirements. The proposed method were named the 2-D method, which regresses number of walking trips on simple density and diversity measures. Different regression techniques were used in the 2-D method, including ordinary least squares (OLS) regression, log-transformed regression, and negative binomial regression. Given the simplicity of the OLS regression models, the estimated OLS models were used as the forecast equations for the Jacksonville case. This section details the development of various regression models using the Triangle dataset and demonstrates the procedure of pedestrian trip prediction using the case study of Jacksonville, NC.

The Triangle Model I: Using 2-D Measures in Estimation

Given the focus on trip generation, the dependent variable is the number of pedestrian trips produced by households per day, which is a count variable. See Figure C-4 for the frequency distribution of this dependent variable. The independent variables are three land use variables at the traveler's residence that

are usually easy to measure and are often available to transportation planners. Those land use variables are:

- ê Population density: number of residents per acre within the census block group
- ê Employment density: number of jobs per acre within the census block group
- ê Service use share: percentage of service jobs within the census block group

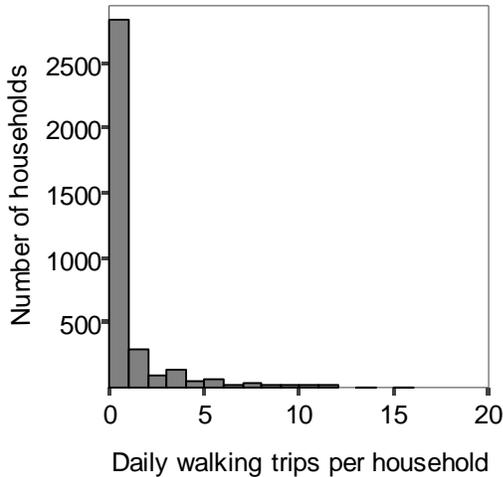


Figure C-4. Frequency Distribution of Daily Walking Trips per Household in the Triangle Area

Table C-3 presents descriptive statistics for land use variables used in the 2-D method. The mean population density of the 448 census block groups is 1.54 persons per acre. The mean employment density is 1.745 employees per acre. On average, census block groups in the Triangle area have about 48.4% service employments out of the total employments within the census block groups. Employment data falling into the service category are generally classified as hotels, personal and business services, auto repair, and other service type establishments (SIC Groups 70-89, 99).

Table C-3. Descriptive Statistics for the Triangle Land Use Variables Used in the 2-D Method (N = 448)

Variable	Mean	Std Dev	Min	Max
Population density	1.540	1.427	0	7.367
Employment density	1.745	3.961	0	58.697
Service use share	.5176	.22618	.518	.22618

The unit of analysis is the census block group. The 448 census block groups in the study area have an average size of 2,223 acres and a range from 46 acres to 21,703 acres. All three land use measures are expected to be positively related to pedestrian trip productions. Compact land use patterns with high development density put trip origins and destinations in close proximity, which can lead to shorter distance and more walking trips. More service jobs in a neighborhood or area can not only provide more nearby activity locations, but also indicate that the environments are friendlier to pedestrians. Figure C-5 and Figure C-6 present population density and employment density in the Triangle region. Both population density and employment density are higher in central cities than the outer suburban area, as expected. Research Triangle Park (RTP) is located in southern Durham County and western Wake County. The RTP area has relatively low population density but high employment density.

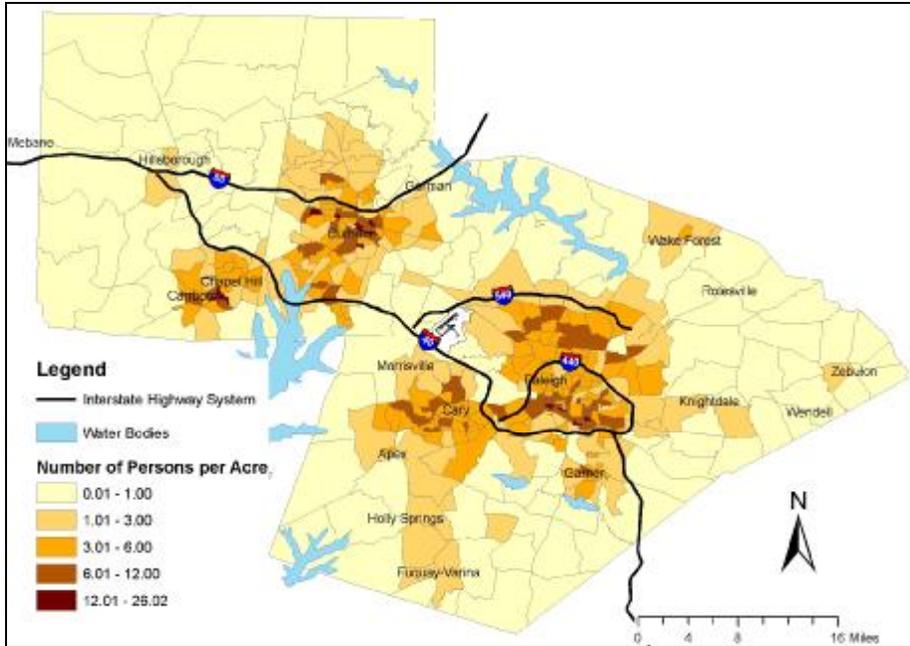


Figure C-5. Population Density in Orange, Durham, and Wake Counties (2005)

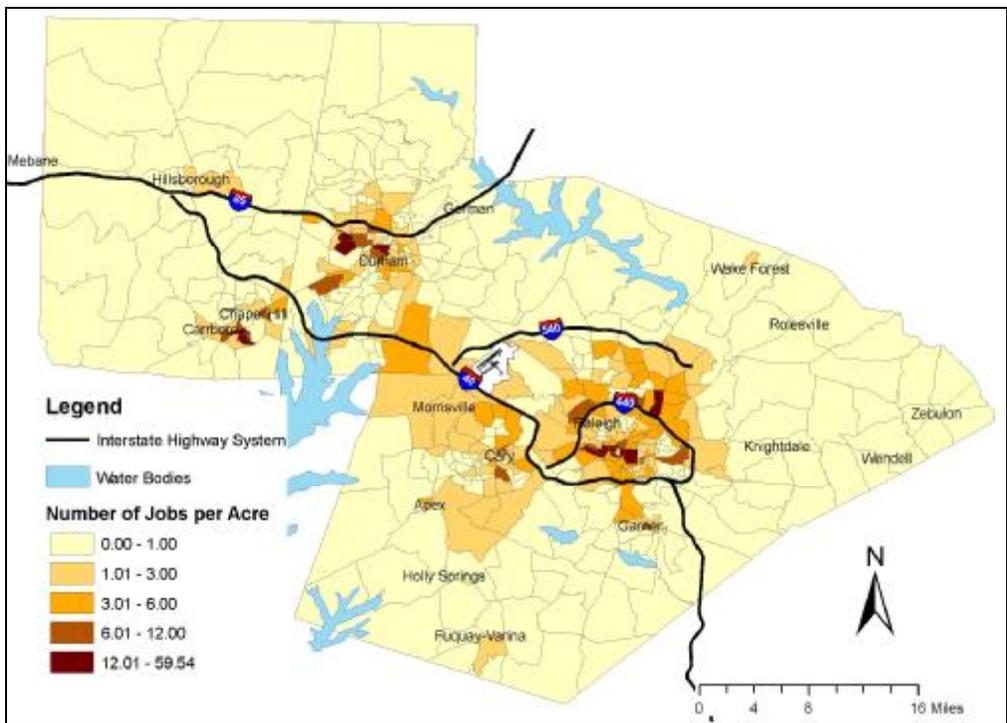


Figure C-6. Employment Density in Orange, Durham, and Wake Counties (2005)

To try alternative model specifications, the following models were estimated as well as the model we mentioned above:

Model 2: Residential and employment density, workers and total employment

Model 3: Residential and employment density, workers, retail employment, service employment and other employment

Model 4: Residential and employment density, workers, service employment and all other employment

Table C-4 below shows the modeling results. All models are non-segmented and include 3,480 households. As shown in the Table C-4 below, the original model specification given as Model 1 provides a slightly better fit compared with the other models; employment variables in the block group of the survey respondents do not seem to add much explanatory power to the model. Thus, Model 1 in Table C-4 is the preferred model.

Table C-4. Comparison of Alternative Model Specifications

Variable	Model 1	Model 2	Model 3	Model 4
1-worker	0.2188**	0.2173**	0.2177**	0.2175**
2-worker	0.4739***	0.4691***	0.4720***	0.4709***
3+-worker	0.5336***	0.5242***	0.5265***	0.5259***
Population density	0.0792***	0.0776***	0.0793***	0.0793***
Employment density	0.0318***	0.0432***	0.0352***	0.0360***
Total employment		-0.000037***		
Retail employment			-0.000089	
Service employment			0.000044	0.000040
Emp. excluding retail and service			-0.000053***	
Emp. excluding service				-0.000056***
Service Use Share	0.7722***			
Constant	-0.2963***	0.1701*	0.1463	0.1422
N	3480	3480	3480	3480
R ²	0.0434	0.0375	0.0381	0.0381
Adjusted R ²	0.0417	0.0358	0.359	0.0361
Prob > F	0.0000	0.0000	0.0000	0.0000

Legend: * p<0.10; ** p<0.05; *** p<0.01; Model 1 is the final selected model for the 2-D analysis.

11. OLS Regression Modeling Results

As trip rates vary by household type, this analysis estimated four regression models for four different household types. To provide basis for comparison, the analysis also estimated a non-segmented model including all the 3,480 households in the Triangle dataset. The five regression models have the same model specification as Model 1 in Table C-4, as shown below.

$$Y = b_0 + b_1 X_1 + b_2 X_2 + b_3 X_3 + b_4 X_4 + b_5 X_5 + b_6 X_6$$

where,

Y denotes the number of walking trips per household per day;

$X_1 - X_3$ denote the three land use variables at the household's residential location. They are population density (residents per acre), employment density (number of jobs per acre), and service use share (% of service jobs).

$X_4 - X_6$ are dummy variables representing work status of the persons in the household. Among them:

$X_4 = 1$, if the household contains one worker;

$X_5 = 1$, if the household contains two workers;

$X_6 = 1$, if the household contains three or more workers.

Table C-5 shows the modeling results of the five OLS regression models. Results show the land use variables are significant in all of the five models with expected signs. Population density is significantly and positively related to pedestrian trip generation of 1-person households, 2-person households and household with 4 persons or more. Employment density and service employment percentage are significantly and positively related to pedestrian trip generation of all households. As shown in Table C-5, the influence of land use variables on pedestrian trip generation is stronger for large-size households (household size ≥ 3 persons) than small-size households with 1 or 2 persons. For a one-person household, a one-unit increase in the residential density (measured in terms of residents per acre) at the residential location is associated with a significant increase in daily pedestrian trips (+0.05). For a 4+-person household, a one-unit increase in residential density is associated with a larger increase in daily walking trips (+0.16 $>$ +0.05), as expected. Regardless of household type, a one-unit increase in residential density is related to a 0.08 increase in daily walking trips; a one-unit increase in employment density (in the census block group of a person's residence) is associated with a 0.03 increase in daily walking trips; and a 10% increase in the percentage of service jobs near the residence is associated with an average increase of 0.77 in daily walking trips for a household, with all other variables held constant. The model results are reasonable.

Table C-5. OLS Regression Analysis for Different Household Types

Variable	1-person HH	2-person HH	3-person HH	4+-person HH	ALL HH
Population density	0.047***	0.058***	0.063	0.160***	0.079***
Employment density	0.014*	0.043***	0.253***	0.063**	0.032***
Service Use Share	0.326*	0.635***	1.479***	1.418***	0.772***
1-worker	0.097	0.310**	-0.214	-0.894	0.219**
2-worker		0.2434**	0.123	-0.734	0.474***
3+-worker			-0.032	-0.954	0.534***
Constant	0.0688	-0.1540	-0.370	0.544	-0.296***
N	913	1376	506	685	3480
R ²	0.0235	0.0418	0.1030	0.0736	0.0434
Adjusted R ²	0.0192	0.0383	0.0922	0.0654	0.0417
Prob > F	0.0002	0.0000	0.0000	0.0000	0.0000

Legend: * p<0.10; ** p<0.05; *** p<0.01

Figure C-7 through Figure C-9 illustrate how pedestrian trip generation respectively changes with population density, employment density and service employment percentage. Results show that pedestrian trip generation increases as density increases and the magnitude of increase could be large. For example, for a household with 4 or more persons located in a neighborhood with the highest density in the region (26 persons per acre), the household makes about 5 walking trips per day, on average. For a same household located in a neighborhood with density as low as one person per acre, on average, the household only makes about one walking trip per day. In other words, households in area with a density as high as 26 persons per acre make 4 more walking trips than households in area with a density of 1 person per acre. Also note that the 4+ person households exhibit higher sensitivity to population density than smaller households.

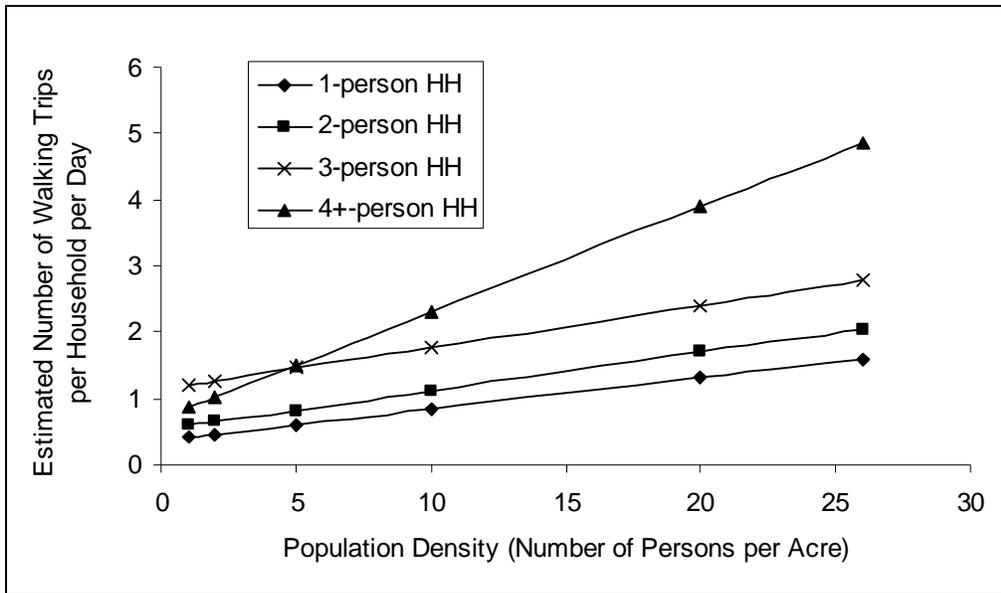


Figure C-7. Estimated Pedestrian Trip Generation by Population Density

Figure C-8 shows that, for a 3-person household located in area with the highest employment density in the region, the household makes about 12 more walking trips per day than a 3-person household located in area with a employment density as low as 1 employee per acre. Persons living in larger households of 4 or more individuals show a substantially higher sensitivity to employment density with regards to walking trips.



Figure C-8. Estimated Pedestrian Trip Generation by Employment Density

Figure C-9 shows that people living in larger households in areas with more service jobs are more likely to walk. For 3 or more person households located in an area where 25% of the jobs are in the service sector, an average of 1 walking trip per day is observed.

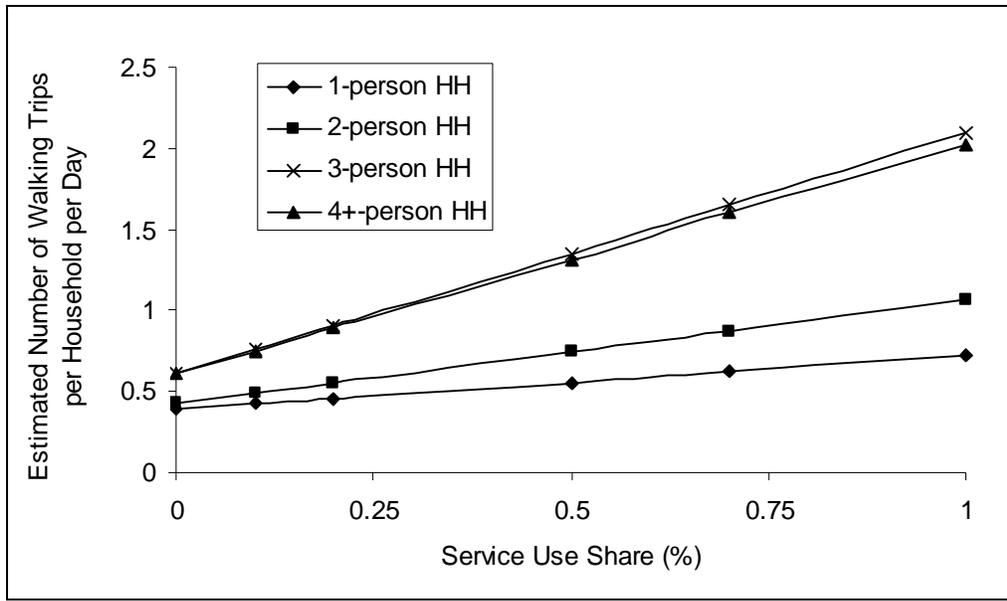


Figure C-9. Estimated Pedestrian Trip Generation by Service Use Share

12. Log-Transformed Regression Modeling Results

As the number of walking trips and land use variables does not have negative values and the distributions of those variables are mostly positively skewed (see Figure C-4 for the distribution of walking trip frequency), log-transformed regression may generate more interesting results. In each of the five models (the 1-person household, 2-person household, 3-person household, 4+-person household, and non-segmented models), the dependent variable and the land use independent variables are all log-transformed. The model specification is shown below.

$$\log(Y) = b_0 + b_1 \log(X_1) + b_2 \log(X_2) + b_3 \log(X_3) + b_4 X_4 + b_5 X_5 + b_6 X_6$$

where,

Y denotes the number of walking trips per household per day;

$X_1 - X_3$ denote the three land use variables (which are the same as the simple regression models);

$X_4 - X_6$ are dummy variables representing work status of the persons in the household (same as the simple regression models).

Table C-6 presents the results of the log-transformed regression analysis. Note that taking the log on both sides provides an estimate of the elasticity. In general, the log-transformed regression results in Table C-6 are consistent with the OLS regression results in Table C-5. Land use variables are mostly significant in predicting daily walking trips at the household level. And all the three land use variables have positive relationships with pedestrian trip rates, as expected. As the household size becomes larger, more walking trips are made for the same increase in employment density. For a 1-person household, a one-percent increase in employment density (jobs/acre) at the residential location is associated with a 0.44% increase in daily walking trips. For a 4+-person household, a one-percent increase in employment density is associated with a 0.58% increase in daily walking trips. The R-squares in the log-transformed regression models are relatively low, although they are not comparable with the R-squares in the OLS models, presented in Table C-5. Population density is not significant in the log-transformed segmented models but

it is significant in the OLS models, indicating the low explanatory power of the log-transformed models. Overall, we prefer the OLS models over the log-transformed models.

Table C-6. Log-transformed Regression Analysis for Different Household Types

Variable	1-person HH	2-person HH	3-person HH	4+-person HH	ALL HH
Population density	0.183	0.120	0.257	0.301	0.193*
Employment density	0.436***	0.514***	0.567**	0.579***	0.481***
Service use share	0.914***	1.224***	1.147**	0.898*	1.031***
1-worker	0.013	1.045**	-0.610	-5.614**	0.408
2-worker		0.799**	-0.030	-4.760*	1.102***
3+-worker			0.266	-5.538**	1.226**
Constant	-8.519***	-8.222***	-6.967***	-1.916	-8.338***
N	913	1376	506	685	3480
R ²	0.033	0.041	0.050	0.052	0.039
Adjusted R ²	0.029	0.038	0.039	0.044	0.037
Prob > F	0.000	0.000	0.000	0.000	0.000

Note: Dependent variables and land use independent variables are all log-transformed.

Legend: * p<0.10; ** p<0.05; *** p<0.01

13. Negative Binomial Regression Modeling Results

Negative binomial regression is used to regress the number of daily walking trips on the simple land use measures for various household types. Such models are appropriate because the dependent variable (walking trip frequency) is a discrete and positive count variable (see Figure C-4 for the distribution of the dependent variable). The specification of negative binomial models is shown below.

$$I = e^{b_0 + b_1 X_1 + b_2 X_2 + b_3 X_3 + b_4 X_4 + b_5 X_5 + b_6 X_6}$$

where,

I denotes the mean number of walking trips per household per day;

$X_1 - X_3$ respectively denote residential density (residents/acre), employment density (jobs/acre), and % of service jobs;

$X_4 - X_6$ are dummy variables representing work status of the persons in the household, which are the same as the OLS models and the log-transformed models.

Table C-7 shows consistent results with previous models. Residential density, employment density, and service jobs are positively related to pedestrian trip generation, and they are mostly significant in the models. Note that the R-squares in the previous OLS models or log-transformed models are not comparable with the pseudo R-squares estimated in the negative binomial models. That is, we cannot tell whether the negative binomial models explain more variation in the data than previous models. However, given the characteristics of the dependent variables in this research, theoretically and methodologically, negative binomial regression is more appropriate than the previous OLS and log-transformed regression models.

The coefficients are not directly interpretable, but Incident Rate Ratios provide a sense of how the dependent variable changes in response to the independent variable. As shown in Table C-7, for 1-person households, a one-unit increase in residential density (residents per acre) is associated with a 10.3% increase in daily walking trips (IRR=1.103). For households of 4 or more individuals, a one-unit increase in residential density is associated with 15.8% increase in daily walking trips (IRR=1.158). The

significant alpha parameters in Table C-7 tell us that negative binomial regression is more appropriate compared with Poisson regression—an alternative regression model for count data.

Table C-7. Negative Binomial Regression for Different Household Types

Variable	1-person HH		2-person HH		3-person HH		4+-person HH		ALL HH	
	Coef.	IRR	Coef.	IRR	Coef.	IRR	Coef.	IRR	Coef.	IRR
Pop_den	0.098***	1.103	0.080***	1.083	0.119**	1.126	0.146***	1.158	0.105***	1.111
Emp_den	0.022	1.022	0.066**	1.068	0.111*	1.118	0.032	1.032	0.036***	1.037
Svc_share	0.539	1.715	1.074***	2.927	1.344***	3.835	1.178***	3.248	0.996***	2.706
1-worker	0.163	1.177	0.356	1.428	0.388	1.474	-0.452	0.636	0.274*	1.315
2-worker			0.274	1.315	0.714	2.043	-0.227	0.797	0.590***	1.804
3+-worker					0.612	1.844	-0.505	0.603	0.618**	1.855
Constant	-1.552***	0.212	-1.701***	0.183	-2.063***	0.127	-0.886	0.412	-1.743***	0.175
N	913		1376		506		685		3480	
Pseudo R ²	0.010		0.015		0.026		0.021		0.016	
Alpha	6.231***		5.099***		4.936***		4.597***		5.375***	
LL	-798.074		-1343.570		-568.728		-833.283		3563.515	
Prob > Chi ²	0.002		0.000		0.000		0.000		0.000	

Legend: * p<0.10; ** p<0.05; *** p<0.01; Pop_den: population density; Emp_den: employment density; Svc_share: service use share

14. Modeling Result Comparison

Table C-8 compares results across OLS, log-transformed OLS, and negative binomial models. The results used for comparison come from the non-segmented models (all HH models) in Table C-5, C-6, and C-7.

OLS regression results show that a one-unit (resident per acre) increase in residential density is associated with 0.079 additional daily walking trips per household. Negative binomial regression results show that a one-unit increase in residential density is associated with an 11% increase in walking trip frequency. These two results are consistent with each other. Most households produced a small number of walking trips per day. As the average walking trip frequency is 0.76 trips per household, a 0.079 unit increase in walking trip frequency is about the same as an 11% increase.

Coefficients from log-transformed models are elasticities, which can be interpreted as the ratio of the proportional change in one variable with respect to proportional change in another variable. These coefficients are not comparable to OLS coefficients or negative binomial models' incident rate ratios.

Table C-8. Results Comparison across OLS, Log-transformed OLS, and Negative Binomial Models

Changes in land use variables	Changes in walking trip frequency		
	OLS	^a Log-transformed OLS	Negative Binomial
+1 resident per acre	0.079	0.19%	11.1%
+1 employee per acre	0.032	0.48%	3.7%
+10% service use share	0.077	1.03%	10.5%

Note: ^a For the log-transformed OLS model, changes in land use variables are respectively 1% increase in residential density, 1% increase in employment density, and 1% increase in service use share.

15. Using 3-D Measures in Estimation

In addition to the density and diversity (2-D) measures, it is theoretically important to incorporate the design dimension, especially sidewalk coverage, into modeling walking trip density. Given the richness of the Triangle GIS data, we are able to generate a sidewalk density indicator—meters of sidewalks per

acre—and include this indicator in walking trip generation models. On average, census block groups in the Triangle area have 12.5 meters of sidewalks per acre. The range of the sidewalk density indicator is from 0 to 113 meters per acre. However, since sidewalk GIS data are not available for the Jacksonville cases, the estimated models can not be applied to the Jacksonville case. Table C-9 presents non-segmented walking trip generation models that include the sidewalk density indicator.

As shown in Table C-9, sidewalk density significantly and positively relates to walking trip frequency in the OLS model. One additional meter of sidewalks per acre is associated with 0.007 additional walking trips per household per day. Sidewalk density is not significant in either the log-transformed OLS model or the negative binomial model.

Table C-9. Regression Results on Density, Diversity, and Sidewalk Measures

Variable	OLS	Log-transformed OLS	Negative Binomial
Population density	0.058***	0.114	0.093***
Employment density	0.018**	0.430***	0.026*
Service use share	0.731***	1.015***	0.966***
Sidewalk density	0.007***	0.160	0.004
1-worker	0.220**	0.409	0.278*
2-worker	0.473***	1.098***	0.585***
3+-worker	0.543***	1.240**	0.620**
Constant	-0.267**	-8.619***	-1.721***
N	3480	3480	3480
R ²	0.046	0.039	
Adjusted R ²	0.044	0.037	
Prob > F	0.000	0.000	

Legend: * p<0.10; ** p<0.05; *** p<0.01; for the negative binomial model, Log-likelihood = -3562.64; Pseudo R2 = 0.0163; Prob > chi2 = 0.000; Alpha=5.364***.

The Jacksonville Case

Based on NCDOT staff recommendation, Jacksonville, NC was selected as a site where the travel demand models can be applied for prediction purposes. The Jacksonville travel demand data contain housing and employment information for 2002 at the Traffic Analysis Zone (TAZ) level. Housing data, developed from the Census and crosschecked with 2002 windshield survey data from the City, identifies households by size and the number of workers. Employment data, developed based on information from InfoUSA, NCDOT, and the City of Jacksonville, contains the number of employees by employment type (industrial, retail, highway retail, office, and service). The Jacksonville TAZs (a total of 143 TAZs) were developed within the TransCAD platform and were converted into a GIS shapefile format. Jacksonville TAZs have an average size of 960 acres, ranging from 17 acres to 13,241 acres, which is about the half size of Triangle census block groups (mean area size=2,223 acres).

16. Create Matching Land Use Measures

To apply the estimated Triangle models to the Jacksonville case, matchable independent variables in the Triangle data and the Jacksonville data are required. The three land use measures used in the Triangle models, including population density (residents/acre), employment density (jobs/acre), and service use share (% of service jobs), were created for Jacksonville, NC as well.

After the housing and employment data were converted into a GIS format, ArcGIS was used to create land use measures and to visualize the measures. Figure C-10 and Figure C-11 visually present the 2002

population density and employment density in Jacksonville, NC. See Appendix C-1 for the specific values of the land use measures for all the 143 TAZs in Jacksonville, NC.

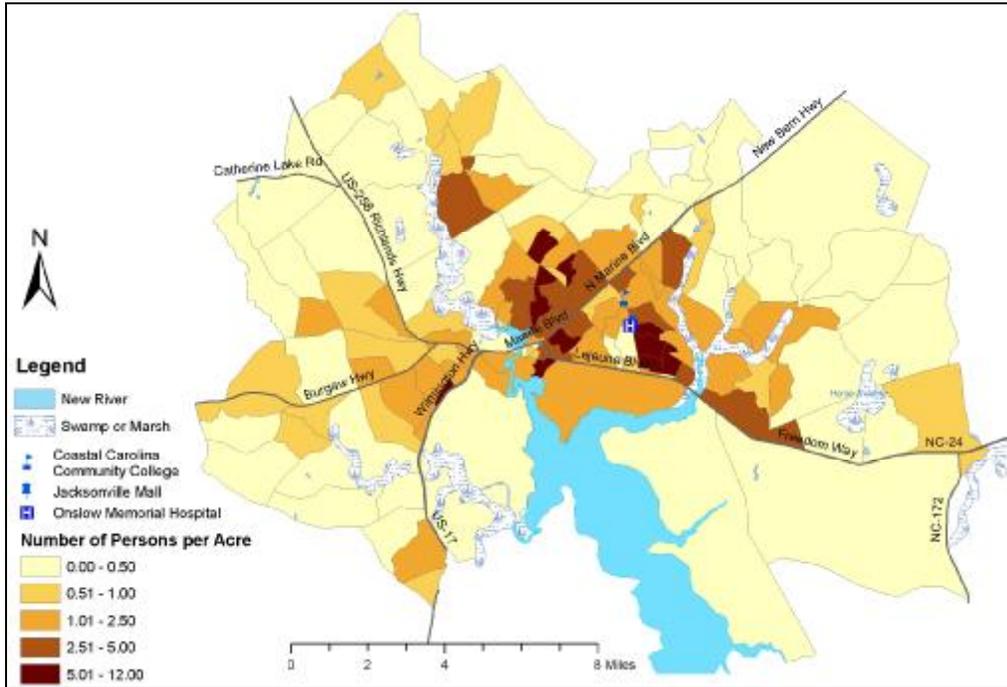


Figure C-10. Population Density in Jacksonville, NC (2002)

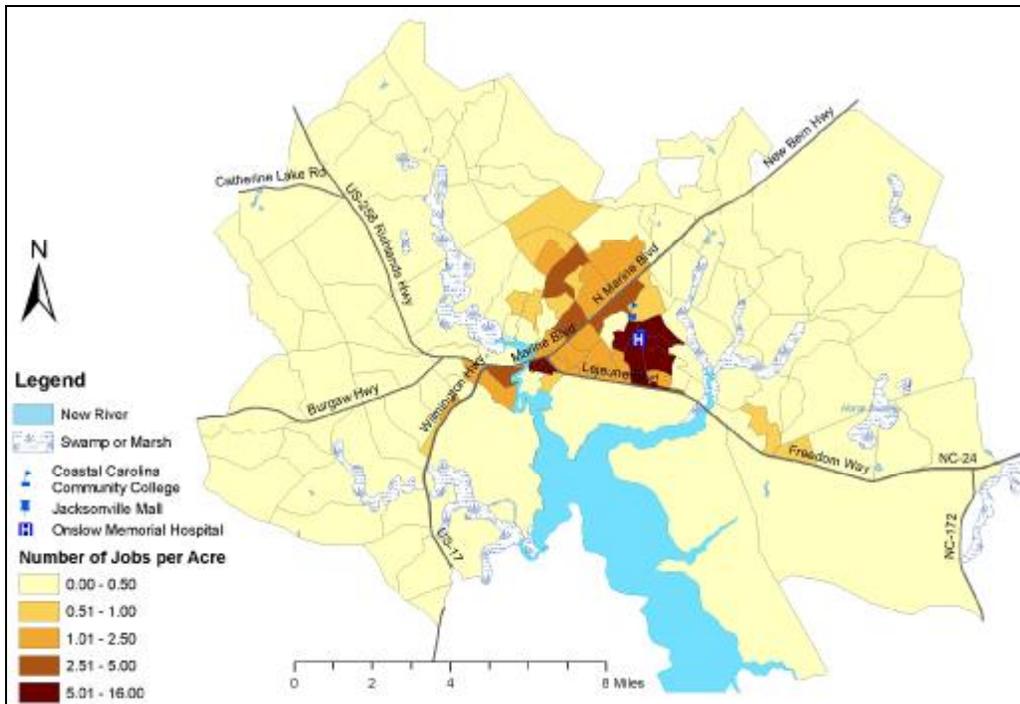


Figure C-11. Employment Density in Jacksonville, NC (2002)

17. Develop Forecast Equations

To simplify the prediction, the estimated OLS models were used as the forecast equations for the Jacksonville case. The OLS modeling results in Table C-5 show that the work status indicators are not statistically significant in the 1-person household model, the 2-person household model, and the 4+-person household model. The final specifications of those three models excluded the indicators of work status from the models. The final models that can be used for predication are shown in the following equations:

$$\begin{aligned}
 Y_{1-personHH} &= 0.141 + 0.047X_1 + 0.014X_2 + 0.322X_3 \\
 Y_{2-personHH,0worker} &= -0.154 + 0.058X_1 + 0.043X_2 + 0.635X_3 \\
 Y_{2-personHH,1worker} &= 0.156 + 0.058X_1 + 0.043X_2 + 0.635X_3 \\
 Y_{2-personHH,2worker} &= 0.089 + 0.058X_1 + 0.043X_2 + 0.635X_3 \\
 Y_{3-personHH} &= -0.359 + 0.061X_1 + 0.253X_2 + 1.483X_3 \\
 Y_{4+-personHH} &= -0.207 + 0.135X_1 + 0.064X_2 + 1.446X_3
 \end{aligned}$$

where,

$X_1 - X_3$ respectively denote the three land use variables, i.e., population density, employment density, and service use share.

Note that due to the use of ordinary least squares regression for estimation, some constants in the above equations are negative. This can potentially result in negative trip rate predictions, when the values of independent variables are on the lower side. This is acceptable, given the simplicity of the least squares regression models compared with the more complex Poisson or negative binomial models. The final models above were applied to the Jacksonville case in the following section.

18. Apply Equations to TAZs

As each TAZ contains information about the number of households by size and the three land use measures, we can estimate the number of walking trips within each TAZ based on the estimated Triangle models in the previous section. In the following text, we demonstrate the steps needed to calculate the pedestrian trip generation rates using three TAZs as examples.

TAZ #1:

Number of households located in TAZ#1: 0

Total number of walking trips in TAZ#1 = 0

TAZ #2:

\hat{e} Number of 1-person households located in TAZ#2: 3

$$Y_{1-personHH} = 0.141 + 0.047 * 0.107 + 0.014 * 13.955 + 0.322 * 0.161 = 0.393$$

$$\text{Number of walking trips made by 1-person households} = 3 * 0.393 = \underline{1.179}$$

\hat{e} Number of households with 2 or more persons: 0

$$\text{Number of walking trips made by households with 2 or more persons: } \underline{0}$$

$$\text{Total number of walking trips in TAZ \#2} = 1.179 + 0 = \underline{1.179}$$

TAZ #3:

ê Number of 1-person households located in TAZ#3: 20

$$Y_{1-personHH} = 0.141 + 0.047 * 1.127 + 0.014 * 1.144 + 0.322 * 0.388 = 0.335$$

$$\text{Number of walking trips made by 1-person households} = 20 * 0.335 = \underline{6.699}$$

ê Number of 2-person households with 0 workers: 0

Number of walking trips made by this kind of households: 0

ê Number of 2-person households with 1 worker: 4

$$Y_{2-personHH,1worker} = 0.156 + 0.058 * 1.127 + 0.043 * 1.144 + 0.635 * 0.388 = 0.517$$

$$\text{Number of walking trips made by this kind of households} = 4 * 0.517 = \underline{2.068}$$

ê Number of 2-person households with 2 workers: 20

$$Y_{2-personHH,2worker} = 0.089 + 0.058 * 1.127 + 0.043 * 1.144 + 0.635 * 0.388 = 0.450$$

$$\text{Number of walking trips made by this kind of households} = 20 * 0.450 = \underline{9.000}$$

ê Number of 3-person households: 7

$$Y_{3-personHH} = -0.359 + 0.061X * 1.127 + 0.253 * 1.144 + 1.483 * 0.388 = 0.575$$

$$\text{Number of walking trips made by this kind of households} = 7 * 0.575 = \underline{4.023}$$

ê Number of 4+-person households: 0

Number of walking trips made by 4+-person households: 0

$$\text{Total number of daily walking trips in TAZ \#3} = 6.699 + 0 + 2.068 + 9.000 + 4.023 + 0 = \underline{21.790}$$

Using the steps described above, the number of walking trips produced in each TAZ is calculated. The predicted results are shown in Appendix C-1. Figure C-12 visually presents the estimated daily pedestrian trip rates in all the TAZs in Jacksonville, NC.

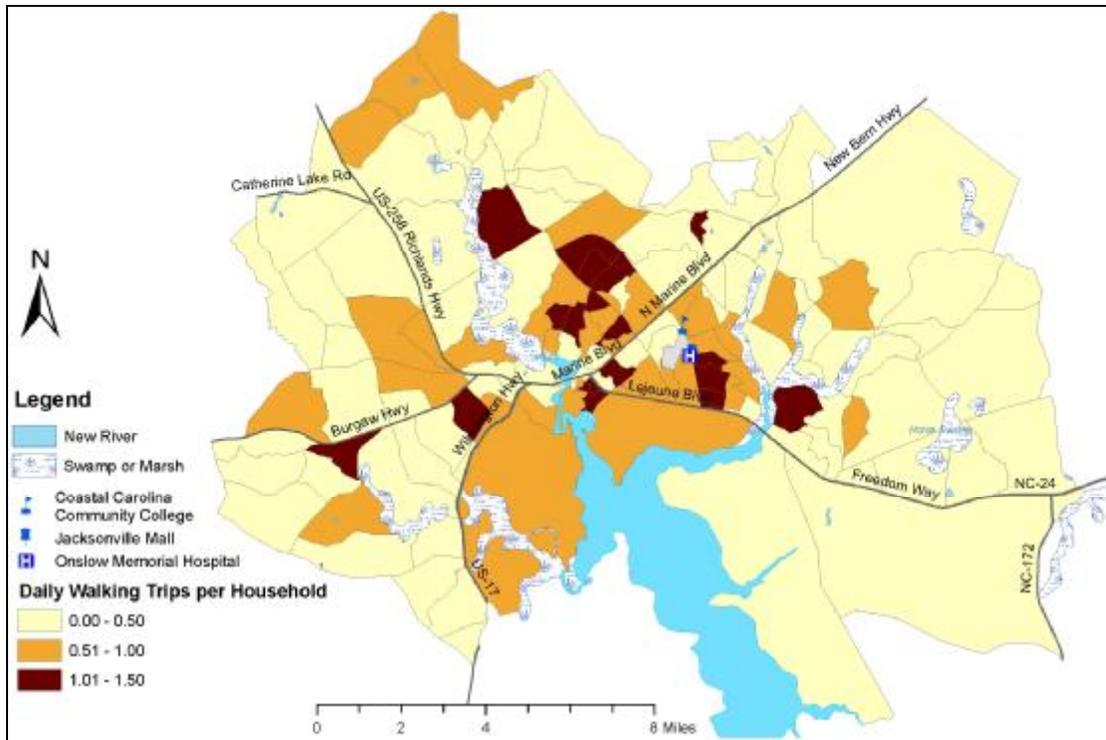


Figure C-12. Estimated Pedestrian Trip Rates in Jacksonville, NC (2-D method)

Sub-dividing these trips into home-based work, home-based other and non-home-based is possible. However, owing to the small number of walking trips in the dataset and consequent small variation in such trips, we decided to stay with total walk trips.

The Land-Use Characterization (LUC) Method

Although the 2-D method described in the previous section is relatively straightforward to implement and has a low data demand, it only takes into account a small number of land use variables in predicting pedestrian trip generation. Theoretically, land use is multi-dimensional, and appropriate measures require comprehensive consideration of all the sub-dimensions. The full consideration of land use elements that may influence walking behavior can generate more accurate estimates of the land use-travel relationship.

This section provides the land-use characterization method, which involves a greater data demand and more sophisticated analysis techniques, i.e., factor and cluster analysis. However, the application for prediction purposes is relatively simple, as shown below.

The Triangle Model II: Using Factors in Estimation

19. Land Use Measures

Built upon the “three D’s” concept developed by Cervero and Kockman [12], this research creates multiple measures on each of the density, diversity, and design dimensions at the location of the residence. The density dimension was summarized using the number of housing units per area and the number of employees per unit area. To capture the diversity dimension, this analysis created measures of different land uses including the percentages of residential uses, service uses, retail uses, and office uses. In terms of the design dimension, measures of street width, road density, transit stop density, and

sidewalk coverage were created. See Table C-10 for the definitions of all the direct land use measures at the census block group level in this research. Besides the nine measures at the neighborhood (census block group) level, we also generated four direct land use measures at the household location level. See Table C-10 for more details.

Table C-10. Land Use Measures at the Census Block Group Level and the Household Location Buffer Area Level

Land Use Variable	Definition
<i>Census block group level</i>	
Housing density	Number of housing units per acre within the census block group
Employment density	Number of employees per acre within the census block group
Residential use share	% of residential land uses within the census block group
Service use share	% of service land uses within the census block group
Retail use share	% of retail land uses within the census block group
Industrial use share	% of industrial land uses within the census block group
Other use share	% of other land uses within the census block group
Road density	Miles of roads per acre within each census block group
Bus stop density	Number of bus tops per care within each census block group
Sidewalk density	Miles of sidewalks per acre within each census block group
<i>Household location buffer area level</i>	
Retail counts in buffer	# of retail stores within the 0.25-mile buffer area around the home location
Distance to Interstate	Distance from the household location to the nearest Interstate highway
Bus stop counts in buffer	# of bus stops within the 0.25-mile buffer area around the home location
Sidewalk length in buffer	Miles of sidewalks within the 0.25-mile buffer area around the home location

Table C-11 summarizes the descriptive statistics of all the land use measures in the Triangle region. The highest residential density in the region is 7.4 dwelling units per acre. The average housing density is 1.54 dwelling units per acre and the average employment density is about 1.75 employees per acre. The average road density is about 0.017 miles per acre and the average bus stop density is about 0.023 bus stops per acre. The land use measures at the household location level show that, on average, the surveyed households have about 3 retail stores within a 0.25-mile buffer area around their household locations. The average distance from the surveyed household locations to the nearest Interstate highway is about 3 miles. On average, the surveyed households have about 2 bus stops within a 0.25 buffer area around there household locations (although this seemed on the high side, rechecking the data showed that this was the case). Results show that residents in the Triangle region have adequate accessibility to transit, retail stores, and the Interstate Highway System.

20. Factor Analysis

Although the thirteen land use indicators in Table C-11 can comprehensively measure the land use patterns in the Triangle region, directly putting all the indicators into a model would create a serious collinearity problem. Correlation analysis shows that many of the indicators are highly correlated with each other. For example, housing density is highly correlated with bus stop density and road density (Pearson correlation coefficients > 0.75). Therefore, it is important not only to fully consider all the land use elements, but also to generate compact and efficient factors. This research uses principal factor analysis to reduce redundancy and condense variables into more compact sets. Table C-12 shows the results of the rotated factors loadings.

Table C-11. Descriptive Statistics of All the Land Use Measures

Variable		Mean	Std Dev	Min	Max
Land Use Measures at the Census Block Group Level (N=448)	Housing density	1.540	1.427	0	7.367
	Employment density	1.745	3.961	0	58.697
	Residential use	0.484	0.201	0	0.930
	Service use	0.001	0.004	0	0.031
	Retail use	0.025	0.045	0	0.404
	Industrial use	0.026	0.059	0	0.464
	Other use	0.464	0.193	0.046	1.000
	Road density	0.017	0.009	0	0.048
	Bus stop density	0.023	0.033	0	0.214
Sidewalk density	0.009	0.013	0	0.070	
Land Use Measures at the Household Location Level—0.25 mile buffer (N=3,480)	Retail counts in buffer	2.726	6.165	0	73
	Distance to Interstate	3.191	2.871	0.016	16.827
	Bus stop counts in buffer	2.330	3.905	0	29
	Sidewalk length in buffer	1.184	1.584	0	12.337

Table 12: Factor loadings of each land use indicators

	Three Dimensions		
	Density & Design	Commercial Mix	Industrial Mix
Housing density	0.777		
Road density	0.860		
Bus stop density	0.855		
Sidewalk density	0.891		
Bus stop counts in buffer	0.775		
Distance to Interstate	-0.408		
Sidewalk length in buffer	0.835		
Employment density	0.527	0.509	
Retail counts in buffer	0.402	0.465	
Service use share		0.778	
Retail use share		0.782	
Residential use share			-0.794
Industrial use share			0.762

Note: Factor loadings below |0.40| not shown.

Based on the rotated factor loadings, three factors were identified corresponding to the following dimensions: 1) density and street design, 2) commercial mix, and 3) industrial mix. Next, factor scores were generated on each of these three factors for the 3,480 households using the default regression method (in Stata 8.0 statistical software) suggested by Thompson. Factors are scaled such that means and standard deviations equal zero and 1, respectively.

The generated three factors were used as independent variables in a model to estimate the effect of land use patterns on pedestrian trip generation. In addition, the derived factor scores were further used to cluster together those households that are most similar in terms of the factors.

21. OLS Regression Modeling Results

OLS regression is used to examine the effects of the three land use factors on pedestrian trip generation. The model specification is shown as below.

$$Y = b_0 + b_1X_1 + b_2X_2 + b_3X_3 + b_4X_4 + b_5X_5 + b_6X_6$$

where,

Y denotes the number of walking trips per household per day;

$X_1 - X_3$ denote the three land use factors (density & design, and diversity captured through commercial mix and industrial mix);

$X_4 - X_6$ are dummy variables representing work status of the persons in the household.

$X_4 = 1$, if the household contains one worker;

$X_5 = 1$, if the household contains two workers;

$X_6 = 1$, if the household contains three or more workers.

Table C-13 shows the estimated coefficients and their significance from the OLS models. Results show that all the land use factors are mostly significant in predicting walking trips of various household types. As shown by the coefficient signs in Table C-13, the density and design factor and the commercial mix factor have positive relationships with pedestrian trip rates, while the industrial mix factor has a negative association with walking trips.

Table13: OLS regression results on the three land use factors

Variable	1-person HH	2-person HH	3-person HH	4+-person HH	ALL HH
Density & design factor	0.221***	0.330***	0.849***	0.732***	0.390***
Commercial mix factor	0.012	0.154***	0.201*	-0.090	0.046
Industrial mix factor	-0.001	-0.061	-0.170*	-0.198**	-0.096***
1-worker	0.099	0.304**	-0.225	-0.916	0.219**
2-worker	0.000	0.239**	0.167	-0.749	0.492***
3+-worker	0.000	0.000	0.114	-0.894	0.580***
Constant	0.418***	0.476***	1.049*	1.985*	0.441***
N	913	1376	506	685	3480
R ²	0.035	0.050	0.119	0.089	0.053
Adjusted R ²	0.031	0.047	0.109	0.081	0.052
Prob > F	0.000	0.000	0.000	0.000	0.000

Legend: * p<0.10; ** p<0.05; *** p<0.01

Since factors were scaled such that means and standard deviation equal zero and one, respectively, we can compare coefficients across different factors. The coefficients in Table C-13 show that the density and design dimension has a stronger impact on pedestrian trip generation than the diversity dimensions including the commercial mix factor and the industrial mix factor. For 3-person households, a one-unit increase in density & design factor increases daily walking trips by 0.85 trips, while a one-unit increase in the commercial mix factors is only associated with a 0.20 increase in daily walking trips. More commercial land uses (such as retail and service uses) in the neighborhood are associated with more walking trips, while more industrial uses are associated with less walking trips. This result is consistent with the general expectation that retail uses and service uses can create inviting pedestrian environments while industrial uses can not.

While there are clear advantages to using factor analysis, the disadvantage is the difficulty of interpreting the estimated coefficients. To better understand the results, we can use the factor ranges to interpret the changes in walking trips by the land use factors. For example, the derived density and design factor has a range from -1.33 to 6.38. Therefore, compared to the 3-person households living in the sprawled locations with extremely low values (-1.33) on the density and design factor, the 3-person households living in the compact locations with the highest density and the best transit/sidewalk coverage in the region (the

density & design factor =6.38) made 6.5 more walking trips per day per household, with all other variables held constant ($6.5=0.849*(6.38+1.33)$). The commercial mix factor has a range from -1.52 to 5.51. Thus, the 3-person households living in locations with extremely high values on the commercial mix factor made 1.4 more walking trips per day ($1.4=0.201*(5.51+1.52)$) than the 3-person households living in locations with extremely low degree (-1.52) of mix in commercial uses. Likewise, the industrial mix factor has a range from -1.47 to 3.92. The 3-person households living in locations with extremely high industrial mix made 0.9 less walking trips per day than the 3-person households living in locations with extremely low values on the industrial mix factor ($-0.9=-0.17*(3.92+1.47)$).

22. Log-Transformed Regression Modeling Results

Log-transformed models were estimated as well. Only dependent variables in the factor models are log-transformed. Land use independent variables are not log-transformed because they are derived factors with means at zero and standard deviations at 1 and contain negative values. See the model specification below.

$$\log(Y) = b_0 + b_1X_1 + b_2X_2 + b_3X_3 + b_4X_4 + b_5X_5 + b_6X_6$$

where,

Y denotes the number of walking trips per household per day;

$X_1 - X_3$ denote the three land use factors;

$X_4 - X_6$ are dummy variables representing work status of the persons in the household.

According to Table C-14, R-squares show that log-transformed models are not explaining much variation in the data. Results from the log-transformed models are generally consistent with the OLS modeling results, showing that both the density & design factor and commercial mix factor is positively related to pedestrian trip generation. The industrial mix factor is negatively related to pedestrian trip generation.

Table C-14. Log-transformed Regression Results on the Three Land Use Factors

Variable	1-person HH	2-person HH	3-person HH	4+-person HH	ALL HH
Density & Design Factor	0.897***	1.114***	1.634***	1.449***	1.092***
Commercial Mix Factor	0.110	0.279*	0.459*	0.140	0.171*
Industrial Mix Factor	0.021	-0.170	-0.162	-0.186	-0.137
1-worker	0.029	0.958**	-0.352	-5.430**	0.397
2-worker		0.747*	0.439	-4.610*	1.177***
3+-worker			0.621	-5.137**	1.384***
Constant	-9.338***	-9.219***	-8.162***	-2.770	-9.232***
N	913	1376	506	685	3480
R ²	0.047	0.046	0.071	0.063	0.047
Adjusted R ²	0.042	0.042	0.060	0.055	0.045
Prob > F	0.000	0.000	0.000	0.000	0.000

Legend: * p<0.10; ** p<0.05; *** p<0.01

23. Negative Binomial Regression Modeling Results

Negative binomial regression is also used to estimate the association between daily walking trips and the three land use factors. As stated in the 2-D method section, such models are appropriate because the dependent variable (walk trip frequency) is discrete and positive. The model specification is shown as below.

$$I = e^{b_0 + b_1 X_1 + b_2 X_2 + b_3 X_3 + b_4 X_4 + b_5 X_5 + b_6 X_6}$$

where,

I denotes the mean number of walking trips per household per day;

$X_1 - X_3$ denote the three land use factors;

$X_4 - X_6$ are dummy variables representing work status of the persons in the household.

Table C-15 shows the estimated coefficients, incident rate ratios (IRR), and their significance in the negative binomial models. Results show that the density and design factor is positively and significantly related to walking trips. The industrial mix factor is negatively and significantly related to walking trips. However, the commercial mix factor is only marginally significant in the 2-person household model, which is not consistent with the OLS regression results. Results show that the density and design factor has a strong effect on pedestrian trip generation than the two diversity factors. Regardless the household type, when the density & design factor score increases by one, the number of daily walking trips increases by 60% ($1.598-1=0.60$). Results also show that a one-unit increase in the industrial mix factor is associated with a 13% ($1-0.873=0.13$) decrease in daily walking trips.

Table C-15. Negative Binomial Regression Results on the Three Land Use Factors

Variable	1-person HH		2-person HH		3-person HH		4+-person HH		ALL HH	
	Coef.	IRR	Coef.	IRR	Coef.	IRR	Coef.	IRR	Coef.	IRR
Density & Design	0.421***	1.524	0.431***	1.538	0.833***	2.301	0.515***	1.674	0.469***	1.598
Commercial Mix	0.017	1.017	0.131*	1.139	0.085	1.089	-0.037	0.964	0.049	1.050
Industrial Mix	-0.047	0.954	-0.102	0.903	-0.181	0.834	-0.204**	0.816	-0.136***	0.873
1-worker	0.164	1.178	0.359	1.432	0.800	2.225	-0.571	0.565	0.306**	1.358
2-worker			0.275	1.316	1.083	2.952	-0.394	0.674	0.614***	1.848
3+-worker					1.063	2.895	-0.562	0.57	0.690***	1.994
Constant	-0.936***	0.392	-0.731***	0.481	-1.158	0.314	0.456	1.578	-0.818***	0.442
N	913		1376		506		685		3480	
Pseudo R ²	0.015		0.016		0.038		0.020		0.018	
Log Likelihood	-794.453		-1342.546		-562.046		-833.612		-3555.085	
Prob > Chi ²	0.000		0.000		0.000		0.000		0.000	

Legend: * p<0.10; ** p<0.05; *** p<0.01

The Triangle Model III: Using Clusters in Estimation

Disadvantages of the factor analysis approach lie in its limited geographic generalizability and the difficulty in interpreting the impact of factors. Data coming from different regions may produce different number of factors and derive different sets of dimensions. For example, even if the Jacksonville case has all the land use measures in Table C-10 available, using Jacksonville data may end up with more than or less than three factors. Further, factors derived from the Jacksonville data may reflect or capture a set of environment elements that are not the same as the three dimensions (density & design, commercial mix, and industrial mix) derived from the Triangle data. Thus, it is difficult to directly apply the Triangle factor model to the Jacksonville case. Nonetheless, the factors will be valuable in clustering.

In order to develop an integrated land use and pedestrian trip generation model that can be applied to other NC regions, we used cluster analysis to identify a neighborhood typology of the households and estimated the average pedestrian trip rate of each neighborhood type. Transportation planners and engineers can assign appropriate neighborhood type to each TAZ in their communities and then use the documented pedestrian trip rates to predict the pedestrian trip rates in each TAZ.

24. Cluster Analysis

Cluster analysis identifies neighborhood typologies using K-means cluster analysis and the three land use factors derived in the previous factor analysis section. K-means cluster analysis uses Euclidean distance. Initial cluster centers are chosen in a first pass of the data. Then, each additional iteration categorizes observations based on nearest Euclidean distance to the mean of the cluster. Cluster centers change at each pass. The process continues until cluster means do not shift more than a given cut-off value or the iteration limit is reached, which ensures that variation is minimized within clusters and maximized between clusters.

To select the neighborhood typologies that make the most sense, we performed a series of analyses by varying the number of clusters from 4 to 8. Based on our local knowledge and judgment, the five-cluster scenario is the most appropriate and representative of the neighborhood types within the Triangle region. Figure C-13 shows the histogram of the mean factor scores of the five identified clusters including downtown, urban mixed use, urban residential, inner suburban, and outer suburban.

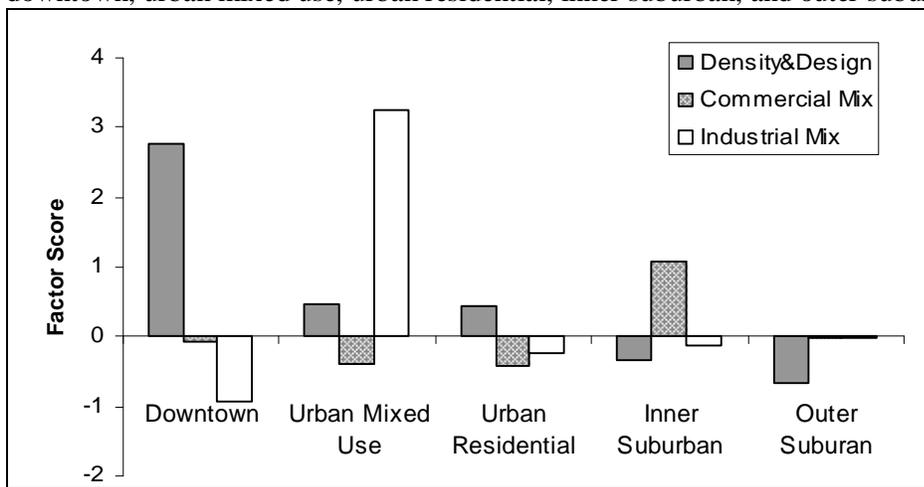


Figure C-13. Mean Factor Scores by Neighborhood Type

Figure C-14 displays the spatial distribution of the categorized households in different colors. The five identified neighborhood types are described as below.

- ê Downtown neighborhoods, shown in red in Figure C-14, are located in the central business districts in the Triangle region. They are the commercial hearts in the Triangle cities including Carrboro, Chapel Hill, Raleigh, and Durham. Those neighborhoods tend to have high density and great diversity. In addition, the downtown area often has the best transit service and sidewalk coverage in the cities. Only 190 of the total 3,480 surveyed households lived in the downtown neighborhoods.
- ê Urban mixed use neighborhoods, shown in orange in Figure C-14, are located near the downtown districts. The density in the urban neighborhoods is high but not as high as the downtown area. Those neighborhoods contain industrial uses and often have a high concentration of low-income residents. Only 175 households were identified as households in the urban mixed use neighborhoods.

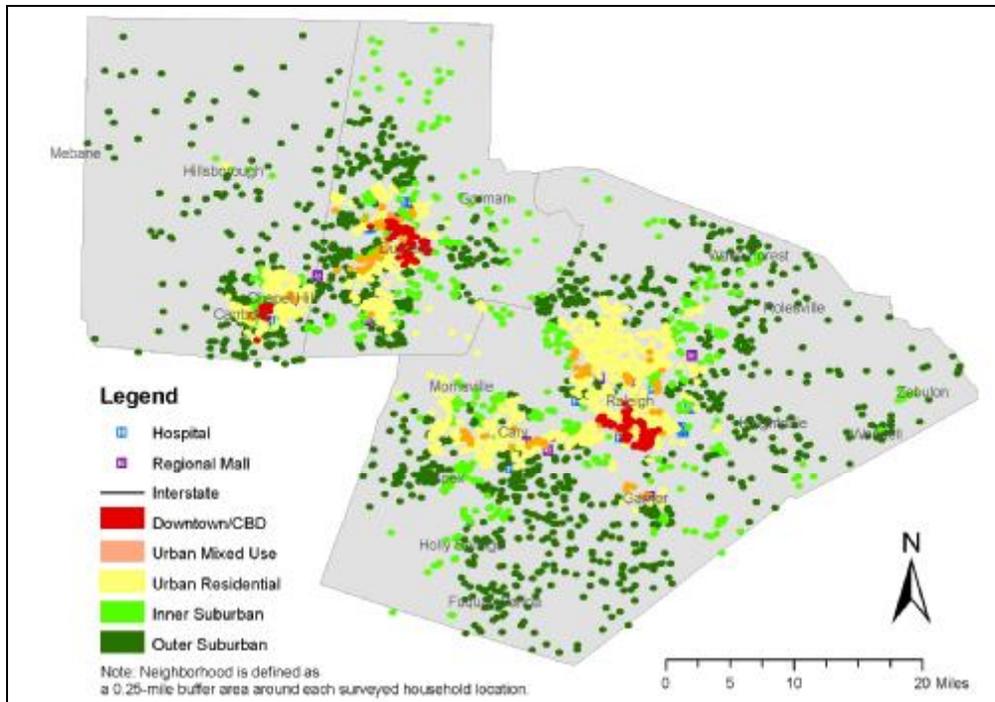


Figure C-14. Identified Clusters of Survey Households Based on Land Use Factors

- ê Urban residential neighborhoods, shown in yellow in Figure 14, are also located near the downtown districts. The density in urban residential neighborhoods is similar to urban mixed use neighborhoods. However, urban residential neighborhoods consist primarily of residential uses, and do not have a good mix in commercial land uses. Out the 3,480 surveyed households, 1,180 households were identified as households in urban residential neighborhoods.
- ê Inner suburban neighborhoods, shown in green in Figure C-14, are located on the outskirts of the cities. The neighborhoods have low density. However, as the ongoing decentralization of service and retail businesses have contributed a fair amount of commercial uses to these suburban neighborhoods. The neighborhoods have good accessibility to commercial land uses. 548 households were identified as inner suburban households in the Triangle region.
- ê Outer suburban neighborhoods, shown in dark green in Figure C-14, are located further away from the city. Most homes are owner-occupied and single-family houses. Outer suburban neighborhoods are the most typical neighborhood type in the Triangle region. More than 30% of the surveyed households lived in the outer suburban area (N=1,387).

25. Mean Comparison

Table C16 and Figure C-15 show how daily pedestrian trip generation rates vary by household type and neighborhood type. As we expected, households located in suburban area made less walking trips than households in urban and downtown area. For 2-person households in downtown, urban mixed use, urban residential, inner suburban, and outer suburban neighborhoods, on average, they respectively made 1.36, 1.58, 0.83, 0.49, and 0.44 walking trips per day.

Table C-16. Pedestrian Trip Generation Rates by Household Type and Neighborhood Type

Household Type	Downtown /CBD	Urban Mixed Use	Urban Residential	Inner Suburban	Outer Suburban	Total
1-person	0.94	0.83	0.64	0.62	0.24	0.56
2-person	1.36	1.58	0.83	0.49	0.44	0.67
3-person	3.19	2.11	1.42	0.69	0.43	0.95
4 or more persons	3.21	0.88	1.43	0.88	0.71	1.07
Total	1.61	1.29	0.96	0.63	0.46	0.76

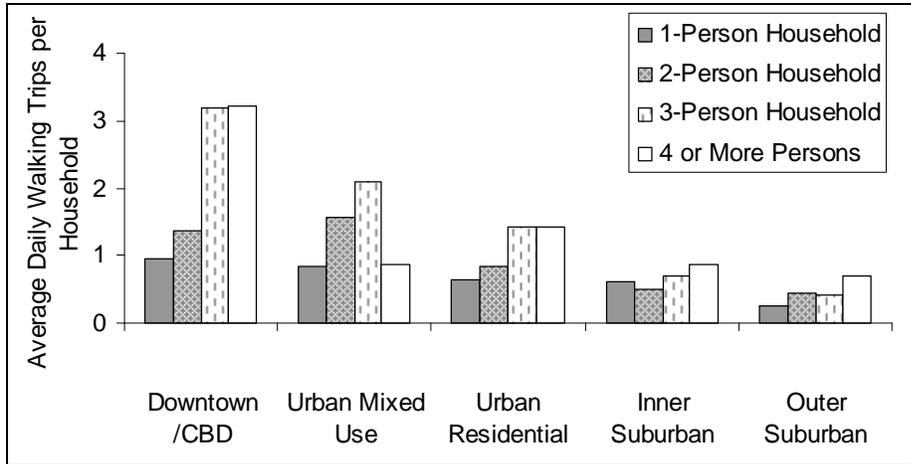


Figure C-15. Pedestrian Trip Generation Rates by Household Type and Neighborhood Type

The pedestrian trip generation rates presented in Table C-16 can be used to predict pedestrian trips in other regions. The detailed prediction process is demonstrated using the Jacksonville case in the section after next.

26. OLS Regression Modeling Results

In addition to the mean comparison analysis, simple OLS regression was also used to estimate how the pedestrian trips rates change by neighborhood type. The model specification is shown below.

$$Y = b_0 + b_1X_1 + b_2X_2 + b_3X_3 + b_4X_4$$

where,

Y denotes the number of walking trips per household per day;

$X_1 - X_4$ are dummy variables, respectively denoting the four neighborhood clusters – downtown, urban mixed use, urban residential, and inner suburban. The outer suburban neighborhood type was used as the baseline category.

Table C-17 present the results of the OLS models. Regardless the household type, compared to the outer suburban households, downtown households made 1.15 more walking trips per day; households living in urban mixed use neighborhoods made 0.82 more daily walking trips; urban residential households made 0.49 more daily walking trips; and inner suburban residential households mad 0.17 more daily walking trips.

Table C-17. OLS Regression Results on Neighborhood Clusters

Variable	1-person HH	2-person HH	3-person HH	4+-person HH	ALL HH
Constant	0.238***	0.442***	0.431***	0.707***	0.462***
Downtown	0.703***	0.918***	2.757***	2.500***	1.148***
Urban mixed use	0.595***	1.137***	1.677***	0.168	0.824***
Urban residential	0.400***	0.384***	0.987***	0.722***	0.493***
Inner suburban	0.380***	0.045	0.264	0.172	0.167*
N	913	1376	506	685	3480
R ²	0.027	0.037	0.083	0.054	0.031
Adjusted R ²	0.022	0.034	0.076	0.048	0.030
Prob > F	0.000	0.000	0.000	0.000	0.000

Note: Outer suburban neighborhood type was used as the baseline category in the models above.

Based on the estimated results in Table 17, forecast equations are developed and shown below.

$$Y_{1-person HH} = 0.238 + 0.703 X_1 + 0.595 X_2 + 0.400 X_3 + 0.380 X_4$$

$$Y_{2-person HH} = 0.442 + 0.918 X_1 + 0.1137 X_2 + 0.384 X_3 + 0.045 X_4$$

$$Y_{3-person HH} = 0.431 + 2.757 X_1 + 1.677 X_2 + 0.987 X_3 + 0.264 X_4$$

$$Y_{4+-person HH} = 0.707 + 2.500 X_1 + 0.168 X_2 + 0.722 X_3 + 0.172 X_4$$

where,

$X_1 = 1$ if the household living in downtown neighborhoods, 0 otherwise;

$X_2 = 1$ if the household living in urban mixed use neighborhoods, 0 otherwise;

$X_3 = 1$ if the household living in urban residential neighborhoods, 0 otherwise;

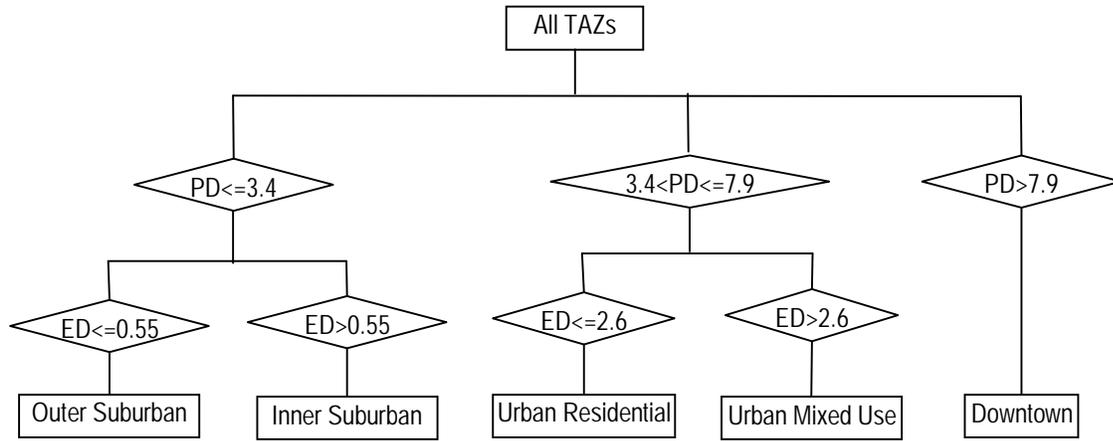
$X_4 = 1$ if the household living in inner suburban neighborhoods, 0 otherwise;

The Jacksonville Case

Applying the pedestrian trip generation rates to the Jacksonville case requires three steps. First, we assign neighborhood types to all the TAZs in Jacksonville. Then, we obtain household type data for each of the Jacksonville TAZs. Finally, we calculate total pedestrian trips in each TAZ by multiplying appropriate trip rates in Table 16 with number of households in each TAZ and summing them up. The total pedestrian trips in each TAZ can also be calculated by applying the equations in the previous section to each TAZ. Detailed procedures and guidance to complete each step are described as follows.

27. Assign TAZ to Neighborhood Types

Local planners can manually identify the neighborhood type of each TAZ based on their local knowledge about the land use environments. Alternatively, the analysis demonstrated below assigns neighborhood types to TAZs based on the decision tree in Figure C-16. The criteria in Figure 16 were defined based on Table C-18, which summarizes the quartiles of population density and employment density by neighborhood type.



Note: PD-population density; ED-employment density

Figure C-16. Criteria for Neighborhood Type Assignment

Table C-18. Quartiles of Population Density and Employment Density by Neighborhood Type

	Population Density (persons/acre)			Employment Density (jobs/acre)		
	Lower Quartile	Median	Higher Quartile	Lower Quartile	Median	Higher Quartile
Downtown	7.91	9.51	11.20	1.27	2.39	3.88
Urban Mixed Use	4.04	3.39	6.66	2.61	4.30	10.59
Urban Residential	3.39	4.56	6.66	0.38	1.01	2.39
Inner Suburban	0.78	1.75	2.38	0.38	0.91	1.75
Outer Suburban	0.74	1.40	2.45	0.28	0.28	0.55

Note: Bold denotes the quartiles used in Figure 16.

To demonstrate the assignment process, three examples were developed as shown below.

TAZ #1:

PD = 0 persons/acre; ED = 1.5 jobs/acre

PD <= 3.4 and ED > 0.55 _ inner suburban neighborhood type

TAZ #2:

PD = 0.107 persons/acre; ED = 13.955 jobs/acre

PD <= 3.4 and ED > 0.055 _ inner suburban neighborhood type

TAZ #7:

PD = 3.053 persons/acre; ED = 15.903 jobs/acre

3.4 < PD <= 7.9 and ED > 2.6 _ urban mixed use neighborhood type

Based on Figure C-16, neighborhood types were assigned to all the 143 Jacksonville’s TAZs. See Appendix A for the assignment results. The map below (Figure C-17) displays the assigned neighborhood typology in Jacksonville, NC, including 2 downtown TAZs, 4 urban mixed use TAZs, 18 urban residential TAZs, 28 inner suburban TAZs, and 91 outer suburban TAZs. Based upon the information collected during the project team’s field trip to Jacksonville, the assigned neighborhood typology is reasonable and shows consistency with the existing land use patterns in Jacksonville, NC.

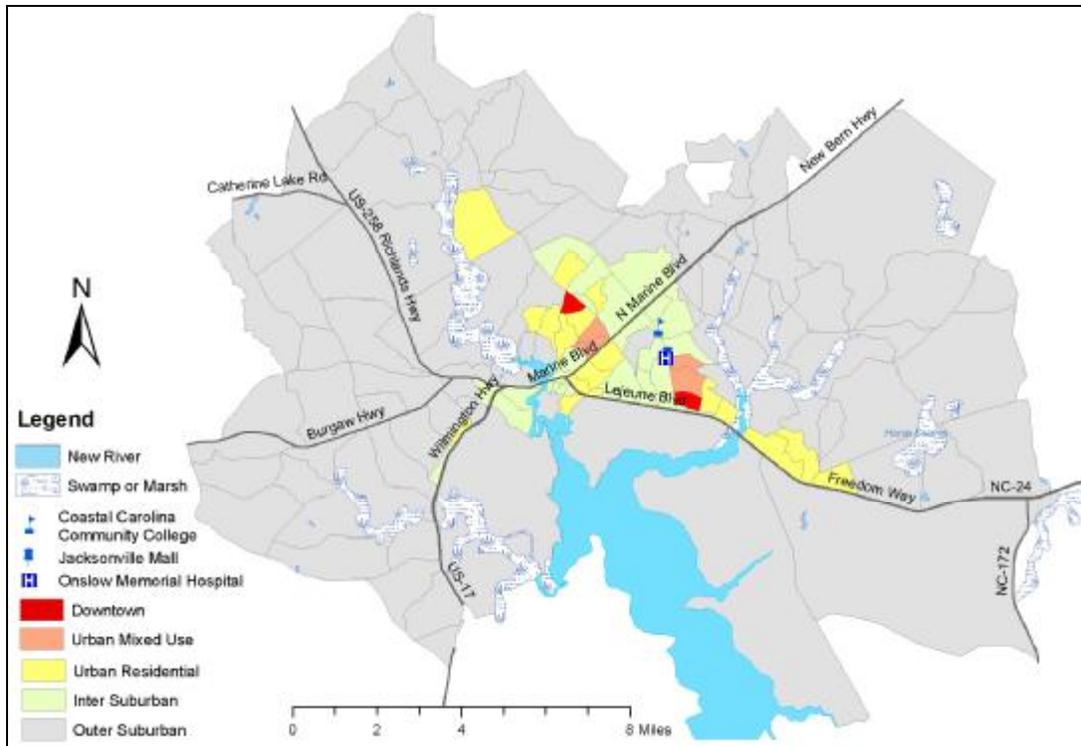


Figure C-17. Neighborhood Type Assignment in Jacksonville, NC

28. Obtain TAZ Household Type Data

The distribution of households by size is often available at the TAZ level. The household type data used in this analysis was obtained from the Jacksonville Travel Demand Model Estimation (2002). See Appendix C-1 for number of households by size in each TAZ.

29. Calculate Total Pedestrian Trips in Each TAZ

After assigning neighborhood types to TAZs and obtaining household type data, the pedestrian trip generation rates by household type and neighborhood type in Table C-16 are applied to calculate the total pedestrian trips in each Jacksonville TAZ. To demonstrate the calculation process, TAZ#3 is used as an example here. See Appendix C-1 for the predicted number of pedestrian trips in each TAZ.

Using the pedestrian trip rates reported in Table C-16, for TAZ # 3:

Neighborhood type: inner suburban

Pedestrian trip rates for inner suburban type in Table C-16:

- 1-person household: 0.62
- 2-person household: 0.49
- 3-person household: 0.69
- 4+-person household: 0.88

Distribution of households by size in TAZ#3:

- 1-person household: 20
- 2-person household: 24
- 3-person household: 7
- 4+-person household: 0

Total pedestrian trips in TAZ #3:
 $= 0.62*20+0.49*24+0.69*7+0.88*0 = \underline{28.99}$

Alternatively, the equations developed from the OLS regression estimates (Table C-17) can be used, which generates the same prediction results as using the trip rates reported in Table C-16.

Using the equations developed from the OLS regression estimates in Table C-17, for TAZ #3:

Neighborhood type: inner suburban

$\bar{O} X_1 = 0; X_2 = 0; X_3 = 0; X_4 = 1.$

$\bar{O} Y_{1-personHH} = 0.238 + 0 + 0 + 0 + 0.380 * 1 = 0.62$
 $Y_{2-personHH} = 0.442 + 0 + 0 + 0 + 0.045 * 1 = 0.49$
 $Y_{3-personHH} = 0.431 + 0 + 0 + 0 + 0.264 * 1 = 0.69$
 $Y_{4+-personHH} = 0.707 + 0 + 0 + 0 + 0.172 * 1 = 0.88$

Distribution of households by size in TAZ#3:

- 1-person household: 20
- 2-person household: 24
- 3-person household: 7
- 4+-person household: 0

Total pedestrian trips in TAZ #3:
 $= 0.62*20+0.49*24+0.69*7+0.88*0 = \underline{28.99}$

Figure C-18 visually presents the daily pedestrian trip rates per household in all the TAZs in Jacksonville, NC, estimated from the LUC method.

Method Comparison and Validation

This research uses a case study of Jacksonville, NC to demonstrate how to apply the Triangle modeling results to predict pedestrian trip rates in other NC regions. Among the three Triangle models, the factor model (Model II) has limited geographic generalizability and can not be easily applied to other regions. The 2-D method (Model I) and the LUC method (Model III) were applied to the Jacksonville case. Table C-19 summarizes the descriptive statistics of the walking trip rates in Jacksonville TAZs estimated from those two models.

Table C-19. Estimation Outcome Comparison of 2-D and LUC Methods

Estimation Method	N (TAZs)	Mean	Std. Dev.	Min	Max
The 2-D Method (simple regression model)	143	153	258	0	1845
The LUC Method (neighborhood cluster model)	143	187	279	0	1826

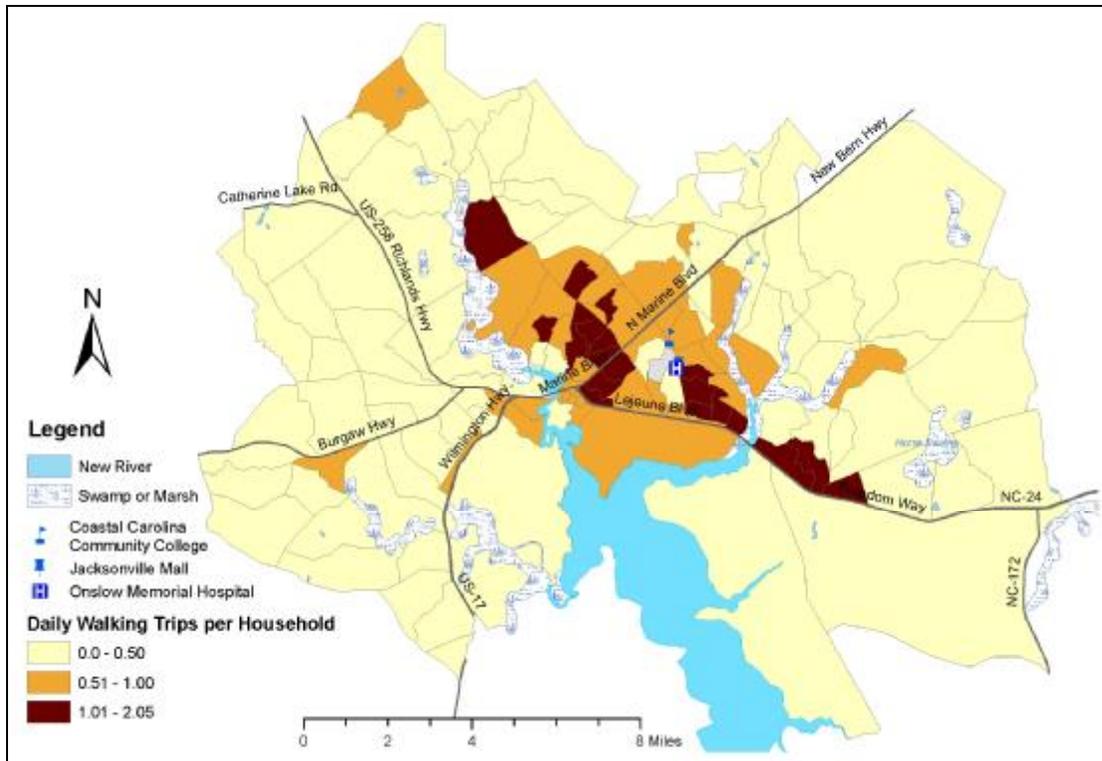


Figure C-18. Estimated Pedestrian Trip Rates in Jacksonville, NC (LUC method)

Based on the estimation results from the 2-D method, on average in Jacksonville, 153 walking trips are produced per day within each TAZ. Based on the estimation results from the LUC method, on average in Jacksonville, 187 walking trips are produced per day within each TAZ. The pedestrian trip rates estimated from the 2-D method are lower than those from the LUC method. We also conducted a paired t-test between the two outcomes. Test results show that the 2-D method outcome is significantly different from the LUC method at the 0.05 level, but not at the 0.01 level ($p=0.0141$, 2-tailed test). However, the correlation between the two prediction outcomes is as high as 0.8017, which indicates good reliability of those two methods.

Figure C-19 visually presents the estimated results from those two methods. Results from the LUC method using the neighborhood cluster model show more consistency on the spatial dimension, as high pedestrian trip generation rates mostly occur within the central city. Compared to the LUC method, pedestrian trip rates estimated from the 2-D method are relatively discretely (less continuously) distributed on the spatial dimension.

Due to the data unavailability in Jacksonville, we did not have data that can validate our estimation results. Thus, we cannot determine which method produces better and more accurate results. Furthermore, those two methods come with different advantages and disadvantages. Given the fact that the Triangle region is more urbanized than the Jacksonville area, the LUC method may overestimate the trip rates for Jacksonville. However, the LUC method has its strength because it takes a comprehensive set of land use elements into account, while the 2-D method does not.

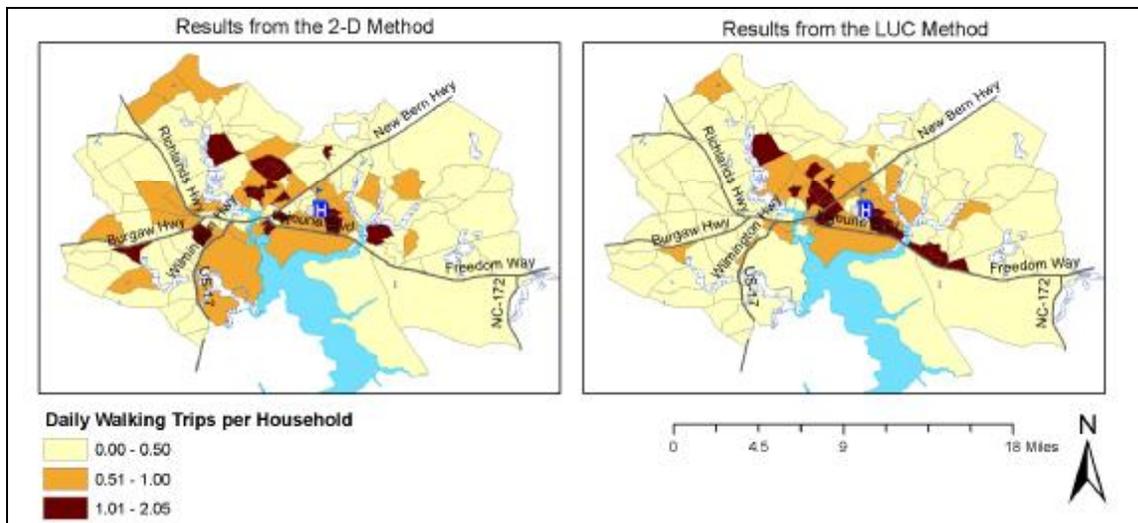


Figure C-19. Result Comparison of 2-D and LUC Methods

Conclusion

This portion of the report documents three analyses to examine the relationship between land use patterns and pedestrian trip generation rates, including a regression analysis using three simple land use measures, a regression analysis using three derived factors from factor analysis, and a method using the identified neighborhood typology from cluster analysis. The first analysis has a low data demand and is relatively easy to conduct. The last two analyses are methodologically appealing but demands more detailed GIS data and more skills in both statistical and spatial analyses.

The study area is the Triangle region including Orange, Durham, and Wake Counties. Travel behavior data from the 2006 Greater Triangle Travel Survey were linked to the land use GIS data obtained from local GIS agencies and regional GIS offices. In general, we suggested three improvements to the transportation demand model structure:

- ê Considering trips separately for different modes (such as walking versus driving) to avoid obscuring important factors associated with trip-making;
- ê Including land use factors (densities, mix of uses, design, availability of sidewalks, etc.) as one set of the travel demand predictors to generate better estimation of trip generation rates;
- ê Comparing trip generation rates from different methods to examine the spatial generalizability of the new model structure.

Analysis results show that the density & design dimension is positively related to walking trips. Indicators associated with the density & design dimension include housing density, employment density, road density, bus stop density, sidewalk coverage, and accessibility to retail stores. In terms of the diversity dimension, commercial land uses (such as retail and service uses) are positively related to walking trips, while industrial land uses are negatively related to walking trips. Neighborhood type is significantly related to pedestrian trip generation. Households living in the downtown area have the highest pedestrian trip rates. When residential neighborhoods are more sprawled, households make fewer walking trips, as expected.

As shown in Appendix C-2, daily driving trips and walking trips respond differently to land use variables, which indicates the importance of considering trip generation separately for modes. Residential density, employment density, service uses, commercial uses, bus stop density, and sidewalk coverage are all

positively related to walking, but are negatively related to driving. Industrial uses are negatively related to both walking and driving.

Two sets of pedestrian trip generation models were compared, including the 2-D method and the LUC method. The two methods were demonstrated in a case study of Jacksonville, NC. The forecast outcomes using the two methods were compared for validation and calibration purposes. Results show that the LUC method generates significantly higher pedestrian trip rates than the 2-D method. However, the LUC method shows more consistency on the spatial dimension. The correlation between the forecast outcomes from the two methods is as high as 0.8, indicating good reliability of the two methods. In general, the two methods come with different advantages and disadvantages. The practitioners may select the appropriate method to use based on the characteristics of the communities, the available GIS information and software packages, and their local knowledge of the land use environments.

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Appendix C-1: Predicted Pedestrian Trips in Jacksonville, NC

TAZ ID	HH2			HH3	HH4	Pop. Density	Job Density	Service Share	NB Type *	Walking Trips		
	0 worker	1 worker	2 workers							2-D Method	LUC Method	
1	0	0	0	0	0	0.000	1.500	0.077	4	0	0	
2	3	0	0	0	0	0.107	13.955	0.161	4	1	2	
3	20	0	4	20	7	0	1.127	1.144	0.388	4	22	29
4	1	0	0	0	0	0	0.047	9.834	0.322	4	0	1
5	11	1	1	0	0	1	0.589	14.808	0.614	4	10	9
6	1	1	1	2	1	1	0.519	9.716	0.855	4	10	4
7	18	5	14	9	6	14	3.053	15.903	0.390	4	96	41
8	33	8	24	16	24	32	3.473	1.286	0.094	3	54	141
9	16	0	0	16	16	13	3.889	2.283	0.440	3	51	65
10	27	0	29	0	18	20	1.244	2.558	0.059	4	30	61
11	67	21	35	62	66	37	1.993	1.333	0.406	4	158	177
12	86	20	30	30	37	33	1.448	0.136	0.646	5	138	95
13	82	23	52	23	41	58	5.654	0.857	0.851	3	319	275
14	43	5	26	39	55	81	0.830	0.315	0.743	5	191	122
15	31	19	21	26	38	64	1.284	0.002	0.000	5	15	98
16	50	19	21	25	38	36	0.530	0.076	0.538	5	86	83
17	95	27	56	104	80	84	1.359	0.151	0.344	5	163	199
18	60	12	25	46	85	114	2.280	0.156	0.928	5	367	168
19	23	7	16	7	13	19	1.994	0.759	0.205	4	29	55
20	52	25	55	25	49	23	6.840	1.886	0.049	3	137	223
21	27	4	6	11	13	8	0.680	0.046	0.100	5	10	27
22	33	8	4	4	20	13	1.257	1.977	0.165	4	27	54
23	34	5	10	18	22	34	1.650	0.031	0.500	5	65	56
24	15	15	10	8	18	15	0.175	0.001	0.000	5	5	37
25	8	0	0	50	67	81	0.137	0.016	0.000	5	6	110
26	79	70	57	82	133	224	2.180	0.465	0.772	5	592	327
27	31	27	14	13	36	35	0.545	0.001	1.000	5	138	72
28	56	16	22	43	46	28	1.766	0.360	0.051	5	34	89
29	1	2	1	0	1	3	0.049	0.465	0.129	5	1	4
30	58	37	31	44	49	57	4.440	0.712	0.945	3	317	281
31	99	63	29	45	47	61	3.660	0.937	0.950	3	355	331
32	100	28	78	95	128	89	10.393	2.796	0.537	1	733	1061
33	13	35	24	0	25	25	2.091	0.066	0.500	5	63	58
34	54	41	32	28	43	63	2.986	0.022	0.200	5	86	121
35	120	28	84	61	102	136	6.158	0.137	0.517	3	477	560
36	105	18	49	59	67	92	4.931	0.502	0.287	3	238	398
37	86	27	42	46	54	55	2.848	1.662	0.206	4	141	195
38	63	22	27	37	45	62	4.236	3.328	0.601	2	270	338
39	90	18	28	31	42	47	4.081	3.717	0.326	2	200	326
40	121	21	112	60	101	139	2.611	2.246	0.339	4	354	362
41	12	2	5	5	8	1	0.949	2.789	0.303	4	17	20
42	39	23	25	49	58	91	6.032	0.852	0.000	3	132	318
43	41	21	23	43	50	49	1.930	3.694	0.886	4	277	146
44	111	25	82	107	125	133	5.675	1.532	0.843	3	748	616
45	60	11	36	47	60	126	0.689	0.960	0.985	4	361	236
46	1	0	0	1	1	1	0.041	0.539	0.776	5	3	2

47	11	0	0	23	14	24	0.203	0.000	0.000	5	4	36
48	54	12	62	34	112	207	1.659	1.600	0.205	4	196	346
49	4	1	1	2	8	17	0.954	0.016	1.000	5	38	18
50	22	13	11	17	24	19	0.410	0.184	0.150	5	13	47
51	29	13	17	13	25	27	1.051	0.344	0.149	5	21	56
52	123	45	68	36	96	82	5.539	2.016	0.809	3	542	456
53	88	30	45	24	64	68	3.423	1.027	0.123	3	120	327
54	110	33	52	39	81	87	2.078	1.330	0.558	4	280	261
55	21	11	8	3	11	20	0.801	3.952	0.047	4	23	49
56	62	30	21	8	42	54	2.210	0.459	0.233	5	72	97
57	0	0	0	0	0	0	1.028	7.723	0.283	4	0	0
58	2	1	0	1	1	2	0.119	2.113	0.477	4	4	5
59	0	1	0	0	0	0	0.009	13.515	0.458	4	1	0
60	13	8	0	3	4	3	0.609	10.309	0.186	4	23	19
61	40	0	23	56	48	33	3.095	3.291	0.213	4	132	126
62	41	0	23	56	57	73	1.455	0.948	0.492	4	154	168
63	14	11	15	12	10	10	1.515	0.099	0.091	5	12	31
64	89	6	51	64	73	85	3.344	5.597	0.153	4	294	240
65	26	26	34	26	44	99	2.401	0.034	0.636	5	198	133
66	84	7	55	68	66	61	5.678	5.447	0.271	2	353	468
67	33	3	27	33	80	91	1.859	0.025	0.444	5	140	135
68	63	30	53	81	108	157	5.496	5.668	0.437	2	650	677
69	176	36	63	97	131	115	7.777	0.153	0.414	3	535	626
70	113	46	82	124	168	85	11.272	1.565	0.380	1	735	1258
71	11	0	10	0	3	4	1.600	14.317	0.110	4	29	17
72	1	0	0	0	0	0	0.049	3.226	0.197	4	0	1
73	81	21	37	57	80	93	4.912	0.495	0.111	3	163	394
74	78	33	37	44	92	74	0.731	0.004	0.800	5	259	161
75	64	23	26	31	61	55	0.399	0.015	0.167	5	33	116
76	31	13	15	19	43	32	0.507	0.005	0.000	5	10	69
77	13	13	15	19	32	53	0.946	0.236	0.991	5	153	75
78	47	22	25	29	62	57	0.382	0.046	0.395	5	77	112
79	37	16	18	21	32	37	0.423	0.045	0.136	5	19	73
80	30	17	14	22	33	30	0.554	0.005	0.000	5	10	66
81	74	29	33	41	86	81	0.420	0.009	0.333	5	89	158
82	34	18	15	24	23	40	0.284	0.009	0.833	5	109	72
83	32	14	12	18	17	37	0.169	0.004	0.000	5	9	61
84	27	16	13	21	31	46	0.450	0.017	0.000	5	9	74
85	34	12	10	15	18	21	0.242	0.015	0.571	5	49	47
86	63	40	34	53	90	120	1.190	0.036	0.129	5	55	195
87	46	18	15	24	23	22	0.972	0.030	0.100	5	21	62
88	65	25	29	34	78	119	0.699	0.032	0.956	5	330	172
89	37	40	28	21	45	62	1.494	0.015	0.667	5	153	111
90	29	11	12	14	22	24	0.192	0.232	0.193	5	16	50
91	35	19	21	25	59	70	1.123	0.020	0.000	5	15	112
92	20	9	11	13	25	17	0.213	0.062	0.000	5	6	42
93	14	10	12	14	30	20	0.167	0.003	0.600	5	50	46
94	41	30	29	28	39	78	0.333	0.001	0.000	5	15	120
95	36	14	14	13	28	25	0.397	0.216	0.086	5	13	56
96	12	9	9	9	13	21	0.190	0.012	1.000	5	65	35

97	17	20	20	19	38	77	0.585	0.036	0.757	5	144	101
98	15	6	6	6	10	19	0.073	0.004	1.000	5	54	29
99	43	26	26	25	49	66	0.239	0.005	0.500	5	97	112
100	4	5	5	4	4	8	0.058	0.000	0.000	5	2	15
101	20	20	20	19	30	31	0.992	0.006	0.500	5	64	66
102	29	5	30	25	46	65	0.544	0.002	0.500	5	94	99
103	12	2	9	7	7	13	0.048	0.003	0.429	5	17	23
104	34	7	39	32	55	63	0.795	0.044	0.381	5	84	111
105	8	3	15	12	11	16	2.813	0.063	0.000	5	13	31
106	17	3	17	13	24	15	0.344	0.024	0.133	5	11	40
107	39	19	21	25	49	52	0.229	0.035	0.429	5	70	96
108	205	64	173	204	367	565	3.649	0.130	0.776	3	1648	1826
109	69	29	43	66	113	154	2.087	0.068	0.390	5	225	235
110	42	9	8	12	15	10	0.172	0.108	0.107	5	12	36
111	4	1	6	5	6	4	0.075	0.022	0.000	5	2	12
112	9	3	17	13	9	10	0.118	0.015	0.053	5	7	28
113	86	68	90	68	165	253	3.182	0.089	0.182	5	254	371
114	6	2	5	2	0	4	0.132	0.411	0.000	5	2	8
115	33	13	40	26	27	40	0.655	0.013	0.375	5	62	83
116	33	14	11	11	25	28	0.254	0.045	0.019	5	9	54
117	11	2	10	7	7	17	0.017	0.002	0.286	5	12	26
118	21	11	13	21	27	45	0.471	0.295	0.686	5	91	68
119	5	3	2	2	2	1	0.183	0.000	0.000	5	1	6
120	1	3	2	2	8	3	0.049	0.110	1.000	5	18	9
121	17	10	17	19	32	27	0.145	0.003	0.000	5	7	57
122	52	50	66	49	125	188	1.933	0.128	0.380	5	244	272
123	43	15	13	13	34	41	0.978	0.048	0.143	5	23	72
124	59	11	29	42	38	30	1.904	0.226	0.357	5	86	88
125	80	31	80	114	87	191	2.377	0.101	0.000	5	94	291
126	16	4	7	8	15	14	0.346	0.004	0.000	5	5	29
127	13	4	8	8	8	19	0.206	0.008	0.167	5	8	29
128	144	17	54	115	140	135	1.799	0.223	0.989	5	611	272
129	23	14	36	51	79	232	1.533	0.030	0.000	5	23	249
130	52	25	40	31	60	74	0.316	0.003	0.500	5	119	133
131	3	1	2	1	3	1	0.007	0.000	0.000	5	1	4
132	37	22	22	15	35	34	0.501	0.145	0.260	5	34	74
133	67	21	34	26	55	58	1.695	0.010	0.500	5	134	117
134	11	2	70	163	352	95	4.026	0.000	0.000	3	116	838
135	85	2	63	147	139	170	4.505	0.735	0.072	3	250	671
136	104	22	62	49	83	105	3.487	0.793	0.131	3	164	445
137	47	13	35	27	46	52	0.380	0.036	0.236	5	41	101
138	57	17	23	31	57	48	0.467	0.035	0.068	5	21	104
139	138	41	55	75	151	195	0.708	0.000	0.000	5	45	312
200	1	0	0	0	0	1	0.000	0.000	0.200	5	0	1
201	2663	0	57	115	264	988	0.445	0.000	0.000	5	455	1530
202	278	14	164	193	650	854	1.956	0.009	0.714	5	1845	1116
203	564	4	28	24	103	268	0.233	0.006	1.000	5	768	395

Note: Neighborhood type=1: downtown; 2: urban mixed use; 3: urban residential; 4: inner suburban; 5: outer suburban.

Appendix C-2: Comparison of Pedestrian Models and Auto Models

This appendix aims at understanding how the relationship between land use and trip generation varies by mode. The appendix estimated separate trip generation models for walking, driving, and total daily travel. In this appendix, we focus on empirically testing whether the land use and travel demand connection varies by mode, rather than on developing rigorous models to predict mode-specific trip productions. Given the modest goal, we developed non-segmented OLS models for driving trips, walking trips, walking and driving trips, and total daily trips. Log-transformed regression and negative binomial regression were not used in this analysis. Three sets of models were developed, respectively regressing mode-specific trip generation rates on three set of land use variables: the simple land use measures, the derived land use factors, and the identified neighborhood clusters. See detailed specifications of the models below.

Model set #1: using the simple land use measures

$$Y = b_0 + b_1 X_1 + b_2 X_2 + b_3 X_3 + b_4 X_4 + b_5 X_5$$

where,

Y denotes the number of walking/driving/walking and driving/total trips per household per day;

$X_1 - X_3$ denote the three simple land use variables at the person's residence. They are population density (residents per acre), employment density (number of jobs per acre), and service use share (% of service jobs);

X_4 denotes household size – number of persons in the household;

X_5 denotes number of workers within the household;

Model set #2: using the derived land use factors

$$Y = b_0 + b_1 X_1 + b_2 X_2 + b_3 X_3 + b_4 X_4 + b_5 X_5$$

where,

Y denotes the number of walking/driving/walking and driving/total trips per household per day;

$X_1 - X_3$ denote the three derived land use factors using factor analysis, including the density & design factor, and the two diversity factors captured through commercial mix and industrial mix;

X_4 denotes household size – number of persons in the household;

X_5 denotes number of workers within the household;

Model set #3: using the identified neighborhood clusters

$$Y = b_0 + b_1 X_1 + b_2 X_2 + b_3 X_3 + b_4 X_4 + b_5 X_5 + b_6 X_6$$

where,

Y denotes the number of walking/driving/walking and driving/total trips per household per day;

$X_1 - X_4$ are dummy variables, respectively denoting the four neighborhood clusters – downtown, urban mixed use, urban residential, and inner suburban. The outer suburban neighborhood type was used as the baseline category.

X_5 denotes household size – number of persons in the household;

X_6 denotes number of workers within the household;

Tables C-I, B-II, B-III present the modeling results of the three sets of OLS regression analyses. Results in Table B-I show that household size and number of workers within the household are positively related

to both walking trips and driving trips. However, the land use measures are related to walking and driving in opposite directions. Population density, employment density, and the percentage of service jobs within the census block group at the household's residence are significantly and positively related to the number of walking trips made by the household, but are significantly and negatively related to the number of driving trips. This indicates the importance of considering trip generation separately for different modes, especially when integrating land use variables into travel demand modeling.

Table B-II and Table B-III show consistent results with Table B-I. Driving trip generation and walking trip generation respond to land use variables in different directions. An interesting result in Table B-II is that more industrial mix is related to lower trip generation in both walking and driving. However, more commercial mix is related to higher pedestrian trip generation, but lower auto trip generation. Table B-III indicates that compact residential environments are associated with higher pedestrian trip rates but lower auto trip rates.

R-squares show that the models of total travel perform much better than auto models and pedestrian models. In terms of land use measurement techniques, the derived land use factors result in the best model performance in predicting pedestrian trip productions. In predicting auto trip productions and total daily trip productions, the three model sets result in similar model performance. This indicates that the three sets of land use measures capture the spatial variation in daily trips and auto trips to a similar degree, while the derived land use factors capture the spatial variation in pedestrian trips to a higher degree than the simple land use measures and the identified neighborhood clusters.

Table C-I: OLS Regression Analysis on the Simple Land Use Measures

Variable	Walk	Drive	Walk + Drive	Total
Population density	0.083***	-0.131***	-0.048**	0.029
Employment density	0.034***	-0.038***	-0.004	0.005
Service use share	0.788***	-0.135	0.653**	0.825**
Household size	0.161***	1.180***	1.342***	3.906**
Number of workers	0.095**	1.342***	1.437***	0.402**
Constant	-0.521***	2.590***	2.069***	-0.178
N	3480	3480	3480	3480
R ²	0.051	0.292	0.287	0.487
Adjusted R ²	0.050	0.291	0.286	0.486
Prob > F	0.000	0.000	0.000	0.000

Legend: * p<0.10; ** p<0.05; *** p<0.01

Table C-II. OLS Regression Results on the Derived Land Use Factors

Variable	Walk	Drive	Walk + Drive	Total
Density & Design Factor	0.407***	-0.448***	-0.041	0.211**
Commercial Mix Factor	0.057*	-0.140**	-0.084**	-0.048
Industrial Mix Factor	-0.098***	-0.045	-0.143	-0.118
Household size	0.169***	1.175***	1.344***	3.911***
Number of workers	0.103**	1.337***	1.440***	0.409***
Constant	0.223***	2.005***	2.227***	0.346*
N	3480	3480	3480	3480
R ²	0.062	0.292	0.287	0.487
Adjusted R ²	0.060	0.291	0.286	0.486
Prob > F	0.000	0.000	0.000	0.000

Legend: * p<0.10; ** p<0.05; *** p<0.01

Table C-III. OLS Regression Results on the Identified Neighborhood Clusters

Variable	Walk	Drive	Walk + Drive	Total
Downtown	1.262***	-1.684***	-0.422	0.555
Urban mixed use	0.895***	-0.883***	0.012	0.525
Urban residential	0.541***	-0.192	0.349**	0.647***
Inner suburban	0.205**	-0.239	-0.035	0.163
Household size	0.153***	1.204***	1.358***	3.916***
Number of workers	0.094**	1.338***	1.432***	0.399***
Constant	-0.059	2.173***	2.115***	0.047
N	3480	3480	3480	3480
R ²	0.046	0.289	0.288	0.488
Adjusted R ²	0.045	0.288	0.286	0.487
Prob > F	0.000	0.000	0.000	0.000

Legend: * p<0.10; ** p<0.05; *** p<0.01

Note: Outer suburban neighborhood type was used as baseline category in the models above.

APPENDIX D: QUICK RESPONSE APPROACH TO TRIP GENERATION ESTIMATION

Overview

North Carolina state law requires all municipalities to have transportation plans in addition to cities and Metropolitan Planning Organizations (MPO) with populations 50,000 or more as required by the Federal Aid Highways Act (1962). However, relatively little national guidance exists for transportation plans for communities under 50,000 population. For cities of any size NCDOT uses the traditional 4-step travel demand model which is data intensive and time consuming. Most small communities, however, often experience travel patterns or traffic problems that are different from and less complicated than those in large metropolitan areas. Thus, they are candidates for simplified modeling methods in terms of their contexts for travel, economic development and other issues.

The goal of the Multi-Year Travel Model Research project is to develop guidelines and tools for best practices in the transportation modeling process for different sized NC communities, including data sources, models and sub-models, and reasonableness checking methods. In the travel demand forecasting process, trip generation is a critical step which is closely related to the travel demand forecasting results and therefore requires a modeler's attentions, since it calculates the total number of trips produced and attracted to each zone in the planning area. The completed Phase I project developed guidelines and tools for trip generation estimation for small communities with population less than 10,000 [1]. In Phase II, efforts were made to continue developing guidelines and tools to improve trip generation estimation for medium and large communities (Category C, population between 10,000 and 50,000) and MPOs (Category D, population greater than 50,000) according to the guideline matrix addressed in Phase I report [1].

This appendix evaluates different approaches to estimate trip generation in urban areas with populations greater than 10,000. Guidelines for recommended practice for trip generation are developed for urban categories C and D mentioned above. For each category, the guideline is addressed through a case study.

Medium and Large Communities (Category C)

In this research, medium and large communities are defined as Category C which has a population range between 10,000 and 50,000. Although transportation plans in such communities are not emphasized by federal legislation, NC State law requires them to have transportation plans. Therefore, research on travel demand modeling improvements for the smaller communities is needed. Fuquay-Varina, a medium city in North Carolina was used as the case study for Category C in this research.

Planning Area and Land Use Data

Fuquay-Varina is located in southern Wake County, North Carolina, about 18 miles south of Raleigh, the state capital and county seat. The corporate limit of the Fuquay-Varina is currently over 8 square miles, but it continues to increase as it receives requests for annexation and for town services. Because of its proximity to Raleigh, Fuquay-Varina can be considered as a fringe town of the Raleigh metropolitan area. With 29,276 people, the Fuquay-Varina planning area includes 61 internal TAZs (centroids 1 – 61) and 15 external stations (centroids 62 – 76). Figures D-1 and D-2 show the town of Fuquay-Varina and its TAZ structure, respectively.

The land use and socio-economic data for the Fuquay-Varina planning area is available by referring to the Triangle Regional Model. The housing and population data for the Triangle model were obtained from the 2000 census and adjusted by MPO staff using building permit data to reflect 2002 conditions.

Employment data for the Triangle model were obtained from InfoUSA and verified by the MPOs. The zonal data are listed in Table D-1. The suggested data sources can also be referred to Appendix E in the Phase I report [1].

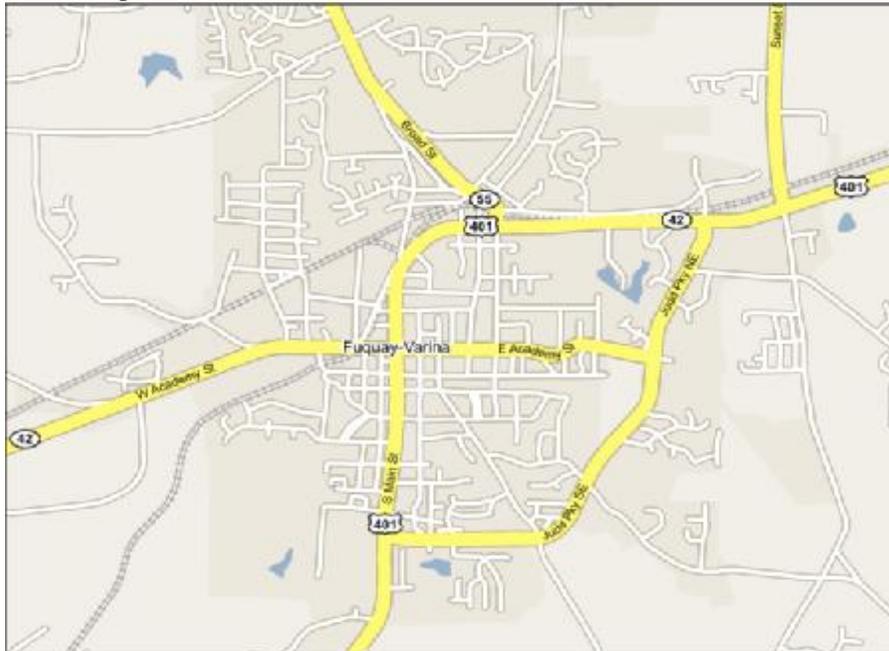


Figure D-1. Town of Fuquay-Varina

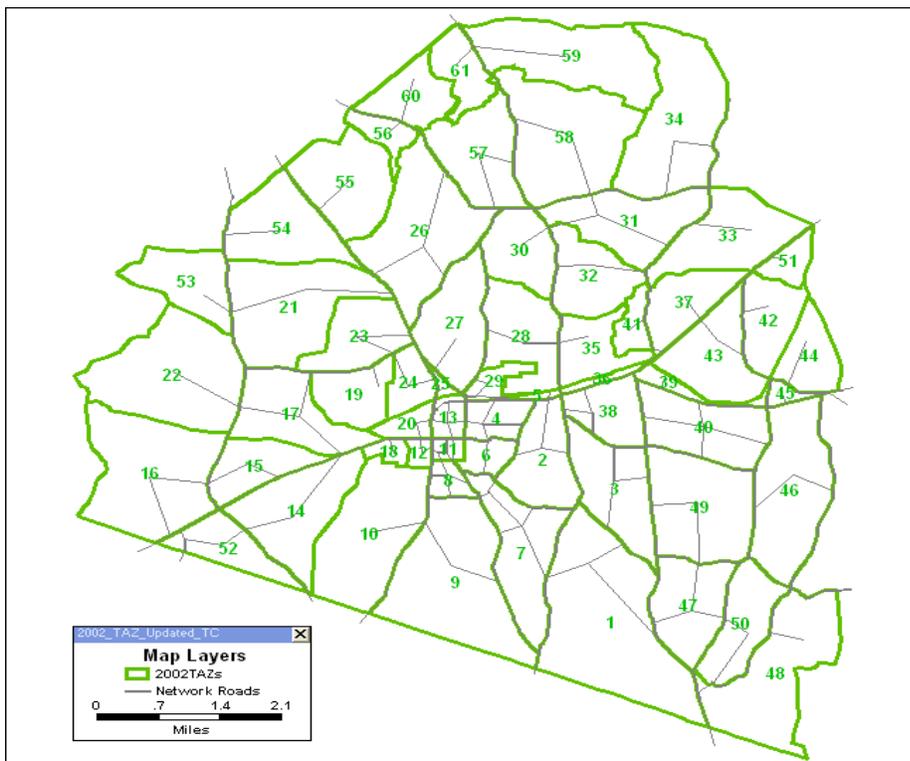


Figure D-2. TAZ Structure in Fuquay-Varina Planning Area

Table D-1. Land Use and Socio-economic Data in Fuquay-Varina

TAZ	AREA	HHOLDS	POP	INDUSTRY	RETAIL	SPC_RETAIL	OFFICE	SERVICE
1	2.86	347	993	5	2	0	0	7
2	0.88	209	552	555	249	109	295	182
3	1.09	133	390	46	70	0	0	6
4	0.35	298	670	0	53	191	5	137
5	0.04	0	0	0	0	0	0	0
6	0.25	144	346	3	0	0	1	12
7	1.17	125	355	2	0	0	0	10
8	0.20	535	1302	0	27	0	0	248
9	2.20	255	746	3	7	2	0	17
10	1.70	579	1331	65	20	70	3	144
11	0.10	211	511	12	68	12	6	3
12	0.10	91	222	0	18	0	22	8
13	0.21	233	542	20	12	41	22	24
14	1.30	139	344	0	5	13	2	6
15	0.67	130	340	5	1	2	1	12
16	2.01	128	331	2	1	0	1	7
17	1.06	163	467	7	0	0	0	19
18	0.13	59	159	2	0	0	0	41
19	0.62	93	268	11	4	0	77	14
20	0.21	300	783	11	19	3	13	53
21	1.71	105	293	3	0	0	0	6
22	2.00	148	434	1	0	0	0	3
23	0.81	446	1165	0	0	0	1	4
24	0.37	330	841	5	100	0	2	234
25	0.06	72	187	10	6	4	0	9
26	1.85	218	584	134	203	5	10	97
27	1.05	233	592	38	10	56	199	137
28	1.01	215	542	47	128	23	3	28
29	0.22	249	709	26	3	15	0	12
30	0.75	149	423	2	0	38	0	6
31	1.15	249	679	32	4	0	0	60
32	0.86	153	414	4	34	0	53	66
33	1.19	304	804	0	51	33	4	25
34	1.87	384	1095	7	1	0	11	20
35	0.62	72	202	7	0	0	1	11
36	0.10	15	24	2	0	8	0	1
37	0.70	19	43	2	75	0	0	0
38	0.61	179	440	174	72	78	0	63
39	0.19	17	69	0	4	0	0	2
40	1.09	147	382	4	1	0	0	4
41	0.26	49	139	0	0	0	86	1
42	0.70	82	250	2	0	0	0	10
43	1.02	139	368	0	2	0	0	26
44	0.57	27	74	4	0	0	0	1
45	0.11	45	113	0	0	0	18	0
46	1.64	199	471	3	0	0	0	5

47	0.99	132	346	13	0	0	0	5
48	1.75	178	508	0	0	0	0	6
49	1.52	64	189	0	0	0	0	1
50	0.84	91	275	0	0	0	0	1
51	0.27	163	442	20	1	49	1	3
52	0.64	80	201	0	3	9	0	2
53	0.82	28	60	0	0	0	0	0
54	1.14	44	106	0	0	0	0	1
55	1.17	175	426	5	0	0	1	10
56	0.28	43	125	0	0	0	0	4
57	1.11	806	2162	18	45	0	9	226
58	1.91	235	691	8	19	0	0	16
59	1.62	58	164	0	0	0	238	37
60	0.63	351	1091	1	2	0	0	19
61	0.51	201	501	0	0	0	0	11

Trip Generation Models

In this study, four different trip generation models will be tested. They are:

- 1) TransCAD quick response method (QRM)
- 2) TransCAD cross-classification approach
- 3) North Carolina trip rates for place cluster (Metrolina survey)
- 4) North Carolina quick response method (Triangle survey)

1) TransCAD Quick Response Method

Trip Production

TransCAD includes a default trip table provided by NCHRP 187 [2], which may be used to calculate productions using the QRM trip production procedure. The default table is a cross-classification table, segmented by the size of the urban area, household income, and auto-ownership. It includes trip rates for three purposes: HBW, HBO and NHB. TransCAD provides a default trip production table called PROD_TRP.DBF. There are four types of cross-classification applications that we may use with the default tables:

- None (Use Average Rates per Household)
- Income per Household
- Autos per Household
- Income per HH and Auto Ownership Split

In this analysis, we will use the average rates per household to estimate trip productions. However, the QRM does not provide the trip model for small areas under 50,000 people. Which population category should we use for the Fuquay-Varina planning area? A recent research study [3] finds that the travel behavior in fringe towns is very much like that of a larger city, and these small towns can safely use data tools from the nearby larger city. Therefore, we can apply the trip rates for the QRM 200,000-500,000 population group to the Fuquay-Varina planning area, because Fuquay-Varina is a fringe town of the Raleigh metropolitan area which has 276,093 people (2000 census).

Trip Attraction

As with QRM trip productions, TransCAD includes a default attraction model from NCHRP 187 that we may use to estimate attractions. For attractions, QRM uses a regression equation that estimates the number of person-trips attracted to a zone based on the retail and non-retail levels of employment in the zone and the number of dwelling units in the zone. The equations are:

$$\text{HBW Attractions} = 1.7(\text{Retail Employment}) + 1.7(\text{Nonretail Employment})$$

$$\text{HBO Attractions} = 10.0(\text{Retail Employment}) + 0.5(\text{Nonretail Employment}) + 1.0(\text{Dwelling Units})$$

$$\text{NHB Attractions} = 2.0(\text{Retail Employment}) + 2.5(\text{Nonretail Employment}) + 0.5(\text{Dwelling Units})$$

Table D-2 shows trip productions and attractions by using the TransCAD Quick Response method.

Table D-2. TransCAD Quick Response Method Results

Trip Purpose	Productions	Attractions	P/A Ratio
HBW	26116	11237	2.32
HBO	71818	34141	2.10
NHB	32645	21018	1.55
Total	130579	66396	1.97

2) TransCAD Cross-Classification Approach

Trip Production

TransCAD provides several default cross-classification tables that may be used for estimating trip productions. The source of these tables is *NCHRP Report 365: Travel Estimation Techniques for Urban Planning* [4].

The default rate tables are located in the Tab folder within the TransCAD program folder. There are seven lookup tables. All are binary files, with the file name beginning with “crcl_”. The remaining part of the file name indicates the classification that is in the table:

- p = urban area population;
- a = autos per household;
- s = household size in persons; and
- i = income per household.

Table D-3 summarizes the available default production trip rate tables:

Table D-3. Summary of the Production Trip Rate Tables

File Name	Classifications				Trip Purposes				
	Urban Pop	Income/HH	HH Size	Autos/HH	ADPT/HH	ADVT/HH	HBWPT/HH	HBOPT/HH	NHBPT/HH
CRCL_P	x				x	x	x	x	x
CRCL_PA	x			x	x				
CRCL_PI	x	x			x		x	x	x
CRCL_PS	x		x		x	x	x	x	x
CRCL_PIA	x	x		x	x		x	x	x
CRCL_PAS	x		x	x	x		x	x	x
CRCL_PIS	x	x	x		x		x	x	x

Where:

- ADPT/HH = Average daily person trips per household;
- ADVT/HH = Average daily vehicle trips per household;
- HBWPT/HH = Home-based work person trips per household;
- HBOPT/HH = Home-based other person trips per household;
- NHBPT/HH = Non-home-based person trips per household.

Because only population and household data are available for the Fuquay-Varina planning area, CRCL_P and CRCL_PS tables were tested in this case study.

- CRCL_P Table

Given the urban population, we can use trip rates listed in the CRCL_P table to estimate trip productions. Table D-4 shows the details of the trip rates.

Table D-4. CRCL_P Table

Urban Population	ADPT/HH	ADVT/HH	HBWPT/HH	HBOPT/HH	NHBPT/HH
[50000, 199999]	9.200	8.100	1.840	5.244	2.116
[200000, 500000]	9.000	7.800	1.890	5.040	2.070
[500000, 1000000]	8.600	7.400	1.892	4.816	1.892
[1000000, ∞]	8.500	6.900	1.785	4.760	1.955

Source: NCHRP 365 & TransCAD 4.0

It is noticed that this table does not give any suggested trip rates for communities with population under 50,000, such as the Fuquay-Varina planning area (population = 29,276). If we consider Fuquay-Varina as a fringe town of the Raleigh metropolitan area (population = 276,093), we can safely use the trip rates of 200,000-500,000 people category.

- CRCL_PS Table

Given the urban population and household sizes, we can use trip rates listed in the CRCL_PS table to estimate trip productions. Table D-5 shows the details of the table.

Table D-5. CRCL_PS Table

URBAN POP	HH SIZE	ADPT/HH	ADVT/HH	HBWPT/HH	HBOPT/HH	NHBPT/HH
[50000, 199999]	1	3.7000	3.2000	0.7400	1.9980	0.9620
	2	7.5000	6.6000	1.6500	4.0500	1.8000
	3	10.6000	9.4000	2.0140	5.9360	2.6500
	4	13.7000	11.9000	2.6030	7.9460	3.1510
	4+	16.7000	14.1000	2.8390	10.3540	3.5070
[200000, 499999]	1	3.6000	3.2000	0.7200	2.0160	0.8640
	2	7.0000	6.3000	1.6100	3.7100	1.6800
	3	11.3000	10.3000	2.4860	6.1020	2.7120
	4	13.4000	11.2000	2.4120	8.1740	2.8140
	4+	16.8000	13.5000	3.1920	9.9120	3.6960
[500000, 999999]	1	3.8000	3.3000	0.8740	2.0520	0.8740
	2	7.2000	6.6000	1.7280	3.8160	1.6560
	3	10.1000	8.7000	2.3230	5.4540	2.3230
	4	12.6000	10.7000	2.6460	7.1820	2.7720
	4+	15.7000	12.8000	2.8260	9.7340	3.1400

[1000000, ∞]	1	4.1000	3.0000	0.9430	2.0500	1.1070
	2	7.1000	5.7000	1.7750	3.6920	1.6330
	3	9.1000	7.5000	2.2750	4.7320	2.0930
	4	12.1000	10.0000	2.5410	7.1390	2.4200
	4+	14.5000	11.0000	2.7550	8.9900	2.7550

Source: NCHRP 365 & TransCAD 4.0

It is noticed that the zonal household data for Fuquay-Varina is not grouped by different household sizes. Therefore, before using the CLCR_PS table, we need to firstly use a sub-model to split the zonal households into different size classifications. Triangle Region Model Service Bureau (TRMSB) is using a household size sub-model which was developed based on 2000 CTPP data for TAZs in the Triangle Region [5]. This model can disaggregate the households in a TAZ into four different household size classifications: 1-person, 2-person, 3-person, and 4 or more-person households by considering the average household size in that TAZ. Figure D-3 and Table D-6 show the details of the sub-model.

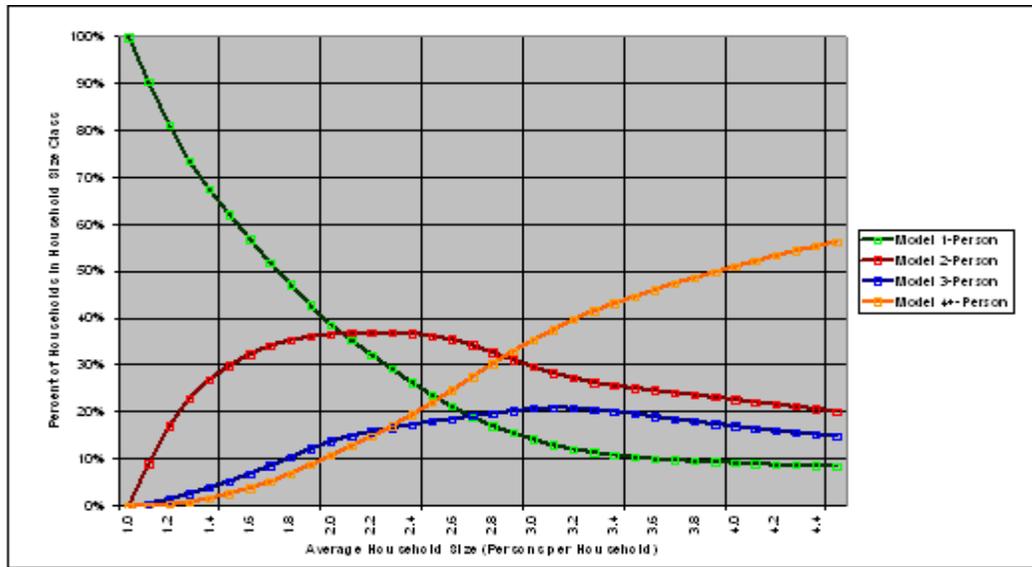


Figure D-3. Household Size Model

Table D-6. Household Size Model

HHSIZE	R_HH1	R_HH2	R_HH3	R_HH4
1.00	100.00	0.00	0.00	0.00
1.10	90.40	9.00	0.50	0.10
1.20	81.30	17.00	1.40	0.30
1.30	73.60	23.00	2.60	0.80
1.40	67.50	27.00	3.90	1.60
1.50	62.10	30.00	5.30	2.60
1.60	56.90	32.40	6.90	3.80
1.70	52.00	34.20	8.60	5.20
1.80	47.30	35.40	10.40	6.90
1.90	42.80	36.20	12.20	8.80
2.00	38.70	36.70	13.80	10.80
2.10	35.30	36.90	15.00	12.80
2.20	32.30	37.00	15.90	14.80
2.30	29.30	37.00	16.70	17.00

2.40	26.40	36.80	17.40	19.40
2.50	23.70	36.30	18.00	22.00
2.60	21.20	35.50	18.60	24.70
2.70	19.00	34.30	19.20	27.50
2.80	17.10	32.80	19.80	30.30
2.90	15.50	31.20	20.30	33.00
3.00	14.20	29.70	20.80	35.30
3.10	13.00	28.40	21.00	37.60
3.20	12.10	27.30	20.90	39.70
3.30	11.40	26.40	20.60	41.60
3.40	10.90	25.70	20.20	43.20
3.50	10.50	25.20	19.70	44.60
3.60	10.10	24.70	19.10	46.10
3.70	9.80	24.20	18.50	47.50
3.80	9.60	23.70	18.00	48.70
3.90	9.40	23.20	17.50	49.90
4.00	9.20	22.70	17.00	51.10
4.10	9.00	22.20	16.50	52.30
4.20	8.80	21.70	16.00	53.50
4.30	8.70	21.20	15.60	54.50
4.40	8.60	20.70	15.30	55.40
4.50	8.50	20.20	15.00	56.30
4.60	8.45	19.70	14.80	57.05
4.70	8.40	19.20	14.60	57.80
4.80	8.35	18.70	14.40	58.55
4.90	8.30	18.20	14.20	59.30
5.00	8.25	17.70	14.00	60.05
5.10	8.20	17.20	13.80	60.80
999.00	8.15	16.70	13.60	61.55

Because Fuquay-Varina is located in the Triangle region, it is reasonable to apply this regional sub-model to the Fuquay-Varina planning area.

CRCL_PS table does not give any suggested trip rates for communities with population under 50,000, too. Similarly, as addressed above, we apply the trip rates of the category between 200,000 and 500,000 to Fuquay-Varina, because Fuquay-Varina can be considered as a fringe town of the metropolitan area of Raleigh which has 276,093 people.

We also notice that there are 5 household size classifications in CRCL_PS table. However, the disaggregate model groups 4-person and 4+-person together and yields 4 household size classifications. In this analysis, we will use trip rates of 4-person household in CRCL_PS table for both 4 and more-person household.

Table D-7 compares the trip productions by using CRCL_P and CRCL_PS tables.

It is clear that the two default tables yield very similar trip productions for the Fuquay-Varina case. Because the household size information is sometimes not available and CRCL_P is more easy-to-use than CRCL_PS, the CRCL_P table can be safely used in medium city like Fuquay-Varina and provide adequate accuracy.

Table D-7. Comparison of CRCL_P and CRCL_PS Tables

	CRCL_P	CRCL_PS	Ratio
HBW	20915	20151	1.03791
HBO	55773	55936	0.99709
NHB	22907	22423	1.02158
Total	99595	98510	1.01101

Trip Attraction

The NCHRP Report 365, distributed by National Cooperative Highway Research Program, also provides the following estimated equations to predict trip attractions:

$$\text{HBW Attr.} = 1.45(\text{Total Employment})$$

$$\text{HBO Attr. CBD} = 2.00(\text{CBD RE}) + 1.7(\text{SE}) + 0.5(\text{OE}) + 0.9(\text{HH})$$

$$\text{HBO Attr. NCBD} = 9.00(\text{NCBD RE}) + 1.7(\text{SE}) + 0.5(\text{OE}) + 0.9(\text{HH})$$

$$\text{NHB Attr. CBD} = 1.40(\text{CBD RE}) + 1.2(\text{SE}) + 0.5(\text{OE}) + 0.5(\text{HH})$$

$$\text{NHB Attr. NCBD} = 4.10(\text{NCBD RE}) + 1.2(\text{SE}) + 0.5(\text{OE}) + 0.5(\text{HH})$$

Where:

HBW = Home-based work;

HBO = Home-based other;

NHB = Non-home-based;

CBD RE = Retail Employment in the Central Business District Zones;

NCBD RE = Retail Employment in the Non-Central Business District Zones;

SE = Service Employment;

OE = Other Employment (Basic and Government);

HH = Households.

To determine the CBD zones, we consider both the local map and the employment density. In this study, those zones with the employment density greater than 500 employments per square acre are considered as the CBD zones. Therefore, TAZ 2, 4, 8, 11, 13, 24 and 38 are considered as CBD zones. Figure D-4 shows the employment density of each zone in the Fuquay-Varina planning area.

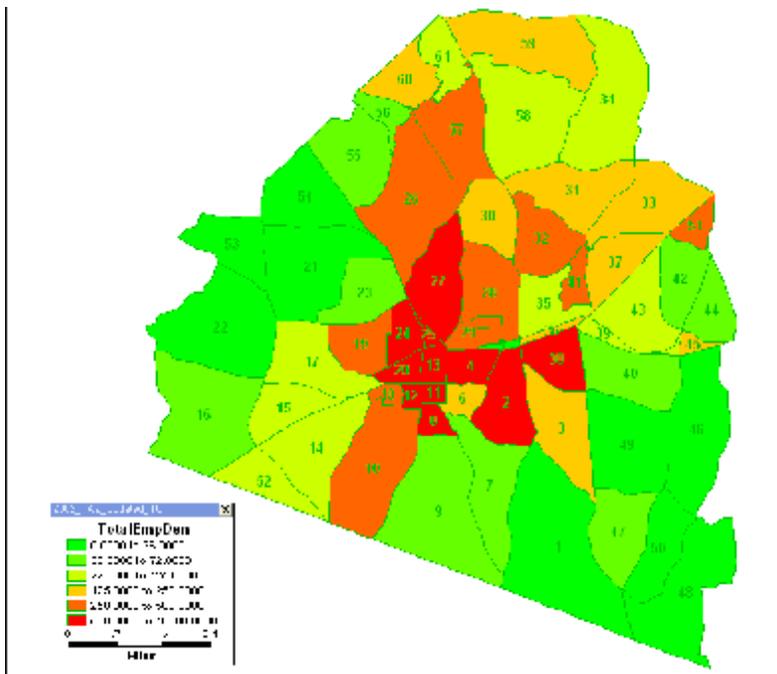


Figure D-4. Employment Density of Each Zone

By using CRCL_P table for trip production and the regression model for trip attraction, we can get comparison results between trip productions and attractions as Table D-8 shows.

Table D-8. TransCAD Cross-Classification Approach Results

Trip Purpose	Productions	Attractions	P/A Ratio
HBW	20915	9585	2.18
HBO	55773	26412	2.11
NHB	22907	15083	1.52
Total	99595	51080	1.95

3) North Carolina Trip Rates for Place Cluster

Trip Production

By defining three urban proximity classes, a specified North Carolina trip rate table was developed based on Metrolina household travel survey. The purpose of these categorizations is to classify towns according to the level of influence they experience from the urban center. The three classifications are:

1. CENTER – areas belonging to the urban center proper
2. FRINGE – areas outside the urban center which behave largely as if they were part of the urban center
3. OUTLYING – areas which behave demonstrably differently from the urban center

Table D-9 shows the trip rates by different place categories and trip purpose.

Table D-9. Trip Production Rates by Proximity Class and Trip Purpose

Proximity Category	HBW	HBO	NHB
CENTER	1.44	4.02	2.76
FRINGE	1.62	4.11	2.85
OUTLYING	1.54	5.38	3.34

In this case study, the Fuquay-Varina is located in a fringe area, therefore the trip rates of the “FRINGE” category are selected to estimate trip productions for the planning area.

Trip Attraction

Based on Metrolina survey data, a set of attraction models were developed for each trip purpose.

Firstly, these models are grouped by two classes with different population range. The classification structure is described as below.

- Own Place Population Group (PIPop):
[0, 5K], [5K, 10K], [10K, 20K], [20K, 50K], [50K, 100K], [100K, ∞]
- Urban Cluster Major Place Population Group (UCPop):
[0, 5K], [5K, 10K], [10K, 20K], [20K, 50K], [50K, 100K], [100K, ∞]

The “Own Place Population Group” measures the population of the target town (not the planning area), while the “Urban Cluster Major Place Population Group” measures the population of the central urbanized area. For this case study, the Fuquay-Varina falls into the range of 5K-10K of the “Own Place Population Group” because the town of Fuquay-Varina has 9,060 people, and also falls into the range of 100K- ∞ because the nearby Raleigh urban area has 276,093 people. After accounting for the analogy and efficiency of all these models, 6 trip attraction models are tested. Table D-10 summarizes the trip rates.

Table D-10. Summary of Attraction Trip Rates

Model		Emp_Total	Emp_Retail	Emp_NonRetail	Household
PIPop1	HBW	3.125			
	HBO	11.866			
	NHB	3.056			
PIPop2	HBW		0.947	0.723	
	HBO		3.247	1.497	
	NHB		4.878	0.932	
PIPop3	HBW	0.369			1.202
	HBO	0.236			4.730
	NHB	0.996			1.651
UCPop1	HBW	1.994			
	HBO	7.013			
	NHB	2.721			
UCPop2	HBW		1.710	0.688	
	HBO		10.683	0.313	
	NHB		6.181	0.841	
UCPop3	HBW	0.641			0.498
	HBO	0.457			3.179
	NHB	1.061			1.200

For example, according to model PIPop1:

$$HBW = 3.125 * Emp_Total, \quad HBO = 11.866 * Emp_Total, \quad NHB = 3.056 * Emp_Total.$$

We can use each of the attraction models to estimate trip attractions and compare with the developed trip productions. Tables D-11 through D-16 show the comparison results.

Table D-11. P&A Comparison by NC Production Rates and PIPOP1 Attraction

Trip Purpose	Productions	Attractions	P/A Ratio
HBW	17876	20656	0.87
HBO	45457	78434	0.58
NHB	31540	20200	1.56
Total	94873	119290	0.80

Table D-12. P&A Comparison by NC Production Rates and PIPOP2 Attraction

Trip Purpose	Productions	Attractions	P/A Ratio
HBW	17876	5245	3.41
HBO	45457	13537	3.36
NHB	31540	14372	2.19
Total	94873	33154	2.86

Table D-13. P&A Comparison by NC Production Rates and PIPOP3 Attraction

Trip Purpose	Productions	Attractions	P/A Ratio
HBW	17876	15738	1.14
HBO	45457	53901	0.84
NHB	31540	24849	1.27
Total	94873	94488	1.00

Table D-14. P&A Comparison by NC Production Rates and UCPOP1 Attraction

Trip Purpose	Productions	Attractions	P/A Ratio
HBW	17876	13180	1.36
HBO	45457	46356	0.98
NHB	31540	17986	1.75
Total	94873	77522	1.22

Table D-15. P&A Comparison by NC Production Rates and UCPOP2 Attraction

Trip Purpose	Productions	Attractions	P/A Ratio
HBW	17876	6674	2.68
HBO	45457	23649	1.92
NHB	31540	16672	1.89
Total	94873	46995	2.02

Table D-16. P&A Comparison by NC Production Rates and UCPOP3 Attraction

Trip Purpose	Productions	Attractions	P/A Ratio
HBW	17876	9746	1.83
HBO	45457	38199	1.19
NHB	31540	20295	1.55
Total	94873	68240	1.39

4) North Carolina Quick Response Method

This approach was the development of a trip rate table specific to North Carolina. The table has data related to production rates for each trip purpose, attraction rates for each trip purpose, and variable type descriptions. The format of the trip rate table applied to this case study is shown in Table D-17.

Table D-17. Adjusted North Carolina Trip Rates

VARTYPE	R_HBWP	R_HBOP	R_NHBP	R_HBWA	R_HBOA	R_NHBA	TYPE
1	1.400	4.100	2.130	0.000	0.500	0.130	HHOLDS
2	0.000	0.000	0.000	1.700	7.600	3.400	RETAIL
3	0.000	0.000	0.000	1.700	3.830	2.000	NONRET

The user has unlimited flexibility in changing the variables, the trip purposes, and the trip rates. For the purpose of this case study, Table D-17 provides initial production and attraction rates which were derived from the Triangle survey data. This method has been applied to small communities (Wendell, North Carolina) in Phase I. Please refer to Appendix E in the Phase I report for the application of this approach.

For the Fuquay-Varina case study, the final results are shown in Table D-18.

Table D-18. North Carolina Quick Response Method Results

Trip Purpose	Production	Attraction	P/A Ratio
HBW	15492	11237	1.4
HBO	45371	38695	1.2
NHB	23571	17572	1.3
Total	84434	67504	1.3

P & A Reasonableness Check and Balancing

After trip productions and attractions are estimated, it is necessary to compare them and check their ratio by trip purposes. The desired ratio should be within $1 \pm (10\%-20\%)$. If the ratio does not fall into the range, further work needs to be conducted to check the production and attraction models and review the land use data. If there is no problem with the land use data, the production and the attraction rates need to be adjusted in order to yield reasonable productions and attractions. In Phase I of this research project, the guidelines for trip generation reasonableness check have been discussed in detail, which are repeated as below [1]:

- Review total trip productions per household for reasonableness – some typical ranges of production rates from previous survey efforts are shown in Table D-19.
- Calculate total trips by purpose and compare percentages by trip purpose to the ranges provided in Table D-20.
- Compare attraction rates with other areas as a reasonableness check. Attraction rates from the Triangle region are shown in Table D-21.
- Review home-based work trip attractions per total employment.
- Review home-based school trips per school enrollment (if used.)
- Review home-based shopping trips per retail employment (if used.)
- Evaluate productions, attractions, and land use variables for reasonable relationships.
- Calculate trip rate per capita (total trips/population). This value should be over 3.0 and generally in the range of 3.5 – 4.0.

Table D-19. Vehicle Trip Production Rates

Housing Classification	1995 Triangle Survey	Triad Survey	National Data [FHWA]
Excellent	9.4*	9.3	11.2
Above Average	9.4*	9.1	11.2
Average	8.3	7.7	8.3
Below Average	6.2*	6.3	5.4
Poor	6.2*	5.7	5.4
All Dwelling Units	7.8	7.4 – 8.0	7.8

*Categories had to be combined to achieve a statistically significant sample

Table D-20. Trip Purpose

Purpose	Triangle Survey*	Triad Survey*	Charlotte Survey*	National*
HBW	22%	20%	19%	18-25%
HBO	46%	49%		47-58%
NHB	32%	31%		18-28%
Non-HBW			81%	

*Incorporates urban and non-urban households

Table D-21. Vehicle Trip Attraction Rates*

Employment Type	HBW	HBO	NHB	IX
Industry	1.2	0.63	1.1	0.34
Retail	1.2	3.4	1.0	0.49
Highway Retail	1.2	4.2	4.0	0.28
Office	1.2	1.2	1.1	0.28
Service	1.2	2.0	1.9	0.28
Dwelling Units	0	0.9	0.13	0.33

*Rates obtained from 1995 Triangle Household Survey

The balancing process is accomplished by applying a balancing factor to the attraction trips for all zones, by trip purpose. The balancing facing factor is designed to change the total number of attractions so that the total number of attractions equals the total number of productions. The regional total of NHB trips produced by the households is judged to be the best estimate of the control total of NHB trips, but the NHB attractions are judged to be the best estimate of where these trips take place. Therefore, after the NHB trip attractions are scaled so that the total attractions equal the total production, the NHB trip productions in each zone are set equal to the NHB trip attractions.

Recommendations and Findings

In the Fuquay-Varina case study, the North Carolina trip rates for place cluster (PIPOP3) yield the best P/A ratio. This model is easy to use and less data intensive. Although this model was developed based on Metrolina household travel survey, it still works for the Fuquay-Varina case study. The fact may indicate that this trip generation model is transferable for medium cities with population between 10,000 and 50,000. In Phase I, the North Carolina quick response method has been verified to be a good tool for small communities. In this case study, this method also produces acceptable results by using default Triangle rates. More accurate trip generation estimation can be expected if necessary adjustments are made to the default trip rates based on the local knowledge of the planning area.

In this case study, the analysis of different trip generation models indicates that the national default trip rates provided by NCHRP 187 (TransCAD Quick Response Method) and NCHRP 365 (TransCAD Cross-Classification Approach) can not be used for medium cities such as Fuquay-Varina. However, the North Carolina regional trip rates can produce acceptable results for medium cities with populations between 10,000 and 50,000. For more accurate estimation, necessary adjustments need to be made to these kinds of default rates based on local surveys or local knowledge of the planning area. Three trip purposes (HBW, HBO and NHB) are recommended for the trip generation step.

Metropolitan Planning Organizations (Category D)

This research defines Metropolitan Planning Organizations (MPO) (excluding regional areas) as Category D which has population over 50,000. For this category, much research has been accomplished for trip generation modeling. The most common trip generation models include cross-classification methods and

regression models based on influencing factors such as automobile ownership, income, household size, and density, and type of land development. Most MPO travel demand models estimate trip generation depending on trip rates obtained by local household surveys. To achieve the major goal of this research which aims at improving current travel demand forecasting techniques and developing cost-effective TDM approaches for appropriate study areas, different trip generation models and trip rates were tested to recommend an efficient way to estimate trip generation in MPO regions. The Jacksonville MPO in North Carolina was used as the case study for the study purpose.

Planning Area and Land Use Data

The Jacksonville study area follows boundary guidelines recommended by the NCDOT Transportation Planning Branch and the City of Jacksonville for this update. This boundary captures all of the local urban area and areas of potential expansion. It follows natural boundaries whenever possible, captures a potential transportation project (US 17 bypass), and covers the jurisdiction of the Jacksonville MPO. As shown in Figure D-5, the Jacksonville study area is located in the heart of Onslow County, North Carolina, surrounded by the Hoffman State forest to the north and the Camp Lejeune Military Base to the south. The Jacksonville planning area is approximately 215 square miles. With 125,807 people in 2000, the Jacksonville planning area has 143 internal TAZs (centroids 1-139, 200-203) and 11 external stations (centroids 501-511). Figure D-6 shows the TAZ structure in

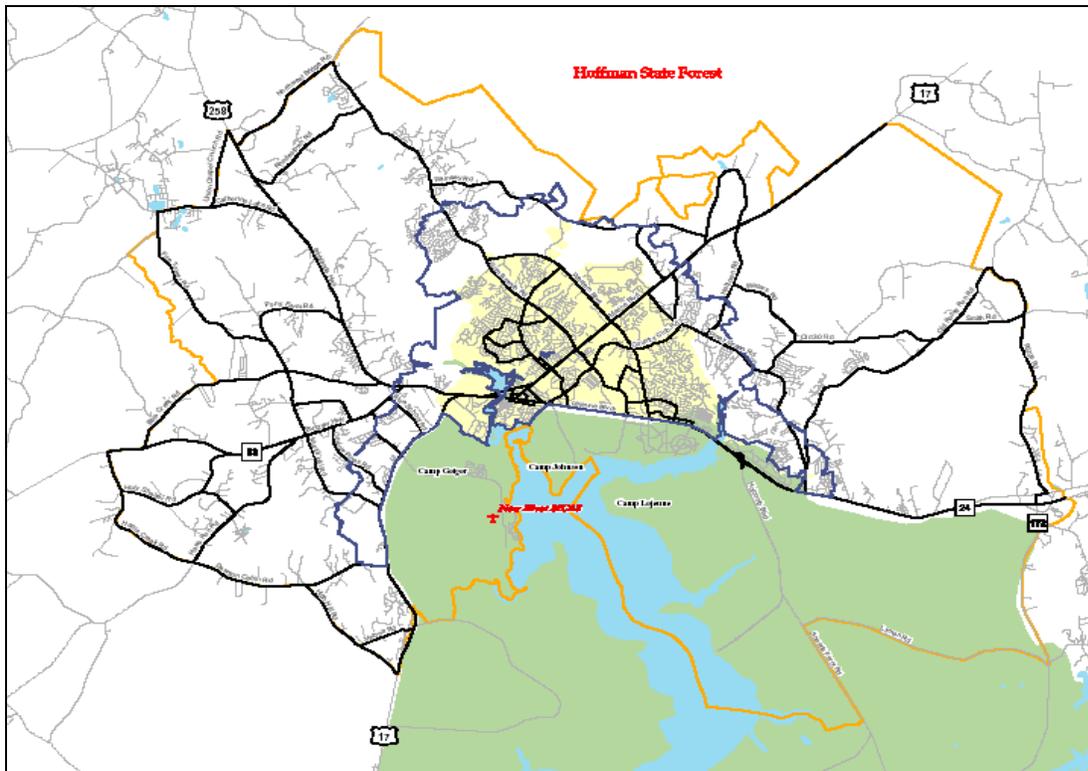


Figure D-5. Jacksonville Planning Area

Jacksonville planning area.

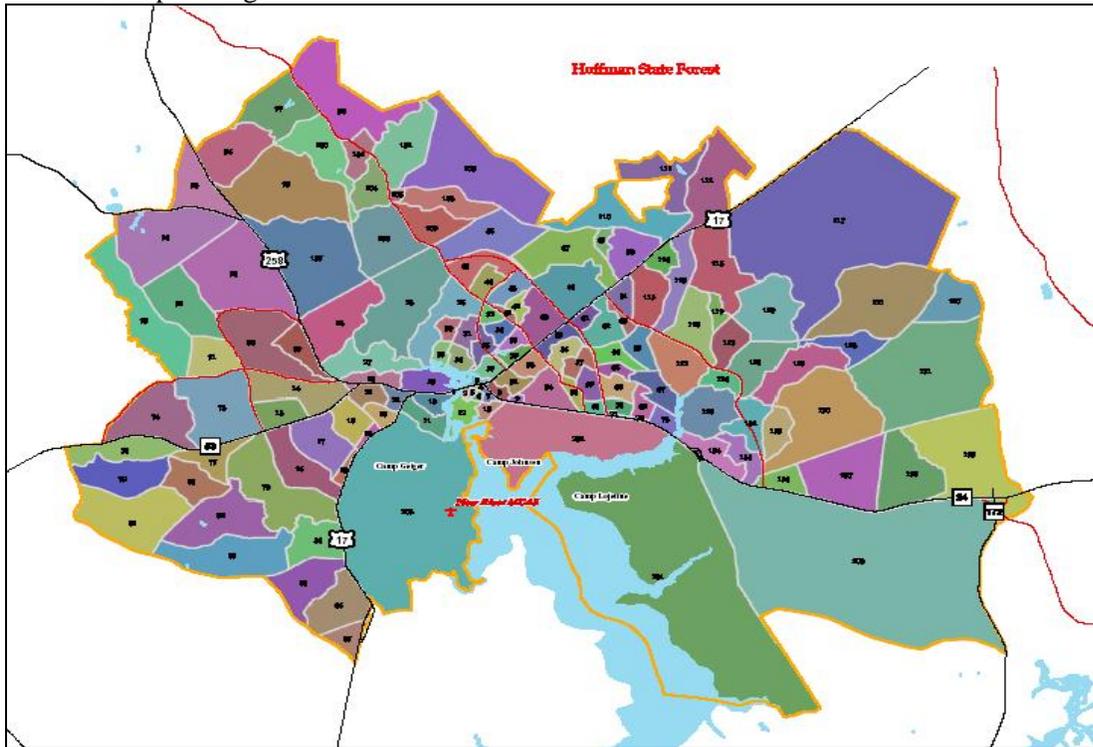


Figure D-6. TAZ Structure in Jacksonville Planning Area

Zonal data for the Jacksonville planning area were obtained from several sources, including the US Census, InfoUSA, NCDOT, the City of Jacksonville, and Onslow County. A 2002 windshield survey for the Jacksonville area was used along with the 2000 Census and 2001 aerial photography to develop the 2002 household totals by TAZ. Information from the 2000 Census and the Census Transportation Planning Package (CTPP) helped in developing household totals by household size and number of workers, along with the number of students in each household [6].

2002 employment data was obtained by location for all of Onslow County, with the verification by calling large employers. Employment data was then grouped into five main categories [6]:

- Industrial (SIC Groups 1-49)
- Retail (SIC Groups 50-59, excluding 55 and 58)
- High Turnover Retail (SIC Groups 55 and 58)
- Office (SIC Groups 60-69, 90-98)
- Service (SIC Groups 70-89, 99)

The special generator categories also used employment data, which was input in the TAZ database. For instance where employment data were used in a special generator field, the data were not used in one of the five main employment types mentioned above. In the Jacksonville planning area, special generators include:

- Military (Camp Lejeune)
- Hospital (ONslow County Memorial Hospital)
- Shopping (Jacksonville Mall, Wal-Mart, Target)
- University (Coastal Carolina Community College – uses enrollment instead of employment)

All land use data in Jacksonville study area are available in the Jacksonville travel demand model [6] which was recently developed by Kimley-Horn to assist the City of Jacksonville, Onslow County and NCDOT in analyzing and forecasting traffic.

Trip Generation Models

In this study, the trip generation result produced by the Kimley-Horn Jacksonville travel demand model is used as a baseline to evaluate alternative trip generation models. The model is a good baseline because it is based on local data and detailed modeling techniques. As before, the four trip generation models tested by Fuquay-Varina (the case study for Category C) are studied as alternative trip generation forecasting approaches. In summary, five trip generation models appear in the Jacksonville case study:

- Baseline: Kimley-Horn model
- Alternatives
 - 1) TransCAD quick response method (QRM)
 - 2) TransCAD cross-classification approach
 - 3) North Carolina trip rates for place cluster (Metrolina survey)
 - 4) North Carolina quick response method (Triangle survey)

The Kimley-Horn model uses four primary trip purposes in the trip generation step: home-based work (HBW), home-based school (HBS), home-based other (HBO), and non-home-based (NHB). For the trip productions, cross-classification models were used for estimating HBW, HBO and NHB trips while a regression-based mode was used for HBS trip purpose. Trip attraction was estimated by using regression models for all attraction categories including five major employment types and special generators. Both trip production and trip attraction models were developed based on local household surveys. The specific model coefficients can be referred to the Jacksonville travel demand model documentation developed by Kimley-Horn [6].

Recall that one of the major goals of this research project is to improve, yet simplify, the transportation modeling process for NC communities consistent with their needs and issues. Thus, the feasibility of reasonable simplifications will be tested for the trip generation step. All of the alternative trip generation models mentioned above will use reduced trip purposes and aggregated land use data. In summary, the simplifications adopted in alternative models are summarized as below:

- Trip purposes
 - § Home-based work (HBW)
 - § Home-based other (HBO): aggregating HBS and HBO in Kimley-Horn model
 - § Non-home-based (NHB)
- Trip attraction categories
 - § Industrial
 - § Retail: aggregating Retail and Shopping special generator in Kimley-Horn model
 - § High Turnover Retail
 - § Office
 - § Service: aggregating Service and Hospital special generator in Kimley-Horn model
 - § Military (special generator)
 - § School (special generator)

1) TransCAD Quick Response Method

The TransCAD quick response method has been discussed above in the Fuquay-Varina case study for Category C analysis. Table D-22 summarizes the estimated trip productions and trip attractions in Jacksonville study area by using TransCAD quick response method.

Table D-22. Trip Generation by TransCAD Quick Response Method

Trip Purpose	Production	Attraction	P/A Ratio
HBW	88,151	79,439	1.11
HBO	336,075	194,388	1.73
NHB	126,717	117,926	1.07
Total	550,943	391,753	1.41

2) TransCAD Cross-Classification Approach

The default TransCAD cross-classification tables for trip production estimation provided by *NCHRP Report 365* have been discussed in detail in Fuquay-Varina case study for Category C analysis. The CRCL_PS table is superior to the CRCL_P table and is used in Jacksonville case since CRCL_PS table offers better accuracy by specifying household characteristics in more detail and the household size data is available in Jacksonville study area. The regression models for trip attraction estimation provided by NCHRP Report 365 are directly used in Jacksonville case study since the area type information is already known.

Table D-23 summarizes the trip generation results in Jacksonville study area according to TransCAD cross-classification approach.

Table D-23. Trip Generation by TransCAD Cross-classification Approach

Trip Purpose	Production	Attraction	P/A Ratio
HBW	69,592	71,919	0.97
HBO	205,877	193,182	1.07
NHB	84,732	109,576	0.77
Total	360,201	374,677	0.96

3) North Carolina Trip Rates for Place Cluster

As mentioned in the Fuquay-Varina case above, a specific North Carolina trip rate table was recommended based on the Metrolina household travel survey. Table D-9 has provided a set of trip production rates in terms of the locations of the target community. Since Jacksonville is clearly an urbanized center area, the trip production rates for the “CENTER” category are used.

For trip attractions, simplified regression models were developed by combining different employment types and accounting for the characteristics of different place clusters. Table D-24 shows the regression model.

Table D-24. Trip Attraction Rates by North Carolina Place Cluster

Trip Purpose	Area Type	Emp_Retail	Emp_NonRetail
HBW	CBD	1.503	1.037
	Urban		
	Rural		
HBO	CBD	10.292	0.280
	Urban	6.997	1.978
	Rural	7.358	5.381
NHB	CBD	9.168	0.632
	Urban	5.951	1.124
	Rural	2.958	2.169

Table D-25 summarizes the trip generation results for Jacksonville study area based on this approach.

Table D-25. Trip Generation by North Carolina Trip Rate for Place Cluster

Trip Purpose	Production	Attraction	P/A Ratio
HBW	56,267	64,288	0.88
HBO	157,077	154,234	1.02
NHB	107,844	114,237	0.94
Total	321,188	332,759	0.97

4) North Carolina Quick Response Method

According to the household travel survey conducted in the Triangle a set of trip rates have been developed. They are based on the North Carolina quick response trip table for trip generation estimation using TransCAD. Table D-17 provides the recommended trip rates. The North Carolina quick response trip rates were also tested in the Jacksonville case study. Table D-26 summarizes the estimated trip generation results.

Table D-26. Trip Generation by North Carolina Quick Response Method

Trip Purpose	Production	Attraction	P/A Ratio
HBW	54,704	79,395	0.69
HBO	160,203	214,544	0.75
NHB	83,228	108,830	0.76
Total	298,135	402,769	0.74

Production and Attraction Reasonableness Check and Balancing

The guidelines for the reasonableness check of trip generation results have been discussed in the early part of this appendix for the Fuquay-Varina case. The desired ratio between trip productions and attractions should be within $1 \pm (10\%-20\%)$. By checking the PA ratios produced by different approaches, the North Carolina place cluster rates appear to produce the best PA ratio. In addition, the best performance of this approach is also validated by comparing the estimated trips with the baseline model results (Kimley-Horn model, see Table D-27), since the trips estimated by North Carolina place cluster rates method best matches the results of the baseline model from an overall point of view.

Table D-27. Trip Generation by Baseline Model (Kimley-Horn Model)

Trip Purpose	Production	Attraction	P/A Ratio
HBW	66,170	66,740	0.99
HBO	126,191	133,152	0.95
NHB	110,636	116,098	0.95
Total	302,997	315,990	0.96

Findings and Recommendations

Although many MPO areas are currently using more detailed stratification of trip purposes in their travel demand models, the trip generation estimates by three basic trip purposes (HBW, HBO and NHB) appear to produce acceptable accuracy according to the Jacksonville case study. In addition, it is feasible to integrate some kinds of special generators (e.g., hospitals and shopping areas) into usual employment types for simplification purpose. These findings indicate that, in an MPO area, the trip generation modeling structure could be simplified by reasonably aggregating and modeling similar travel patterns and those land use with common characteristics.

The determination of the trip rates may be the most expensive and time-consuming procedure during the course of the trip generation estimation in a specific study area. Based on the evaluation of different trip models and trip rates, it is found that the North Carolina trip rates (Metrolina survey) have transferability to other MPO areas. By borrowing trip rates from other places, the travel demand modeling process could be less data intensive and time consuming. According to the analysis of the Jacksonville case, it is also suggested that a reduced number of employment types can be confidently used for trip generation estimation as an alternative approach when insufficient land use data are available for trip generation estimating.

References:

1. John R. Stone, Leta F. Huntsinger and Asad J. Khattak. *Guidelines for Developing Travel Demand Models: Small Communities*, NCDOT Report 2005-11, June 2006.
2. *Quick Response Urban Travel Estimation Techniques and Transferable Parameters*, NCHRP Report 187, Transportation Research Board, 1978.
3. John Horner and John R. Stone. *The Impact on Travel Behavior of Proximity to Major Urban Centers: An Analysis of Recent Travel Surveys from the Charlotte, North Carolina Area*, Transportation Research Board 85th Annual Meeting CD-ROM, Washington, D.C., 2006.
4. William A. Martin and Nancy A. McGuckin. *Travel Estimation Techniques for Urban Planning*, NCHRP Report 365, Transportation Research Board, 1998.
5. *Triangle Region Model – Trip Generation Disaggregation Models (Draft)*, Parson Transportation Group, 2002.
6. *Jacksonville Travel Demand Model*. Kimley-Horn and Associates, Inc., 2002.

APPENDIX E: TRIP DISTRIBUTION

Overview

The trip distribution is the step that links the trip productions to the trip attractions for each zone pair. Trip distribution is a vital part of the planning process because the trip interchanges between each zone pair that eventually have to be accommodated by the transportation system. In most cases ranging from small communities to large multi-MPO regions, the most commonly used trip distribution method is the gravity model. The gravity model is expressed as:

$$T_{ij} = P_i \left(\frac{A_j F_{ij} K_{ij}}{\sum_{k=1}^{\text{zones}} A_k F_{ik} K_{ik}} \right)$$

Where:

T_{ij} = the number of trips from zone i to zone j ;

P_i = the number of trip productions in zone i ;

A_j = the number of trip attractions in zone j ;

F_{ij} = the friction factor relating the spatial separation between zone i to zone j ;

K_{ij} = an optional trip-distribution adjustment factor for interchanges between zone i to zone j .

In the gravity model, the friction factor is the primary independent variable and quantifies the impedance or measure of separation between two traffic analysis zones. In practice, transportation professionals sometimes have difficulty in setting and calibrating friction factors (which should result in real local trip patterns) because the household travel survey data may not be available. In Phase I of this research project, an efficient approach was suggested to estimate initial friction factors by using average trip lengths for small communities with population less than 10,000 [1]. The calculation formula is shown as below:

$$F = \exp \left\{ - \frac{t_{ij}}{ATL} \right\} \times 10000$$

Where:

F = friction factor;

t_{ij} = travel time between zone i to zone j ;

ATL = average trip length.

Similar to Phase I, different average trip length sub-models will be evaluated for the best trip distribution modeling practice in urban Category C (medium and large communities with populations between 10,000 and 50,000) and urban Category D (MPO areas) defined in this research. Two case cities will be studied for the two urban categories.

As discussed in Chapter 2, the destination choice model (DCM) is more promising for trip distribution estimates for unique land uses (e.g., special generator) than the gravity model since the DCM is able to

capture more explanatory variables representing traveler behavior, personal characteristics, and zonal measures. Also, it does not require friction factors or special adjustment factors. The destination choice model is addressed in Chapter 4 for application in larger communities and will not be examined in case cities in this appendix.

Medium and Large Communities (Category C)

Fuquay-Varina is the case study city for Category C medium and large communities which have populations between 10,000 and 50,000.

Three different sub-models to estimate average travel length are evaluated by the Fuquay-Varina case. They are:

- NCHRP Report 365 Method
- Average Trip Length from Network Skims
- Population Based Method

NCHRP Report 365 Method

The closest correlation that has been found between average trip length and urban area size relates the average trip length to the land area of the urbanized area. According to NCHRP Report 365 [2], the average trip length for HBW trips can be estimated using the following formula:

$$HBWATL = 5.0 + 0.10 \times \sqrt{Area}$$

where:

- HBWATL* = average HBW trip length;
- Area* = area of the region (acre).

NCHRP Report 365 also suggests the average trip length for non-HBW trips (both HBO and NHB) according to different sized region (Table E-1).

Table E-1. Average Trip Length for non-HBW Purpose

Trip Purpose	Average Trip Length	
	Pop < 500,000	Pop >1,000,000
HBO	75-85%	60-70%
NHB	HBW Average Trip Length	HBW Average Trip Length

Source: NCHRP Report 365

Because the Fuquay-Varina planning area has 5120 acres (8 square miles), we can estimate the average HBW trip length as 12.2 minutes. A factor of 0.8 is used for both HBO and NHB purposes, so we estimate the average trip lengths for HBO and NHB are both equal to 9.7 minutes. The estimated average trip lengths are summarized in Table E-3.

Average Trip Length from Network Skims

Based on the highway network and TAZ structures in the planning area, we can develop the zone to zone travel time matrix (shortest path matrix). This matrix provides another approach to determine average trip length. By considering the set of internal TAZs, we can create zone to zone travel times and then calculate the mean travel time between zone pairs. The mean value (8.46 min) is directly used as the average trip

length for HBW purpose in this analysis. Table E-2 provides default values for average trip length and relationships between different trip purposes.

By applying a factor of 0.88 for HBO trips and 0.82 for NHB trips to the HBW average trip length, the results are 7.44 for HBO average trip length and 6.94 for NHB average trip length, respectively.

Table E-2. Default Values for Average Trip Length by Trip Purpose

Trip Purpose	Average Trip Length	
	Large Urban Area	Small Urban Area
HBW	15 to 20	7 to 10
HBO	13 to 17	6 to 9
NHB	13 to 17	6 to 8

Source: Calibration and Adjustment of System Planning Models

The average trip length of IE/EI trips can be estimated by calculating all the travel times between external zones and internal zones, according the shortest path matrix. The estimated IE/EI average trip length is 9.23 minutes (Table E-3).

Population Based Method

Based on origin-destination studies done in the 1960's, the "Calibration and Adjustment of System Planning Models" provides a set of equations which can be used to estimate average trip length based on the urban area population. The equations are shown as below.

Home-Based Work: $t = 0.98 \times P^{0.19}$

Home-Based Social Recreation: $t = 2.18 \times P^{0.12}$

Home-Based Shopping: $t = 8.1$

Non-Home-Based: $t = 0.63 \times P^{0.20}$

In this analysis, we will use the formula of Home-Based Social Recreation to substitute HBO purpose. By using a population of 29,276 for the Fuquay-Varina planning area, we can estimate the average trip length for each purpose (Table E-3).

Model Comparison and Determination of Friction Factors

We discussed three different methods to estimate the average trip length above. Table E-3 summarizes the model comparisons.

Table E-3. Comparison of Average Trip Length Models

Model	Average Trip Length			
	HBW	HBO	NHB	IE/EI
NCHRP Report 365	12.2	9.7	9.7	N/A
Network Skims	8.46	7.44	6.94	9.23
Population Based	6.92	7.49	4.93	N/A

According to the population based model, the estimated HBW average trip length is less than HBO. The result conflicts with the fact that the HBW trip length should be greater than trip length of HBO and NHB purpose which have been verified by many household surveys. By comparing NCHRP Report 365 model with other two models, we find that it yields a greater average trip length, especially for HBW and HBO

trips. The maximum internal travel time is almost twenty minutes. Therefore, the average travel time from network skims seems more reasonable for a small urban area such as Fuquay-Varina especially if it is an “isolated” community. However, since Fuquay-Varina is a “fringe” city to Raleigh, the longer trip lengths might be selected for such a special case.

Using the average trip length from the network skims and the formula mentioned earlier, we can calculate friction factors for the Fuquay-Varina planning area (Table E-4).

Table E-4. Friction Factors by Purpose by Time

Time	HBW	HBO	NHB	IE/EI
1	8885	8742	8658	8973
2	7895	7643	7496	8052
3	7014	6682	6490	7225
4	6232	5841	5619	6483
5	5538	5107	4865	5818
6	4920	4464	4212	5220
7	4372	3903	3647	4684
8	3884	3412	3158	4203
9	3451	2983	2734	3772
10	3067	2608	2367	3384
11	2725	2280	2049	3037
12	2421	1993	1774	2725
13	2151	1742	1536	2445
14	1911	1523	1330	2194
15	1698	1332	1152	1969
16	1509	1164	997	1767
17	1341	1018	863	1585
18	1191	890	747	1423
19	1058	778	647	1276
20	940	680	560	1145

Application of Gravity Model

The trip distribution procedure is conducted by using a doubly constrained gravity model with friction factors listed in Table E-4. The resulting average trip length for each trip purpose is shown in Table E-5.

Table E-5. Resulting Average Trip Length

Trip Purpose	Average Trip Length
HBW	7.57
HBO	7.54
NHB	7.16
IE/EI	8.24

Recommendations and Findings for Trip Distribution Analysis

In Phase I, the mean travel time from network skims was verified to be an easy, robust approach to estimating initial friction factors for small communities with population between 5,000 and 10,000. The Fuquay-Varina case study shows that this approach still works for a medium city with a population

between 10,000 and 50,000. If the city is a fringe area city near a larger metropolitan area, then the NCHRP 365 approach appears reasonable.

Metropolitan Planning Organizations (Category D)

In this research, Metropolitan Planning Organization (MPO) (excluding regional areas) is defined as Category D which has population over 50,000. Jacksonville MPO in North Carolina is used as the case study for the study purpose. As mentioned in Appendix D, Kimley-Horn recently developed a travel demand model for the Jacksonville MPO. In this model, the friction factors for Jacksonville were entered into the TransCAD modeling process as a gamma function equation. Each trip purpose has a unique set of friction factors that were developed through an iterative process to replicate the average trip length and trip distribution profile of the travel survey data [3].

Although the gamma function does a very good job for trip distribution and is used by most metropolitan areas where travel survey data is generally available, it is still worthwhile testing the application of mean travel time from network skims in large cities, which has been validated to be a less data intensive, easy, and reliable approach to estimate average travel time for the previous small, medium and large communities (Categories A – C). Table E-6 compares the average travel times obtained from the Jacksonville household survey, the Kimley-Horn model, and the Jacksonville network skims. Since the Jacksonville household survey and the Kimley-Horn model used home-based school (HBS) and home-based other (HBO) separately, the HBO travel time in Table E-6 averages the values of these two trip purposes.

Table E-6. Comparison of Average Travel Time

Trip Purpose	Observed	Kimley-Horn Model		Skim Average Travel Time	
	Average Travel Time	Average Travel Time	Error %	Average Travel Time	Error %
HBW	12.34	13.06	5.83%	14.61	18.40%
HBO	11.01	11.25	2.18%	11.69	6.18%
NHB	8.73	9.38	7.45%	10.96	25.54%
IE Auto	15.70	16.24	3.44%	19.05	21.34%
IE Truck	16.81	17.74	5.53%	19.05	13.33%
CV Auto	N/A	9.9	N/A	N/A	N/A
CV Truck	N/A	9.89	N/A	N/A	N/A

According to Table E-6, it is clear that the gamma function (Kimley-Horn model) produces the better estimation of average travel time than that from the network skims. It is demonstrated again that the gamma function provides satisfactory trip distribution estimates since the resulting percentage errors are all within 10% according to the Jacksonville case. For the Jacksonville case, the average travel time resulting from the network skims are all overestimated by at least 10% except for the HBO trips.

For the Jacksonville case, a feedback loop between the trip distribution and trip assignment will be conducted to build an updated Production-Attraction table using the congested travel time for each iteration. This procedure will be discussed in detail in Appendix G.

Recommendations and Findings for Trip Distribution Analysis

For MPO areas where the population is more than 50,000, the gamma function provides better trip distribution results than the simplified method (e.g., mean travel time from network skims). Although the

network skims can be simply used for estimating average travel time with less data collection efforts, it seems to provide less satisfactory estimation results for larger cities.

References:

7. John R. Stone, Leta F. Huntsinger and Asad J. Khattak. *Guidelines for Developing Travel Demand Models: Small Communities*, NCDOT Report 2005-11, June 2006.
8. Williams A. Martin and Nancy A. McGuckin. *Travel Estimation Techniques for Urban Planning*, NCHRP Report 365, Transportation Research Board, 1998.
9. *Jacksonville Travel Demand Model*. Kemley-Horn and Associates, Inc., 2002.

APPENDIX F: MODE CHOICE

Introduction

In 1959 North Carolina enacted legislation that required all municipalities to have a major street plan to address future travel needs. In 2001, this law was amended to address the provision of a “transportation” system to address future travel demand from a multimodal perspective, not just a thoroughfare perspective. In doing so, the transportation planning process for small urban areas was expanded to include not only highway travel, but other modes of travel as well. Historically, travel analysis and transportation plans in North Carolina have focused on auto travel. As such, robust transit sketch planning analysis tools are not a part of the planning analysis toolbox used by North Carolina planners and engineers.

Geographic Information Systems (GIS) is useful for highlighting areas or corridors within a planning region where there are land use characteristics that are highly correlated to transit ridership. Multiple linear regression models can take this analysis a step further through the investigation of socioeconomic variables that are highly correlated with transit ridership. Other methods such as multinomial logit (MNL) and nested logit models estimate the probability of various modes through the use of utility equations that incorporate variables related to traveler decisions. Three of the methods are discussed below in order of increasing complexity and level of data required for application: GIS tools, regression analysis, and MNL.

Transit Forecasting Methodologies

GIS Screening Tool

GIS is a powerful analysis tool for evaluating and understanding geo-spatial data. In the Atlanta region GIS is used to identify zones with a high transit propensity, where propensity is a measure of the relative demand for transit [1]. Transit propensity is estimated in two different ways. The first, referred to as the threshold method, identifies zones that have developed a sufficient population and employment densities to support fixed route transit [1]. The methodology is derived from the Transit Cooperative Research Program (TCRP) report *Transit Capacity and Quality of Service Manual* (January 1999). This TCRP report provides guidelines and a systematic approach to measuring transit level of service from a passenger’s point of view. GIS is used to map household and employment densities that are considered to be transit supportive. Transit supportive densities are defined as high, medium, and low. Table F-1 shows the corresponding ranges of density for each category for both households and employment used in the Atlanta region.

Table F-1. Transit Supportive Densities from Atlanta Region

Density	Household Density (households/acre)	Employment Density (employees/acre)
Low	0 – 3	0 – 4
Medium	3 – 10	4 – 20
High	> 10	> 20

The second approach to measuring transit propensity, referred to as the statistical method, expands on the population density by considering race, gender, income, and auto ownership as a weighted index that identifies the transit propensity for each zone [1]. The factors and weights are based on TCRP Report 28: *Transit Markets of the Future: The Challenge for Change* [2], and TCRP Report 27: *Building Transit Ridership* [3].

TCRP Report 28 discusses the effect of current demographic, social, economic, land use, and transport policy trends on existing and future transit markets. It highlights the role of public transit in serving existing and potential markets. Census data are used to analyze home-to-work transit patterns. From this a transit use index is developed for various market niches, where an index greater than one reflected that the group was more likely than average to commute using transit (based on 1990 data.)

TCRP Report 27 delves into the issue of transit ridership and market share in an examination of various policies that might have some potential for increasing transit’s market share. 1990 census data is used to identify the overall transit market share. The results are similar to the markets identified in Report 28, with zero vehicle households representing 29 percent of the transit market share, minority households representing ten to seven percent, and females representing a two percent market share. Additionally, the findings summarized in TCRP Report 27 indicate that population density continues to be strongly related to transit market share.

For the development of a transit-screening tool for small urban areas in North Carolina, niche markets were selected to best reflect demographic characteristics for small urban areas in North Carolina. The selected markets and related indexes from TCRP Report 28 are shown in Table F-2.

Table F-2. Transit Niche Markets and Calculated Transit Index (TCRP Report 28)

Market	Transit Index
Women	1.18
Black (Grouped as Minority)	2.72
Hispanic (Grouped as Minority)	1.73
Asian (Grouped as Minority)	1.74
No car households	5.76
Age 65 – 69	1.10
Income < \$5k (Grouped as Low Income)	1.23
Income 5k – 10k (Grouped as Low Income)	1.24
Income 10k – 15k (Grouped as Low Income)	1.08
Income 15k – 20k (Grouped as Low Income)	1.04

To simplify data management and application, aggregate groups were created for minority populations and low-income households. Given the high correlation between population density and transit market share as documented in TCRP Report 27, this variable is also considered in the analysis, but not as a variable in the transit propensity index, only as a geographic overlay. GRTA identifies transit propensity as low for a household density ranges of 0 to 3, medium for a household density range of 3 to 10, and high for a household density range greater than 10.

The transit-screening tool uses a concept similar to the one applied by GRTA for the Atlanta region. To identify geographic regions that have a high propensity for transit use, based on the research of transit market niches as documented in *TCRP Report 28*, a transit propensity index is determined. The index is calculated by summing the weighted values of the density ratios for each of the niche markets. The weights were determined by using the proportional distribution, or combined average distribution, of the transit index from *TCRP Report 28*, as shown as Table F-3. The US Census reports the values for the market variables in total numbers of the observation for a given geographic unit, for example the total number of households with no vehicles or the total number of persons who are female. Rather than using the “count” value as the input into the transit propensity index, niche market variables were scaled using a measure of density where the unit of area is in acres. The resulting transit propensity index formulation is shown below.

$$\text{Transit Pr opennessIndex} = (10)W\text{Den} + (18)M\text{inDen} + (51)0V\text{eh} + (10)65\text{Den} + (11)Pv\text{Den}$$

Where:

WDen = number of women per acre;

MinDen = minority population per acre;

0Veh = zero vehicle households per acre;

65Den = number of persons 65 and older per acre;

PvDen = number of households with income below \$20k per acre.

Table F-3. Transit Niche Market Weights

Market Niche	Index*	Proportion relative to other indices	Assigned Weight
Women	1.18	0.10	10
Minority	2.06	0.18	18
0 Vehicle Households	5.76	0.51	51
Age 65 +	1.10	0.10	10
Low Income	1.15	0.11	11

* Obtained directly from *TCRP Report 28* for uncombined markets and averaged for combined markets

Regression Analysis

The relationship between various demographic characteristics and transit ridership has already been established in TCRP Report 27 and Report 28. Research conducted for the Tennessee Department of Transportation also identifies demographic factors that influence transit demand [4, 5]. Given the documentation of these relationships, it was hypothesized that a predictive regression equation could be developed and used to forecast transit ridership for small and medium sized communities. Two levels of data aggregation were investigated, route level analysis and zone level analysis.

This component of the research is based on the hypothesis that good regression equations can be developed using demographic relationships, it was hypothesized that a regression equation could be developed that would reasonably forecast potential transit ridership for a proposed route. To test this assumption ridership data was obtained for three transit systems in the Triangle region of North Carolina. Demographic data was also obtained from the 2000 census.

For the route level analysis a total of 33 routes were selected for analysis. The sample group reflects various routes in the Triangle region of North Carolina for which ridership data is available. The routes selected for analyses are shown in Table F-4. In addition to route ridership data, demographic data from the 2000 census is utilized. Each of the routes is buffered using both a quarter-mile and half-mile buffer. The underlying census data within each of these buffers is summarized and a unique record created for each route containing the data elements listed below:

- § AGE_65 – persons age 65+
- § DISABILITY – persons with disability
- § PV_5PLUS – low income households
- § NONWHITE – minority households
- § ZEROVEH – zero vehicle households
- § WORKERS
- § POPULATION
- § FEMALE
- § TOTHH – total households
- § HHDEN – households per acre
- § EMPDEN – workers per acre
- § 0VEHDEN – zero vehicle households per acre

- § DISDEN – household with disabled persons per acre
- § POV DEN – low income households per acre

Multiple linear regression models were used to evaluate various combinations of the variables.

For the zone level analysis, ridership data from an on-board transit survey for the Triangle region is utilized. The transit trip records were not available at the individual household level, only at the zone level. Demographic data from the 2000 census is attached to each zone with transit trips. A separate data file was created for trip production zones and trip attraction zones and these files are evaluated separately. Multiple linear regression models were used to evaluate various combinations of variables listed below:

- § HH DEN – households per acre
- § EMP DEN – workers per acre
- § 0VEH DEN – zero vehicle households per acre
- § DISDEN – household with disabled persons per acre
- § POV DEN – low income households per acre

Overall, the result of the regression analysis approach was unsatisfactory yielding very low r-squared values and goodness of fit. Person level analysis may prove to be more predictive, but limitations in the data set prevented an investigation at that level. Due to poor results, the regression analysis was not carried forward to the case study analysis.

Table F-4. Triangle Transit Routes Evaluated Using Regression

ID	Route Name	Co.	Line Nos. (TCAD)	Headway	Fare	Total
1	1-Capital/16-Oberlin	CAT	201/202	30	0.75	1179
2	2-Falls of Neuse/11-Avent Ferry	CAT	203/204	30	0.75	1541
3	2c-Falls/Neuse Connector	CAT	205/206	60	0.75	101
4	3-Glascock	CAT	207/208	20	0.75	387
5	4-Rex Hospital	CAT	209/210	20	0.75	1000
6	7-South Saunders	CAT	213/214	30	0.75	729
7	8-Northclift/18-Worthdale	CAT	217/218	30	0.75	777
8	8c-E Sawmill Connector	CAT	219/220	65	0.75	146
9	10-Longview/21-Caraleigh	CAT	221/222	30	0.75	741
10	11c-Buck Jones Connect	CAT	223/224	60	0.75	133
11	12-Method/19-Apollo Heights	CAT	225/226	35	0.75	878
12	15-Wake Medical	CAT	229/230	19	0.75	1532
13	22-State St	CAT	231/232	30	0.75	391
14	23c-E Millbrook Connect	CAT	233/234	30	0.75	173
15	1- Northgate/3-Village	DATA	401/402	30	0.75	2876
16	2-Angler/4-Durham Regional	DATA	403/404	30	0.75	2026
17	5- Fayetteville	DATA	405/406	30	0.75	1283
18	6-Duke University	DATA	407/408/ 409/410	60	0.75	944
19	7- Southpoint	DATA	411/412	30	0.75	1191
20	9-Dearborn/11-Hillsborough	DATA	415/416	30	0.75	2095
21	12-RTP	DATA	421/422	60	0.75	478
22	14-NCCU (circular)	DATA	425/426	15	0.75	1351
23	17-North Durham	DATA	427/428	60	0.75	280
24	A	CHT	301/302	25	0	1027
25	CM	CHT	305/306	40	0	772
26	D	CHT	309/310	20	0	1474

27	FCX	CHT	353/354	8	0	843
28	HU	CHT	355/356	10	0	1003
29	JFX	CHT	357/358	15	0	236
30	N/S	CHT	319/320	20	0	1753
31	RU	CHT	321/322	15	0	1703
32	T	CHT	325/326	35	0	848
33	V	CHT	329/330	30	0	567

Multinomial Logit Model

A common approach to forecasting transit ridership is with multinomial or nested logit models. The logit model incorporates the notion that a person presented with a choice makes that choice based on the option that has the greatest utility to him or her. In mode choice analysis the person making the choice represents a traveler and the choices available are the various modes available to the traveler. The most basic form of mode choice analysis is multinomial logit (MNL). The probability of choosing a given mode is represented by the equation shown below:

$$P_i = \frac{e^{U_i}}{\sum_{i=1}^m e^{U_i}}$$

The utility equation reflects the various service parameters such as travel time, walk time, fare, and number of transfers. The coefficients are estimated from observed travel data or borrowed from other regions.

$$U_i = (a_i \times IVTT) + (b_i \times WALKTIME) + (c_i \times FARE) + (d_i \times TRANSFERS)$$

It is accepted practice to borrow coefficients from reliable mode choice models rather than to estimate them from survey data if the sample size of transit users is very small. For a region that currently has no transit service the opportunity to collect observed transit ridership data in order to estimate coefficients does not even exist so coefficients must be borrowed. When selecting coefficients and bias constants, experience with mode choice models indicates that large differences between transit out-of-vehicle time and transit in-vehicle should be avoided. A typical ratio should be between 2.0 and 3.0. It is also accepted practice that the coefficient on in-vehicle travel time should be between -0.02 and -0.03. High bias constants should also be avoided as they tend to over predict the mode split computation, rather than having the results based on alternative specific characteristics. The *TMIP Manual on Model Validation and Reasonableness Checking* [6] provides a table with coefficient values used for various cities. Additionally, the mode choice coefficients used in the Triangle Regional Model have undergone FTA review and therefore provide a good resource for selecting coefficient and bias constant ranges.

In previous modeling packages the development and analysis of a transit route system required a high level of user knowledge. Within the TransCAD [7] modeling package, the coding of a transit route system has been streamlined through the use of GIS and a graphical user interface. A simple MNL can also be specified and applied fairly easily with a graphical user interface. This process becomes more streamlined through the development and adoption of coding standards for the route system, path building variables, and MNL specification. Given the more predictive nature of this approach and the relative ease of use a MNL application is the recommended approach for small MPOs desiring to conduct a robust analysis of transit alternatives. Transit route system coding standards and MNL specification and application standards are discussed and recommended here.

The transit route system requires only that the user specify the route system and stops using standard

TransCAD coding tools and route system variables for headway and fare. A basic MNL can be estimated solely on the differences between in-vehicle travel time between auto and bus. However, to better reflect path differences between auto and bus, the transit skim variables should include walk access time, walk egress time, number of transfers, and fare in addition to in-vehicle time. The dialog box for performing transit skims includes various default values. For a simple MNL these default values can be accepted. The application of the MNL requires the specification of a MNL model table. This table is a TransCAD BIN file that is simple to construct using the TransCAD graphical interface. The basic structure and recommended attributes of the table are shown in Table F-5.

For small MPOs the recommended alternatives are simply auto and bus. The model alternative is specified to allow the user to input different values for the mode service parameters or for a mode specific bias constant. The recommended bias constant is for the bus alternative and the value is -4.00. The user must specify the file name and location for each of the service parameters for each zone interchange. The auto travel time is stored in the highway skim matrix and the bus travel time, total walk time for bus, total fare for bus, and the total number of transfers is stored in the transit skim matrix.

Table F-5. Basic Structure of TransCAD MNL Model Table

Alternative	Constant	IVT	Walk Time	Fare	Transfers
Auto		Auto TT			
Bus	D_ASC	Bus TT	Access + Egress Time	Transit Fare	# of Transfers
Model	-4.00	-0.023	-0.054	-0.004	-0.12

Once this table has been created the aggregate MNL application within TransCAD can be performed. The application of the aggregate MNL will result in a matrix with zone to zone probabilities by mode and a matrix with zone to zone utilities by mode. If an OD trip table is specified, the application will also output a matrix with zone to zone trips by mode. The transit trip table can then be assigned to the transit network to yield forecast transit trips for the individual routes. As such the routes can be evaluated against one another to determine the route or routes with the highest potential ridership.

CASE STUDY

The study area for testing the two recommended approaches is Cary, NC, within the Triangle Region of North Carolina. This case study was selected because the data required for the analysis was relatively easy to obtain from the existing database for the Triangle Regional model and the 2000 census. The Town of Cary is located in the western portion of Wake County. For the purposes of this case study it was extracted from the regional model and treated as a small MPO. The main reason for selecting the Town of Cary above all of the other municipalities within Wake County is that Cary has recently launched a new transit service. The analysis process can be compared to the new transit routes selected by the Town of Cary as a point of comparison.

Data

Table F-6 shows the data set for the GIS Transit Screening approach. Table F-7 shows the data required for the MNL application. Both tables indicate the source of the data.

Table F-6. Data for GIS Transit Screening

Data Element	Source
Population	US Census Data
Households	
Women	
Minority Population*	
Low Income (income less than \$20k)	
Zero vehicle households	
Population age 65 plus	
Geographic coverage file	Census or model geography
Acres	Geographic coverage file
Household Density	Calculated as data element per acre
Women Density	
Minority Density	
Low Income Density	
Zero vehicle Density	
Age 65 plus Density	

* Group created by identifying all non-white population categories from US Census

Table F-7. Data for MNL Application

Data Element	Source
Bus in-vehicle travel time	Transit skims
Auto in-vehicle travel time	Highway skims
Total walk time (access time + egress time)	Transit skims
Fare	Transit skims
Number of transfers	Transit skims
Table of coefficients	Borrowed from research

GIS Screening Tool

This appendix will now discuss the approach for using GIS screening to identify traffic analysis zones with a propensity for transit ridership. This first step of this process is to obtain the necessary data elements from the census. All niche market variables listed are either available from the STF3 files or from the CTPP data files. This data can be downloaded from the census website or extracted from the TransCAD census data CD. The preferred method is to use the TransCAD data CD because the data is readily available in a geographic file format for either census blocks, block groups, tracts, or traffic analysis zones. The recommended coverage area is traffic analysis zones. Several new data fields must be added to the geographic file attribute table. The required fields are shown in Table F-8. As discussed previously, the transit propensity index requires the calculation of density values based on acres. The default area unit for TransCAD is square miles. The data field for acres should be filled with the value of the geographic area in acres. The density data fields are filled by calculating the density ratio as “niche market variable/acre.” Fill the transit index field by calculating the transit propensity index using the formula specified previously. An example view of the data table is shown in Table F-8.

Table F-8. Data Fields and Example Data Values for GIS Screening Tool

TAZ	Acres	WDen	MinDen	0Veh	65Den	PvDen	HHDen	TrnIndex
33	496.26	0.08	0.00	0.00	0.01	0.00	0.04	1.00
34	542.08	0.91	0.34	0.06	0.13	0.03	0.77	20.18
35	246.21	2.34	0.84	0.12	0.13	0.89	2.80	55.98

Once the transit propensity index has been calculated, thematic maps of the index can be created using various categories for stratification. The highest index values reflect zones with the greatest potential for transit ridership relative to other areas within the region. Several stratifications were tested and applied to the Greater Triangle region to compare how well the application of the index and various stratifications correspond to existing transit routes in Raleigh, Durham, and Chapel Hill. This comparison was favorable, supporting this technique as a screening tool for identifying geographic areas best served by transit based on transit use propensity. The stratification technique recommended for application is nested averages. In addition to creating a thematic map of transit propensity index using nested averages, a scaled-symbol theme was also used to overlay the ratio of households per acre for high, medium, and low transit propensity.

An example of the transit propensity screening application comparison for existing Triangle routes is shown for Chapel Hill, Durham, and Raleigh in Figures F-1 through F-3 below. From these figures the correlation between the existing transit routes and the areas with high transit propensity is apparent.

The result of the transit propensity screening tool applied to the Town of Cary is shown in Figure F-4. Again, this figure demonstrates a favorable comparison between transit propensity as calculated by the index and the areas served by Cary's route system.



Figure F-1. Transit Propensity Map for Chapel Hill

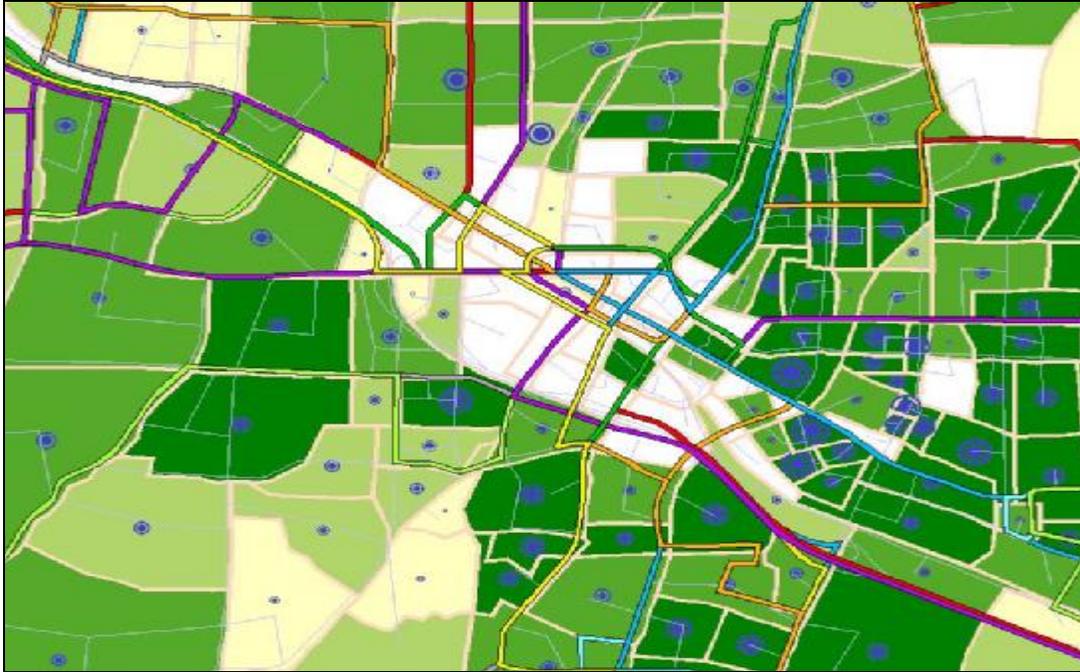


Figure F-2. Transit Propensity Map for Durham

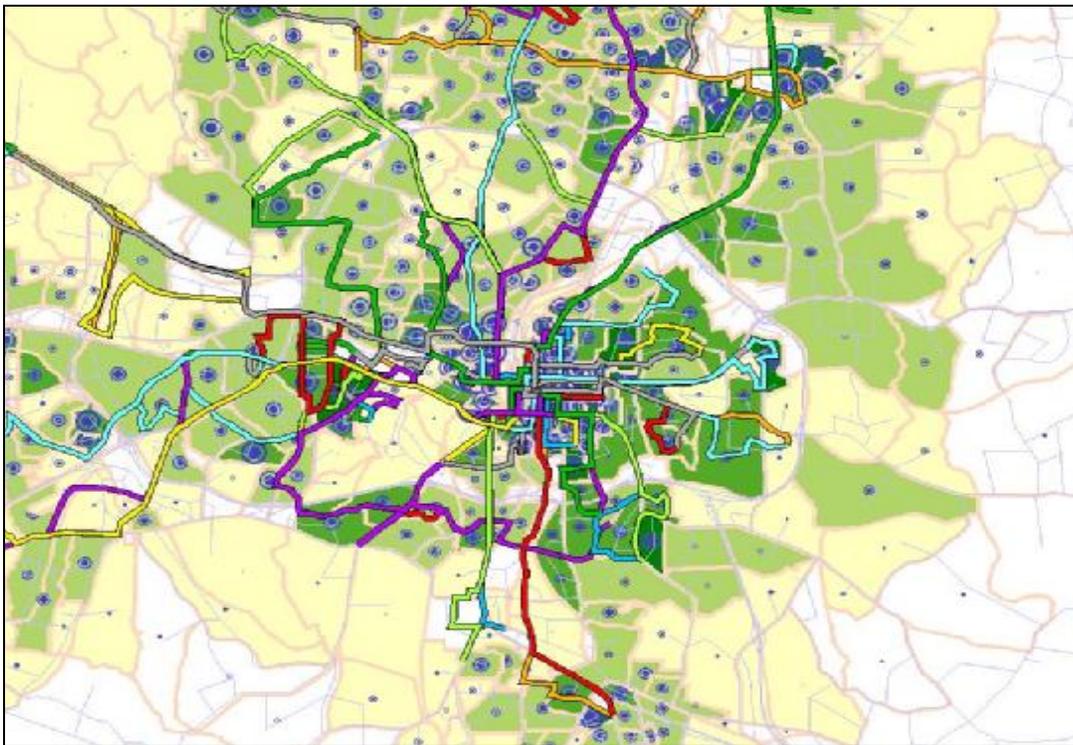


Figure F-3. Transit Propensity Map for Raleigh



Figure F-4. Transit Propensity Map for Cary

Multinomial Logit Model

For the Town of Cary test case the highway geographic layer and zonal trip table were extracted from the Triangle Regional Model. First, create a travel time matrix for all zonal interchanges using the highway travel time field. Add fields to the geographic line layer for bus travel time [AB/BA_BUSTIME] and walk time [AB/BA_WALKTIME]. The bus travel time is slower than the auto travel time and can be calculated with the following formula:

$$Y = a + bX$$

Where:

- Y = bus speed;
- X = highway speed;
- a = 2;
- b = coefficient ranging between 0.7 and 0.9.

The walk speed is calculated as:

$$Length / 3 * 60$$

The next step is to code the routes you wish to evaluate using the TransCAD standard transit coding toolbox. (One option for consideration here it to first utilize the transit screening tool recommended for non-MPO areas to first identify areas with the highest transit propensity index. The analyst can then focus on coding transit routes that serve these areas.) Transit routes must be coded with estimated values of fare and headway. Transit stops must be coded with a field for NODE_ID, this field is filled with the highway

node ID corresponding to the transit stop using a standard TransCAD function. Five routes were coded for the Town of Cary as shown in Figure F-5 and described in Table F-9.

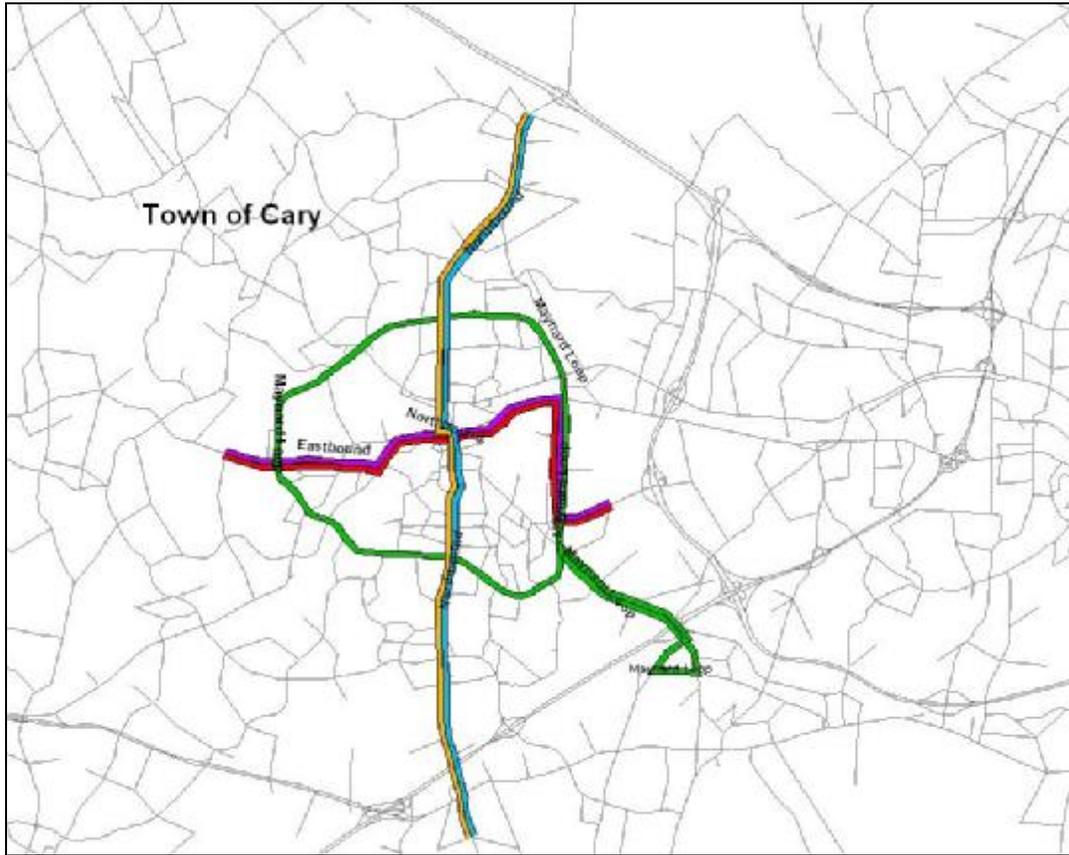


Figure F-5. Map of Transit Route System for Cary

Table F-9. Transit Routes in Town of Cary

Route ID	Route Name	Headway	Fare
1	Eastbound	30	1.00
2	Westbound	30	1.00
3	Maynard Loop	30	1.00
4	Southbound	30	1.00
5	Northbound	30	1.00

All links in the highway layer can be used as walk links unless there are facilities, such as freeways or interstates, where walking is not allowed. Create a selection set of all walk links. Create transit skims accepting the TransCAD default parameters. The skim variables must include in-vehicle travel time, access time, egress time, transfers, and fare. Open the resulting transit skim matrix, add a new matrix and name it “Total Walk Time.” Fill the new matrix with the sum of the access walk time and the egress walk time. Next, create a DBF file with one record for each zone and two fields, one for the TAZ number and the other for the alternative specific bias constant scaling parameter of one. Create the MNL table using default service parameters and coefficients recommended previously and apply the MNL model.

The resulting output is a utility matrix, a probability matrix, and a trip matrix. The range of utility calculated for the transit mode is -5.92 to -4.17 and for auto is -0.46 to -0.03. The range of probability calculated for the transit mode is zero to 0.02 and for auto is 0.98 to 1.00. The maximum zonal interchange for transit is 3.44 trips and for auto 340.18 trips.

The transit trip table was assigned to the five routes and the resulting assignment is shown in Figure F-6 and Table F-10 below.

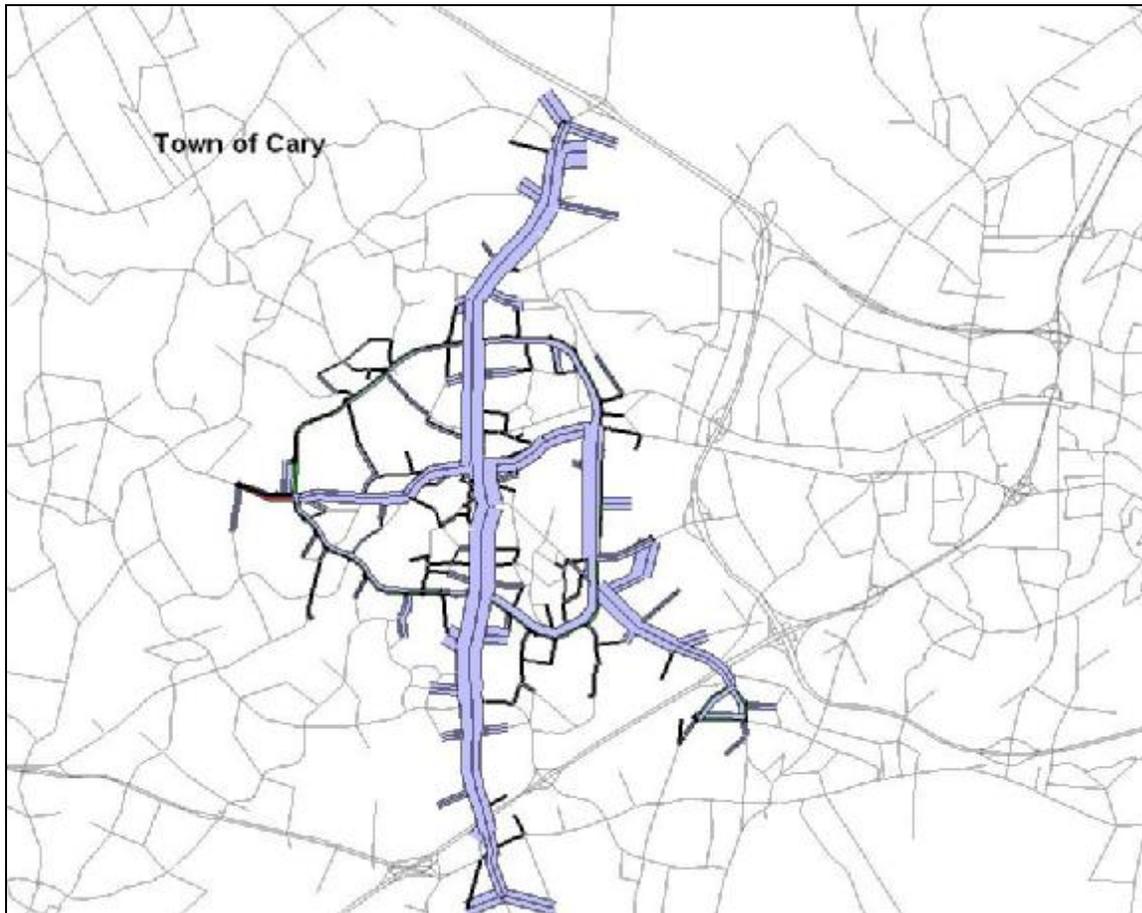


Figure F-6. Transit Assignment for the Cary Route System

Table F-10. Transit Assignment Results for Town of Cary

Route ID	Route Name	Total Boarding
1	Eastbound	71
2	Westbound	54
3	Maynard Loop	118
4	Southbound	150
5	Northbound	160

Findings and Conclusions

The outcome of this analysis supports the assertion that relatively simple analysis tools can be employed as a means to evaluate transit options for small non-MPO and small MPO areas. One advantage to the methodologies discussed in this paper is that they do not require the collection of specialized behavior data but can be applied using existing data sets. Both methodologies provide the analyst with useful output for evaluating transit planning options. The GIS screening tool can be used by small urban areas to identify areas within their community that have a high propensity for transit ridership. This information can inform the development of the transportation plan for that community. The MNL model, perhaps in combination with the GIS screening tool, can be used by small MPO areas to evaluate various transit

routes and forecasted ridership. This tool can be used by the transportation analyst in the development of a multimodal transportation plan.

References:

1. *Regional Transit Action Plan*, Georgia Regional Transportation Authority, June 30, 2003.
2. Rosenbloom, S. *TCRP Report 28 – Transit Markets of the Future: The Challenge of Change*, sponsored by The Federal Transit Administration, 1998.
3. Charles River Associates Incorporated. *TCRP Report 27 – Building Transit Ridership: An Exploration of Transit’s Market Share and the Public Policies That Influence It*, sponsored by The Federal Transit Administration, 1997.
4. Taylor, B. and D. Miller. *Analyzing the Determinants of Transit Ridership Using a Two-Stage Least Squares Regression on a National Sample of Urbanized Areas*, presented at Transportation Research Board, 83rd annual meeting, January 2004, Washington, D.C.
5. *Tennessee Department of Transportation Twenty Five Year Transit Plan, Task 6 Factors Influencing Transit Demand in 2025*, Parsons Brinckerhoff, July 2003.
6. *Model Validation and Reasonableness Checking Manual*, Barton-Aschman Associates, Inc. and Cambridge Systematics, Inc., prepared for Travel Model Improvement Program, Federal Highway Administration, June 2001.
7. *Travel Demand Modeling with TransCAD 4.5*, Caliper Corporation, 2002.

APPENDIX G: TRIP ASSIGNMENT

Introduction

Trip assignment is the fourth and last major step of the traditional four-step travel demand forecasting process. It estimates traffic volumes on each individual link of the highway network. As the Phase I Report [1] addresses, the trip assignment step gives the data needed to:

- § Test alternative transportation plans;
- § Establish priorities between different transportation investment strategies;
- § Analyze alternative locations for roadway improvements; and
- § Forecast volumes and levels of service needed to adequately design and construct new roadway facilities.

In order to replicate the process of identifying the best path between a given origin and a given destination, different algorithms can be used for trip assignment depending on planning needs, path variables of the highway system and characteristics of the system users. For example, either travel time or travel distance may be used as path variables to simulate impedance. In generally, the most common algorithms used in highway traffic assignment for travel demand models are [1]:

- § The all-or-nothing (AON) algorithm assigns all trips between an O-D pair to the minimum network path. This algorithm does not account for congestion or drivers' differing perceptions of travel time.
- § Capacity restraint is basically an AON algorithm where all trips between an O-D are assigned to the minimum path. The difference between this approach and a pure AON approach is that it is an iterative process where the link travel times are adjusted to account for link flows compared to link capacities. As traffic is assigned, new travel times are calculated, and new minimum paths are calculated. This assignment technique is most affective using hourly capacities. There are two basic types of capacity restraint, equilibrium and iterative.
- § Equilibrium assignment assigns the full trip table for each iteration. Link travel time is recalculated with each iteration using the total link demand. The number of iterations is determined by a user defined closure parameter (0.0001 recommended) or until the system reaches equilibrium which is defined by the condition where no individual traveler can improve his/her travel time by selecting an alternative path. The final assignment is an average of the iteration (*i*) assignment and the previous iteration (*i-1*).
- § Stochastic assignment permits alternative near-minimum paths to be used. This is also referred to as equally likely paths. The proportion of trips allocated to equally likely paths is controlled by *theta* (Θ) where a high value of *theta* produces a heavy bias towards the shortest path and a value of 0 produces an equal share between all equally likely paths.

Medium and Large Communities (Category C)

For urban Category C defined as the medium and large communities with population between 10,000 and 50,000, the four assignment algorithms mentioned above are tested by a medium case city, Fuquay-Varina, North Carolina. The estimated link flows were compared with observed ADT. An overall Test Statistic was also calculated for link flows estimated by each assignment method by using the formula below:

$$Test\ Statistic = 1 - \frac{\sum_i (y_i - \hat{y}_i)^2}{\sum_i (y_i - \bar{y}_i)^2}$$

Where:

y_i = observed value;

\hat{y}_i = estimated value;

\bar{y}_i = mean observed value.

Table G-1 lists the assignment results by different route classifications.

Table G-1. Trip Assignment Results

Method	Flow/ADT Ratio				Overall Test Statistic
	Major Arterial	Minor Arterial	Collector	Local	
AON	0.85	0.78	1.74	1.42	0.61
Capacity Constraint	0.79	0.74	1.18	1.00	0.55
User Equilibrium	0.66	0.72	1.14	1.44	0.48
Stochastic	0.96	0.84	1.52	1.35	0.80

The comparison clearly shows that the stochastic assignment best “replicates” the real traffic flows on the highway network in Fuquay-Varina planning area, especially for roads with higher functional classes. Figure G-1 illustrates the stochastic assignment result from a system-wide point of view.

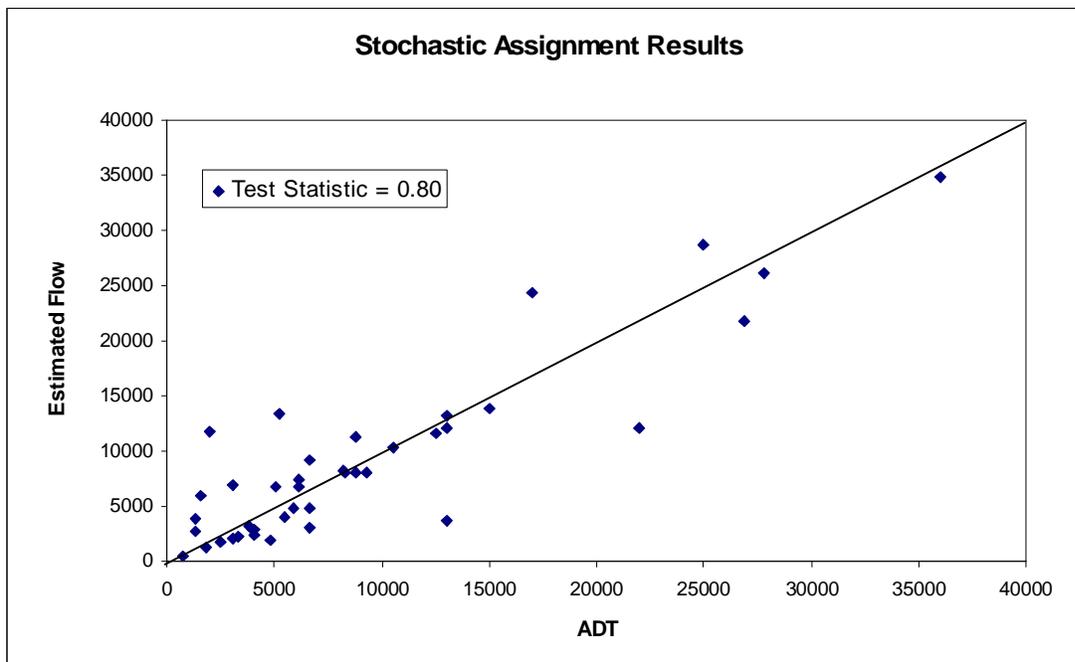


Figure G-1. Stochastic Assignment Results

As addressed in the Phase I Report [1], the primary approach to validate highway assignment is conducted by comparing traffic counts with estimated traffic volumes on the highway network. The candidate validation measurements are repeated here [2]:

- § Compare observed versus estimated volumes on screenlines and cutlines;
- § Compare observed versus estimated volumes for all links with counts;
- § Calculate R^2 (Coefficient of Determination) and compare region-wide observed traffic counts versus estimated volumes. R^2 region-wide should be greater than 0.88;
- § Plot a scatter plot of the counts versus the assigned volumes. Review any data points (links) that lie outside of a reasonable boundary of the 45-degree line; and
- § Compare the deviation of link volume with FHWA validation targets by facility type and volume group.

In addition, Table G-2 and Table G-3 provide the validation guidelines for link assignments.

Table G-2. Percent Difference Targets for Daily Traffic Volumes by Facility Type

Facility Type	FHWA Targets (+/-)
Freeway	7%
Major Arterial	10%
Minor Arterial	15%
Collector	25%

Source: FHWA, *Calibration and Adjustment of System Planning Models*, 1990

Table G-3. Percent Difference Targets for Daily Volumes for Individual Links

Average Annual Daily Traffic	FHWA Desirable Percent Deviation
< 1,000	60
1,000 - 2,500	47
2,500 - 5,000	36
5,000 - 10,000	29
10,000 - 25,000	25
25,000 - 50,000	22
> 50,000	21

The all-or-nothing assignment algorithm is not a good method for a medium city because it does not consider the congestion conditions which usually happen on highway networks in larger cities, especially on major routes or roads in CBD areas. In addition, the all-or-nothing assignment algorithm does not allow the user to adjust assignment parameters to achieve assignment results that better reflect traffic count measurements, assuming that parameters for all previous submodels have been adjusted.

The capacity constraint and equilibrium daily assignments do not work well for a medium city like Fuquay-Varina because a daily capacity is not a true measure of capacity. A better approach may be to use hourly trip tables or peak period trip tables with an hourly capacity. However, the use of an hourly trip table may increase the cycle of the planning process for a medium city with population under 50,000.

The stochastic assignment algorithm is verified to be a robust approach for trip assignment for a medium city with population between 10,000 and 50,000, such as Fuquay-Varina. The daily traffic assignment yields acceptable results, and it is easy to apply. Furthermore, the analyst is able to flexibly simulate the “real world path” by adjusting the value of θ if needed.

Metropolitan Planning Organizations (Category D)

According to a recent TRB assessment of the state-of-the-practice in metropolitan area travel forecasting almost all MPOs use an equilibrium method for traffic assignment [3]. Figure G-2 clearly shows the utilization of different trip assignment methods by MPOs throughout the country. The current travel

demand forecasting practice indicates that equilibrium assignment is the recommended procedure [4] in MPO regions. One of the primary advantages of equilibrium assignment is that it looks a several equally good paths through the network when assigning trips so as to buffer sensitivities by allowing the assignment to run through several iterations, thereby allowing a small change in speed to equal a small change in volume [5].

For large urban areas like MPO regions, more advanced or detailed techniques may be helpful to estimate complex traffic assignment in accuracy, such as a feedback loop between trip distribution and trip assignment as well as time-of-day (TOD) assignment. In this appendix, Jacksonville MPO in North Carolina is analyzed as a case study to evaluate the performance of various assignment algorithms combined with the feedback loop approach and TOD analysis.

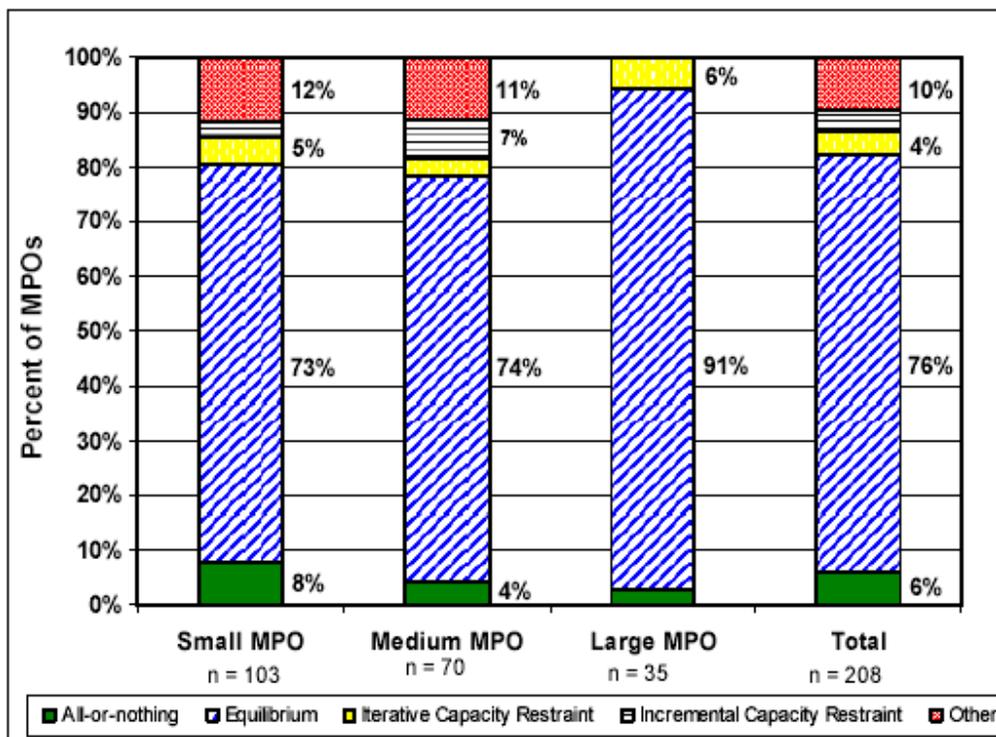


Figure G-2. Highway Traffic Assignment Method

Feedback Loop

As environmental issues (especially vehicle emissions) increasingly become a critical modeling, more attention has been paid to accurately estimate vehicle speeds which significantly affect emissions in many areas, especially non-attainment regions. It is obvious that transportation projects can also definitely benefit from travel demand forecasts with realistic congested travel speed and travel time. To satisfy the multiple planning purposes, a feedback loop methodology (an effective iterative process to calculate congested travel time between trip distribution and assignment) has been introduced to the traditional travel demand forecasting procedure in recent years. The TRB survey of the state-of-the-practice in travel demand forecasting indicates that over 80% of large MPOs and about 40% of mid-size MPOs feed back loaded travel times to the distribution and mode choice steps in order to improve the first iteration that used free flow travel times and minimum paths [3]. This appendix will study the feedback loop methodology by using Jacksonville MPO as a case study on a daily assignment basis.

The purpose of the application of a feedback loop in travel demand model is to produce more realistic congested travel times so that the gravity model allocates trips to zones with more accuracy than by using free-flow travel times. The feedback loop step uses the assignment model to calculate updated congested travel times. These congested travel times are then “fed back” into the network and the highway skim travel time matrix is re-calculated. Since this changes the results of the gravity model, the resulting PA matrix, and any subsequent models, the study area model should be re-run with updated travel times and related information. The feedback loop is repeated several times until either the output flow volumes between successive loop iterations are within a convergence criterion or the number of iterations is reached. Figure G-3 illustrates the feedback loop process used for the Jacksonville case.

It is noted that a factoring process, rather than a standard multinomial logit (MNL) model, is used for the mode choice step in the Jacksonville case due to the high level of investment required to create a sound mode split model and the relatively low number of non-auto users of the highway network [6]. Since the mode split factors are developed based on trip purpose and travel distance [6], the estimated mode shares of auto and non-auto trips actually stay constant during the feedback loop process in the Jacksonville case. After trips are assigned to the highway network for the iterations, the congested travel time is calculated based on a volume-delay function using the coefficients presented in NCHRP Report 365 [4].

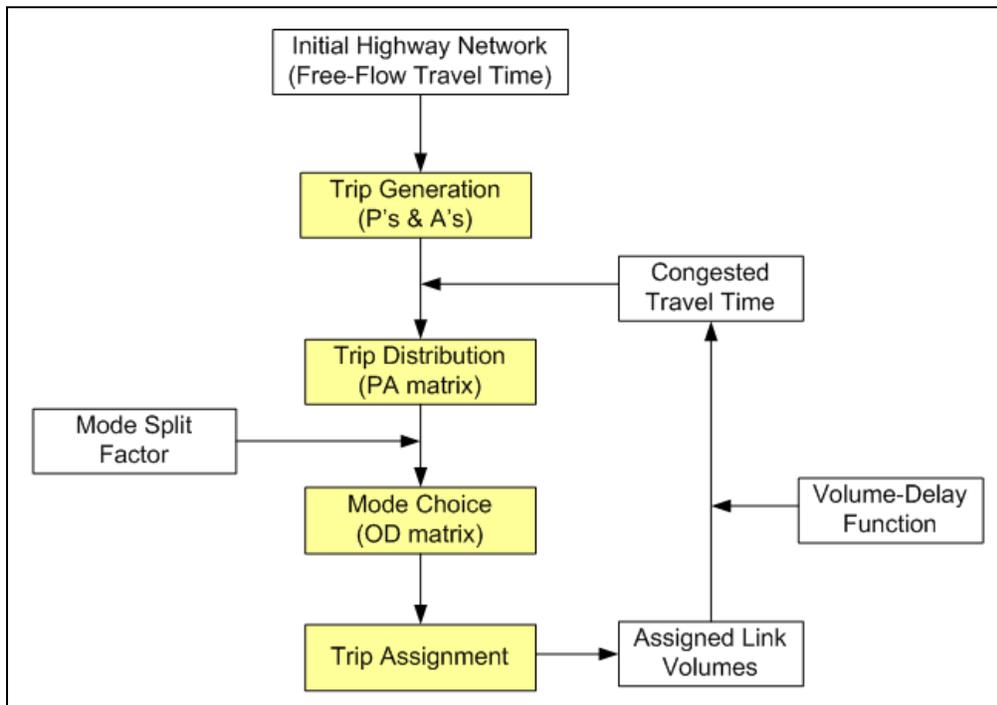


Figure G-3. Feedback Loop Process for Jacksonville Case

For comparison, capacity restraint and stochastic ($\Theta = 5, 2, 0.1$) algorithms are also applied to the Jacksonville case in addition to user equilibrium assignment. Four iterations are conducted for the feedback loop process. The percent root-mean-square-error (RMSE) is used to evaluate the performance of the feedback loops by different assignment methods. The RMSE % is calculated as:

$$RMSE\% = \frac{\sqrt{\sum_i (\hat{x}_i - x_i)^2 / n}}{\sum_i x_i / n}$$

where,

- \hat{x}_i = estimated value for observation i ;
- x_i = observed value for observation i ;
- n = the number of observations.

Table G-4 and Figure G-4 show the resulting RMSE% by different assignment algorithms for the iterations.

Table G-4. Feedback Loop RMSE%

Assignment Algorithm		RMSE%				
		Iteration 0	Iteration 1	Iteration 2	Iteration 3	Iteration 4
Stochastic	$\theta = 5$	28%	63%	32%	59%	36%
	$\theta = 2$	28%	63%	32%	58%	36%
	$\theta = 0.1$	34%	74%	39%	79%	48%
Capacity Restraint		25%	23%	20%	45%	23%
User Equilibrium		25%	25%	20%	23%	19%

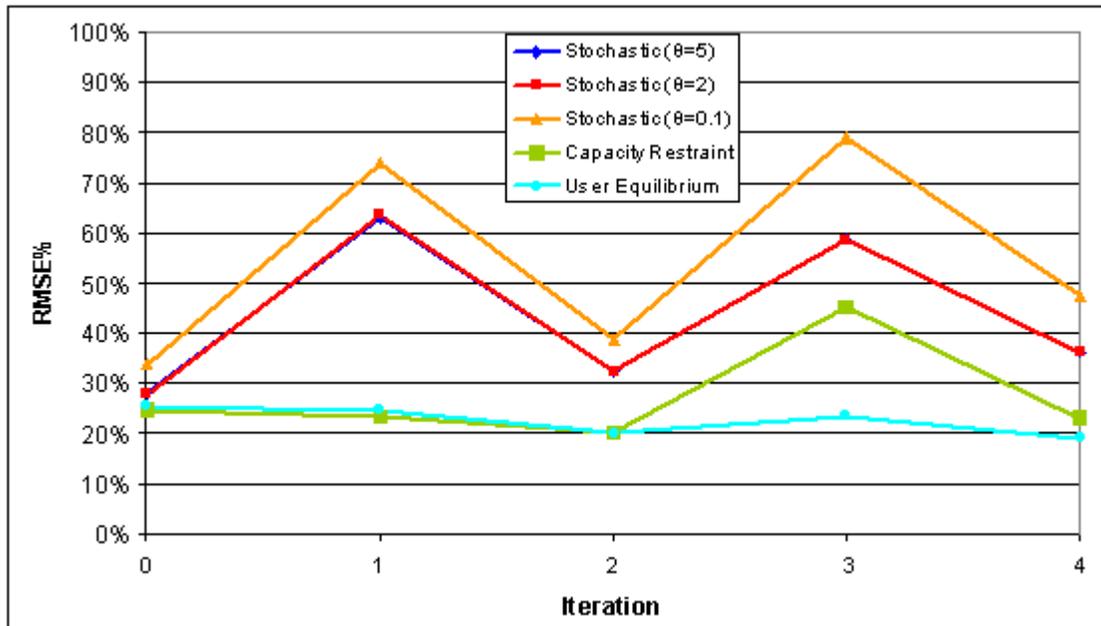


Figure G-4. Feedback Loop RMSE%

The comparison of feedback loop processes with different assignment algorithms shows that only the user equilibrium method results in convergent, stable estimates of assigned link traffic volumes. According to the Table G-4 and Figure G-4, the capacity restraint and stochastic algorithms produce fluctuating RMSE%, peaking at iteration #1 and #3. By examining the link volumes produced by capacity restraint and stochastic methods, a few links (some of which are major routes) have no assigned traffic volumes in iteration #1 and #3, even though they are loaded with large volumes in previous iterations. It is reasonable to believe these unrealistic assignment results are caused by the inappropriate applications of

capacity restraint and stochastic in MPO areas such as Jacksonville case since they can not simulate the path variables of highway system and users' true opinions to select the "best" paths in medium and larger metropolitan regions.

According to iteration #0 through iteration #4, the user equilibrium method produces the smaller RMSE% compared with other algorithms. This indicates that user equilibrium is a preferred assignment algorithm based on the selected measures (see the Guidelines Matrix and Decision Tree). In addition, the feedback loop seems to help improve user equilibrium assignment results because the resulting RMSE% of user equilibrium decreases from 25% to 19% and tends to converge. However, it is noted that the direct application of a feedback loop procedure results in a very low converge speed of modeling results which even has a rebound of RMSE% in the third iteration. These findings indicate that a direct feedback loop may have potential function to improve model accuracy, but it is not efficient enough until other reasonable modeling techniques are integrated, such as the method of successive averaging (MSA) [7, 8, 9] or method of successive weighted averaging (MSWA) [10].

For user equilibrium assignment with a feedback loop process, the resulting system-wide VMT (vehicle miles traveled) shows a decreasing trend and is lower than values produced by other assignment algorithms (Table G-5), which implies decreasing highway traffic congestions. This findings is reasonable because all vehicles try to find shortest trip paths according to dynamic traffic conditions (which are updated by feedback loop iterations) and actually tend to achieve a least traffic VMT (traffic congestion) from a system-wide point of view.

Table G-5. VMT by Feedback Loop Process

Assignment Algorithm		VMT				
		Iteration 0	Iteration 1	Iteration 2	Iteration 3	Iteration 4
Stochastic	$\theta = 5$	2,284,534	2,184,967	2,231,034	2,212,859	2,241,610
	$\theta = 2$	2,276,260	2,173,288	2,221,440	2,196,941	2,231,980
	$\theta = 0.1$	2,252,543	2,114,142	2,201,746	2,134,968	2,235,811
Capacity Restraint		2,226,484	2,108,081	2,130,788	2,328,098	2,172,947
User Equilibrium		2,230,426	2,099,446	2,088,114	2,131,452	2,080,212

The validation guidelines of trip assignment have been discussed in Phase I of this research project and repeated in the previous section of this appendix. These guidelines are still suitable for MPO areas. For the purpose of trip assignment validation in the Jacksonville MPO case study, the link volumes resulting from the user equilibrium feedback loop (iteration #4) are used and checked against FHWA desirable percent deviation by daily traffic (ADT) groups. This validation shows that all grouped links are assigned traffic volumes with satisfactory accuracy which are within FHWA validation targets (Table G-6).

Table G-6. Assignment Validation with FHWA Targets

ADT	Percent Deviation (%)	FHWA Desirable Percent Deviation (%)
< 1,000	22	60
1,000 - 2,500	47	47
2,500 - 5,000	20	36
5,000 - 10,000	28	29
10,000 - 25,000	19	25
25,000 - 50,000	10	22
> 50,000	2	21

The feedback loop process with user equilibrium assignment is then validated by using a system-wide measurement. A scatter plot of the traffic counts versus the assigned volumes is developed to evaluate the assignment results (see Figure G-5). A 1:1 line assists in understanding the relationship between the two groups of estimated and actual volumes. Since the distribution of observations seems to replicate the 1:1 line and results in a R^2 with high value of 0.95 assignment results are acceptable from a system-wide point of view.

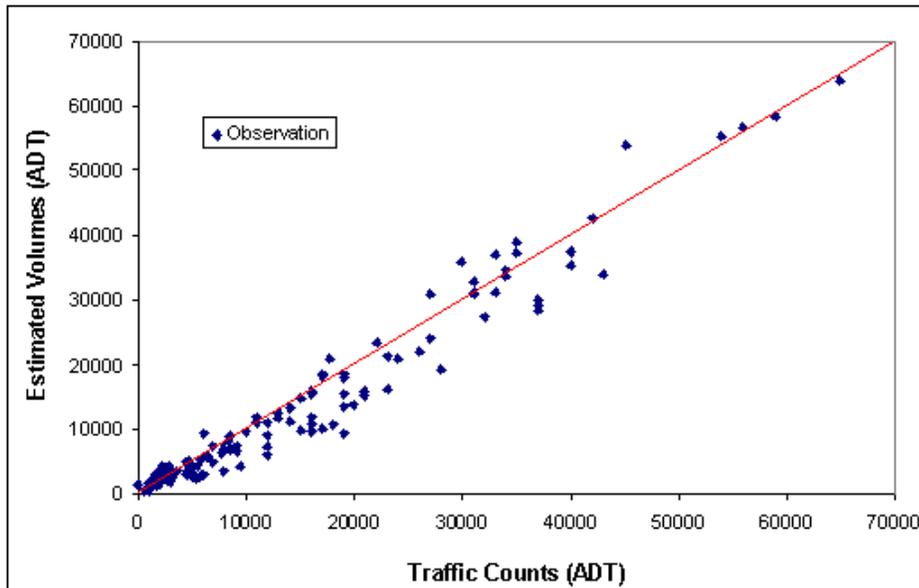


Figure G-5. User Equilibrium Assignment with Feedback Loop

Time-of-Day (TOD) Assignment

For many applications, travel must be estimated for specific periods or hours of the day. During limited periods during the day – the peak time period – the transportation system is loaded, and sometimes overloaded, with travelers. Peak-period speeds and volumes are critical for assessing the level of service provided by the transportation system, the competitiveness of transit with autos on the highway network, and the size of the transit fleet [4]. Such analysis is referred to as a time-of-day (TOD) analysis. Standard procedures include assignment by time of day. The more current and accepted procedure for obtaining daily highway volumes is to sum the results of three separate assignments: AM peak period, PM peak period, and off-peak [4]. Compared to a daily assignment, a TOD assignment generally assigns peak-period trips to a highway network based on corresponding peak-period highway capacity.

In Jacksonville MPO case study, TOD assignment is conducted for the morning peak (7:00 – 9:00am), evening peak (4:00 – 6:00 pm), and off-peak (the rest of the day). For simplification purpose, the percents of HBW, HBO and NHB trips made in each time period are derived from the HOURLY.dbf table (Table G-7) in TransCAD, which is used as defaults when site-specific data is not available.

Table G-7. Default Percent of Vehicle Trips by Hour by Trip Purpose

Hour Period	HBW		HBO		NHB	
	Departure (%)	Return (%)	Departure (%)	Return (%)	Departure (%)	Return (%)
0:00 - 1:00	0.40	0.00	0.35	0.35	0.30	0.30
1:00 - 2:00	0.20	0.00	0.15	0.15	0.10	0.10
2:00 - 3:00	0.00	0.00	0.00	0.00	0.00	0.00
3:00 - 4:00	0.20	0.00	0.05	0.05	0.00	0.00
4:00 - 5:00	0.40	0.00	0.00	0.00	0.05	0.05
5:00 - 6:00	2.70	0.00	0.25	0.25	0.20	0.20
6:00 - 7:00	7.90	0.00	1.00	1.00	0.75	0.75
7:00 - 8:00	19.20	0.00	2.90	2.90	3.30	3.30
8:00 - 9:00	9.20	0.00	1.70	1.70	2.00	2.00
9:00 - 10:00	3.00	0.00	1.50	1.50	1.80	1.80
10:00 - 11:00	0.70	0.00	2.20	2.20	2.80	2.80
11:00 - 12:00	0.60	0.00	2.20	2.20	3.15	3.15
12:00 - 13:00	0.70	1.40	2.00	2.00	5.10	5.10
13:00 - 14:00	0.60	1.40	2.40	2.40	3.60	3.60
14:00 - 15:00	0.60	3.20	2.10	2.10	3.45	3.45
15:00 - 16:00	0.60	5.70	3.10	3.10	4.00	4.00
16:00 - 17:00	0.60	13.10	4.05	4.05	4.00	4.00
17:00 - 18:00	0.60	11.80	4.00	4.00	3.10	3.10
18:00 - 19:00	0.60	3.10	4.25	4.25	2.35	2.35
19:00 - 20:00	0.60	1.70	5.60	5.60	3.15	3.15
20:00 - 21:00	0.60	1.00	3.95	3.95	2.90	2.90
21:00 - 22:00	0.00	2.90	3.00	3.00	1.95	1.95
22:00 - 23:00	0.00	2.80	1.95	1.95	1.20	1.20
23:00 - 0:00	0.00	1.90	1.30	1.30	0.75	0.75
AM (7:00 - 9:00)	28.40	0.00	4.60	4.60	5.30	5.30
Off-peak	20.40	25.10	37.35	37.35	37.60	37.60
PM (16:00 - 18:00)	1.20	24.90	8.05	8.05	7.10	7.10
Total (%)	50.00	50.00	50.00	50.00	50.00	50.00

Source: HOURLY.dbf table in TransCAD

The factors for the other trip purposes (e.g., external trips, commercial vehicle trips) are assumed based on the HBW, HBO, and NHB factors as shown in Table G-7. The congested travel time that is estimated by daily user equilibrium assignment and four iterations of feedback loop is used as travel time input for TOD assignment. The TOD highway link capacity is calculated as:

$$\text{Peak 2-hour period capacity} = \text{LOS_E_DCAP} * 0.2 * \text{PHF}$$

$$\text{Off-peak period capacity} = \text{LOS_E_DCAP} * 0.8$$

Where:

LOS_E_DCAP = one-way volumes at LOS E;

PHF = peak hour factor (equal to 0.9 in Jacksonville case study).

For Jacksonville MPO case, the TOD assignment is compared with daily assignment results by evaluating V/C ratio distribution in terms of facility types (Table G-8), link length distribution in terms of V/C ratios (Table G-9), and region-wide link-length weighted average V/C ratio as well as speed (Table G-10),.

Table G-8. V/C Ratio Distribution by Facility Types

Highway Functional Classification	V/C Ratio			
	Daily	AM	PM	Off-peak
Major Arterial	0.58	0.60	0.63	0.44
Minor Arterial	0.52	0.57	0.62	0.42
Collector	0.28	0.36	0.41	0.27
Local	0.19	0.28	0.31	0.19

Table G-9. Link Length Distribution by V/C Ratios

V/C Ratio	Length (miles) %			
	Daily	AM	PM	Off-peak
< 0.3	50.2%	33.5%	29.8%	53.1%
0.3 - 0.5	24.0%	32.6%	29.1%	28.9%
0.5 - 0.8	15.5%	24.4%	29.1%	15.4%
0.8 - 1.0	8.7%	6.1%	8.1%	1.6%
1.0 - 1.2	0.9%	2.0%	1.7%	1.0%
> 1.2	0.7%	1.4%	2.2%	0.0%
Total	100%	100%	100%	100%

Table G-10. Region-wide Average V/C Ratio and Speed

	Daily	AM	PM	Off-peak
Region-wide average V/C ratio	0.37	0.43	0.47	0.32
Region-wide average speed (mph)	24.85	17.23	15.89	19.27

Table G-8 shows that all types of roads have higher V/C ratios in peak periods (AM and PM) than those in off-peak period and daily period. In addition, PM peak period causes higher V/C ratios (congestions) on all roads than those in AM peak period. These results match what have been observed in the real world: trips are more likely to happen in peak hours, especially during the afternoon peak, which result in more severe traffic congestions than rest of the day. From Table G-8, we can also find that peak-period V/C ratios of lower level highway links tend to increase more compared with daily V/C ratios. For example, compared to daily assignment, AM peak V/C ratios increase 2% for major arterial, 5% for minor arterial, 8% for collectors and 9% for local roads; PM peak V/C ratios increase 5% for major arterial, 10% for minor arterial, 13% for collectors and 12% for local roads. This finding indicates that daily assignment is not capable of capturing variations of congestion conditions on highways, especially on minor roads.

Table G-9 shows the highway link length distribution by V/C ratios in different time periods, which represents the utilization of highways in terms of time of day. It is clear that peak periods (AM and PM) have overall higher V/C ratios than off-peak period and daily period. Furthermore, the PM peak period tends to have higher V/C ratios than AM peak period. All these results are reasonable and match what Table G-8 indicates.

According to region-wide link-length weighted average V/C ratios shown in Table G-10, AM and PM have higher values than off-peak and 24-hour period, which are reasonable and caused by relatively more trips made in the peak periods. For region-wide link-length weighted average speed, it is reasonable to find that the AM and PM peak periods have relatively lower values than daily values due to more severe traffic congestions in peak periods. However, it is noticed that the resulting off-peak average speed (19.27 mph) is lower than daily average speed (24.85 mph). This result is not reasonable since relatively fewer trips are made per off-peak hour and result in less congestion which should improve travel speed. Since

the congested network travel time is used to calculate region-wide average speed in Jacksonville case study, the unreasonable off-peak average speed may be caused by the reasons listed below:

- (1) The congested link travel time used for TOD assignment is actually estimated by a daily assignment with a feedback loop procedure which may not reflect the true link congestion condition as well as travel time in part of a whole day. More reasonable congested travel times (and a more reasonable TOD assignment) are expected to be achieved by conducting a specific TOD assignment with corresponding feedback loop procedure.
- (2) Although the direct feedback loop results in acceptable daily assignment results with a system-wide $R^2 = 0.95$, it converges very slow and produces a modest $RMSE\% = 19\%$ after four iterations. Therefore, the congested travel time estimated by four iterations of the direct feedback loop may be not robust enough to be used for TOD assignment. To obtain a reasonable off-peak average speed, more iterations of the feedback loop are worthwhile doing with the method of successive averaging (MSA) [7, 8, 9] or method of successive weighted averaging (MSWA) [10] which facilitates the converge speed and improve estimation accuracy.
- (3) The default TOD factors of vehicle trips provide by TransCAD may be not suitable in Jacksonville. An adjustment possibly needs to be made to the default TOD factor table based on local knowledge or surveys.

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1. John R. Stone, Leta F. Huntsinger and Asad J. Khattak. *Guidelines for Developing Travel Demand Models: Small Communities*, NCDOT Report 2005-11, June 2006.
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10. Henry Liu, Xiaozheng He and Bingsheng He. *Method of Successive Weighted Averages and Self-Regulated Averaging Schemes for Solving Stochastic User Equilibrium Problem*, 86th Transportation Research Board Annual Meeting, 2007.

APPENDIX H: LAND DEVELOPMENT SCENARIO EVALUATION STUDY

Jacksonville Status Quo vs. Traditional Neighborhood Developments

Introduction

This appendix first depicts two land development scenarios: the current Jacksonville case vs. traditional neighborhood development (TND). The TND scenario is characterized by high-density, mixed use, and design friendly alternative modes like walking and biking. We further identify areas in Jacksonville that are readily transformable to TNDs, and assess the potential impact of the TND growth alternative on vehicular traffic, mode choice, and air pollution. Trip generation rates used in this analysis include:

- § Auto trip generation rates estimated using the NC place cluster method (Appendix D).
- § Pedestrian trip generation rates estimated using the integrated land use and pedestrian trip generation model (Appendix C).
- § Trip rates from the traditional neighborhood development trip generation study jointly conducted by Stone, Khattak, et al. in 2003 (NCDOT Report No. 2003-13).

Jacksonville Baseline Scenario (Status Quo)

In the early twentieth century, most residences and businesses in Jacksonville concentrated along the New Bridge Street corridor. In the early 1940s, the United States Government acquired 246 square miles of property in Onslow County and began the construction of Marine Corps Base (MCB) Camp Lejeune. The construction brought an economic growth period and a period of rapid land consumption to the Jacksonville community. The lack of growth management strategies at that time, coupled with highway construction and the popularity of automobiles, led to the current sprawled and auto-dependent development patterns in Jacksonville, NC. Figure H-1 outlines current land use patterns in the city of Jacksonville.

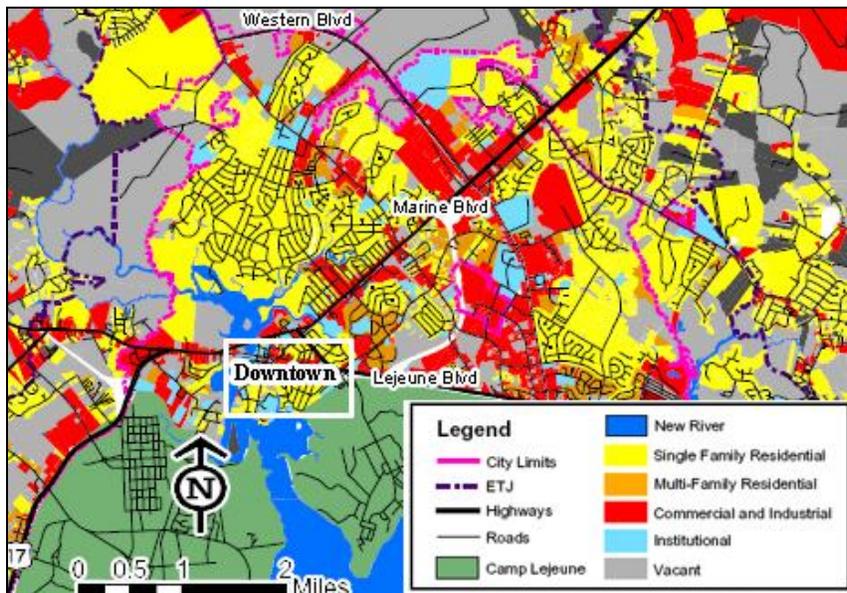


Figure H-1. Existing Land Uses in the City of Jacksonville, NC

Source: Jacksonville's Comprehensive Plan Update (The City of Jacksonville 2006)

As shown in Figure H-1, commercial and industrial uses mainly are located along three major roads in Jacksonville: Marine Blvd, and Lejeune Blvd, and Western Blvd. In downtown Jacksonville, some formerly prosperous retail areas are now largely vacant, and in many places vacant buildings and sites are

randomly interspersed with residences, retail and commercial uses and government buildings (The City of Jacksonville 1998). Most residential neighborhoods in Jacksonville are large-scale single-family residential areas with no mixture of retail, service, and office uses. Figure H-2 shows an example of suburban residential neighborhoods in the current Jacksonville case—the Northwoods neighborhood. The Northwoods neighborhood is located west of Henderson Drive and north of Marine Blvd. The closest commercial uses to this residential area are located at the intersection of Henderson Drive and Gum Branch Road. As shown in Figure H-2, a household located in the center of the neighborhood is about 1.7 miles away from the closest retail store, which makes walking an unattractive transportation option.

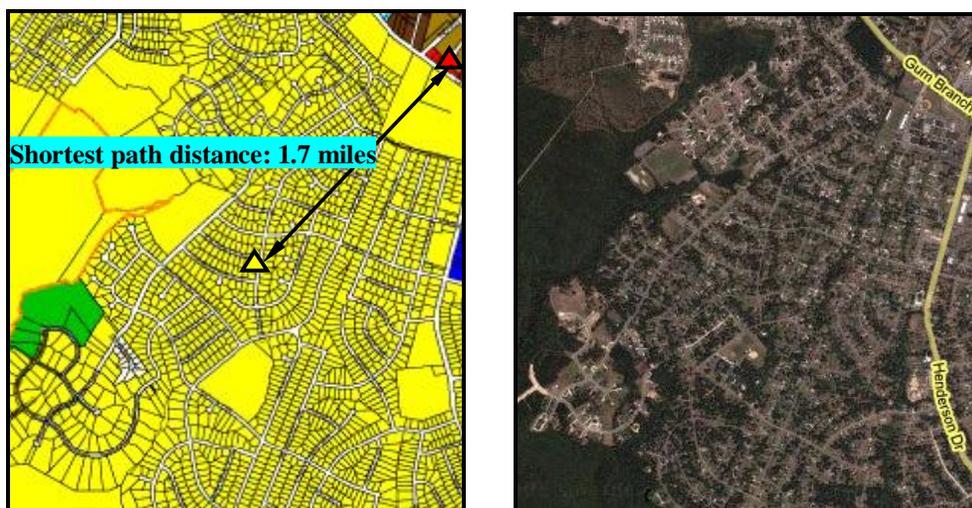


Figure H-2. Northwoods Neighborhood, Jacksonville, NC: An Area with Only Residential Use

Note:

The two figures show the same area. The figure on the left is a snapshot taken from Jacksonville’s most recent zoning map (<https://click2gov.ci.jacksonville.nc.us/ftp/ZoningMap.pdf>; updated on 2/12/2007). The figure on the right is from Google Map.

Jacksonville TND Scenario

TNDs are more densely developed, with residential land uses mixed with or in close proximity to small-scale commercial developments. TNDs are becoming increasingly popular in the United States and North Carolina, and they are expected to encourage walking and increase the percentage of trips taken inside a development due to the mixture of land uses (Stone, Khattak, et al. 2004).

Figure H-3 shows a TND example—Southern Village in Chapel Hill, NC. The commercial core in Southern Village includes restaurants, retail stores, a movie theatre, and other service uses such as a bank, spa and clinic. Office space fills several buildings in the center, and occupies floors above ground-level retail in others. The center attracts trips from both outside and within the neighborhood (Shay, Fan et al. 2006). All the households in Southern Village are less than one mile from the commercial core, promoting internal walking trips within the neighborhood. Two transit routes serve the neighborhood, including one that runs through the residential area.

The results from the Southern Village study show that households in Southern Village, the TND, make about the same amount of total trips, but there are significantly fewer automobile trips, fewer external trips, and fewer vehicle miles, when compared to households in the conventional suburban neighborhoods (Stone, Khattak et al. 2004).

Jacksonville’s Comprehensive Plan Update-Growth Management Element (The City of Jacksonville

2006) explicitly defined four growth alternatives including the existing trends, regional centers, neighborhood centers, and regional corridors scenarios. Among them, the neighborhood centers alternative seeks to revive the TND pattern. Figure H-4 illustrates the primary attributes of the neighborhood centers scenario, including dispersing neighborhood-scale retail and service centers at regular intervals throughout the city and locating multi-family housing adjacent to downtown and neighborhood centers.

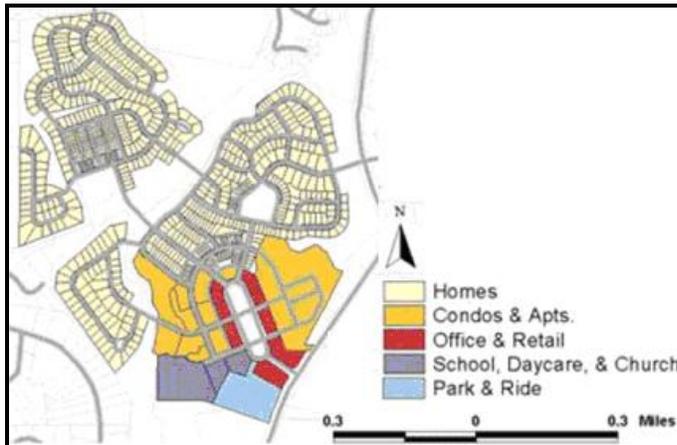


Figure H-3. TND Example—Southern Village, Chapel Hill, NC
 Source: NCDOT Report No. 2003-13 (Stone, Khattak et al. 2004).

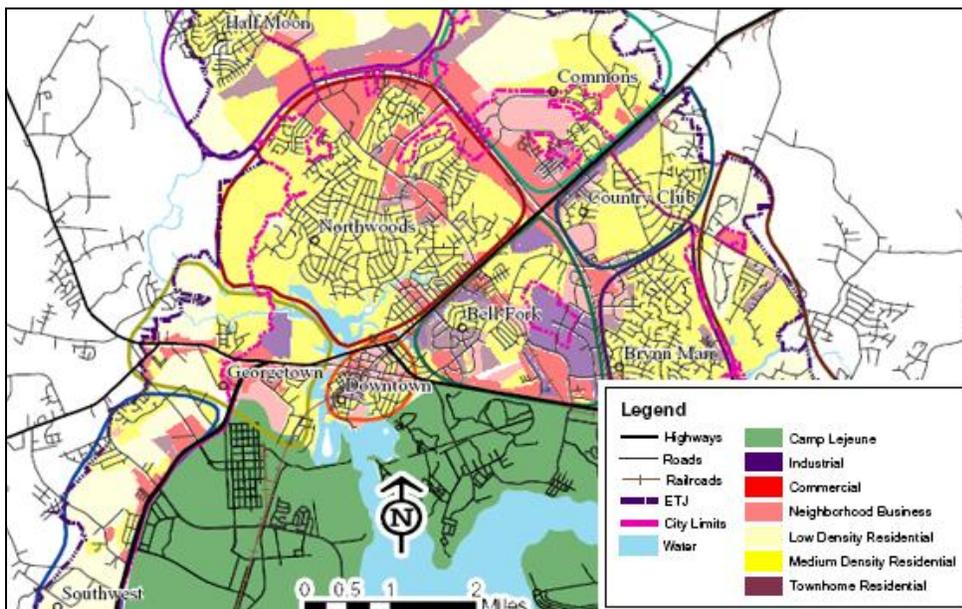


Figure H-4. Jacksonville’s TND Growth Scenario
 Source: Jacksonville’s Comprehensive Plan Update (The City of Jacksonville 2006)

For the Jacksonville case, the ongoing community growth requires more development and increasing public infrastructure and services built in the outlying areas. As TNDs are expected to encourage the use of alternative modes, and increase internal trip capture rates ultimately reducing congestion and vehicle miles traveled, the TND pattern is an attractive growth alternative to address Jacksonville’s existing growth challenges and to avoid inefficient sprawl development patterns.

Figure H-5 visually presents the differences in Jacksonville’s baseline scenario and the TND growth

scenario. Pictures on the left are photos taken on the field trip made by two project team members in October, 2006. The photos show Jacksonville’s commercial heart (the Court Street area) and a typical residential development in Jacksonville. Pictures on the right show the proposed new developments for the same areas in the Downtown Jacksonville Revitalization Plan. As shown in Figure H-5, with denser developments, improved pedestrian environments, and an enhanced and unified public landscape, the proposed new developments show consistency with TND design principles. In the Court Street commercial area, two and three-story buildings were proposed to take better advantage of the site. Food markets or other neighborhood-oriented businesses were proposed to occupy the ground floor, with offices or residential above. In the proposed new developments, the streets have wider sidewalks, well-marked crosswalks, and pedestrian amenities such as pedestrian lights, benches, banners, trash receptacles, planters, directories, and so on.



Figure H-5. Existing Conditions and Proposed New Developments in Jacksonville, NC

TND Transformability

To assess the potential traffic impact of the TND growth alternative, this section identifies areas in Jacksonville that are readily transformable to TNDs. The Jacksonville travel demand model study area (2002) follows the boundaries recommended by the NCDOT Transportation Planning Branch and the City of Jacksonville for this update. This study area contains all of the current urban area for a region as well as the anticipated urban area for the forecast year. The boundary follows natural boundaries whenever possible, captures a potential transportation project (US 17 bypass), and covers the jurisdiction of the Jacksonville MPO. The total study area encompasses approximately 215 square miles and varies in diameter between 17 and 20 miles. Figure H-6 is a map of the Jacksonville travel demand model study area, showing various area types within the study area including downtown, urban, rural, and military base areas.

We identify the urban area as the area that is readily transformable to TNDs because the urban area boundary approximates the City’s extra-territorial jurisdiction (ETJ) boundary. The ETJ area is the planning area defined for growth scenarios proposed in the most recent comprehensive plan of the city of Jacksonville, which provides ample development potential to accommodate projected population and

employment growth. The downtown area is excluded from TND transformable areas because Jacksonville’s downtown already has land use environments similar to TND designs, i.e., dense developments, mixed land uses, and good pedestrian facilities. Downtown residents likely behave like they live in a TND rather than a conventional development. Table H-1 summarizes the number of households and persons by area type.

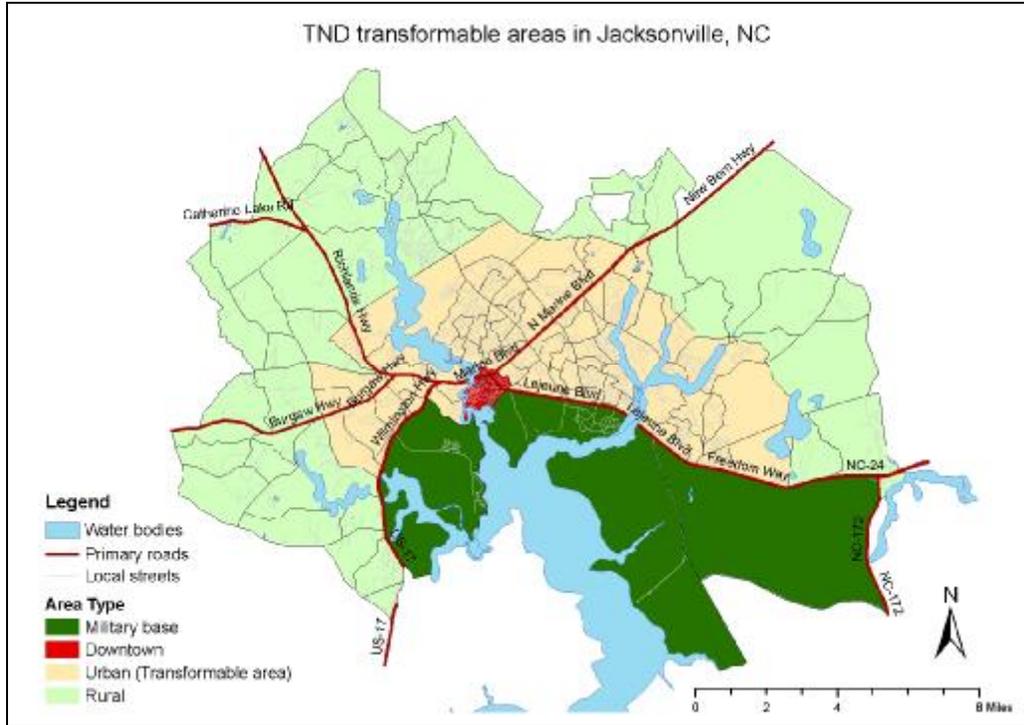


Figure H-6. Areas Transformable to TNDs in Jacksonville, NC

Table H-1. Number of Households and Persons by Area Type

Area type	Number of TAZs	Number of households	Number of residents	Area size (square miles)
Downtown	9	794	1,770	1
Transformable area (urban area)	83	21,736	55,392	55
Rural area	47	9,311	24,126	103
Military base	4	7,233	13,891	55
Total	143	39,074	95,179	214

As shown in Table H-1, out of the 39,074 household in the Jacksonville area, 797 households are in the downtown area that contains nine TAZs and has an area size of 1.2 square miles. There are 21,736 households in the urban area (55 square miles). The 83 TAZs in the urban area are identified as areas that are transformable to TNDs. For the purpose of exploring the potential impacts of TND transformation, this scenario assumes that the 21,736 households living in the area will behave in the manner of TND residents, after the TND transformation. This helps us contrast TNDs relative to the base case. Note that transforming the area practically has to be a process that involves many stages and many stakeholders. Most likely, new residents will replace some of the residents. In addition, land use changes take a long time to implement and depend on the preferences of the local population. The TND scenario is developed for demonstration only and practically fewer areas may be transformable.

Potential Traffic Reduction Effect of the TND Scenario

This section compares the TND scenario with the status quo in Jacksonville and assesses the potential traffic reduction effect of the TND scenario. For Jacksonville’s baseline scenario, we use auto trip generation rates in the NC place cluster analysis conducted by the NCSU team and pedestrian trip generation rates in the integrated land use and pedestrian trip generation study conducted by the UNC team. For Jacksonville’s TND scenario, we use trip generation rates in the Southern Village study (Stone, Khattak et al. 2004). Table H-2 lists the trip rates used in the evaluation. Note that the TND trip rates presented in Table H-2 are findings from the Southern Village, Chapel Hill, NC study, which may or may not be the case for Jacksonville. A proper evaluation of traffic impacts involves applying trip production equations (for example, say $\text{Trips} = 1.2 + 0.8 * \text{HHSize} + 0.5 * \text{NVehicles}$). However, the Jacksonville case does not have auto ownership data available, which makes it impossible to apply the equations developed in the Southern Village study to Jacksonville.

Table H-2. Trip Rates Used for the Comparison of Land Development Scenarios

	2002 baseline scenario	TND scenario
Average daily vehicle trips per household	7.70 ¹	7.10 ³
Average daily pedestrian trips per household	0.56 ²	1.57 ³
Daily miles traveled per household	73 ³	52 ³

Note:

¹ Trip rates from the NC place cluster analysis conducted by the NCSU team (see Appendix D for trip production equations)

² Trip rates from the 2-D analysis in the integrated land use and pedestrian trip generation study conducted by the UNC team (see Appendix C for trip production equations)

³ Trip rates and daily miles traveled from the Southern Village, Chapel Hill, NC study. Auto trip generation equation for single-family households in TND designs: $\text{Trips} = 0.4 + 1.1 * \text{HHSize} + 2.3 * \text{NVehicles}$; trip distance equation for single-family households in TND designs: $\text{Miles} = 9.3 + 6.6 * \text{HHSize} + 15.5 * \text{NVehicles}$; trip distance equation for conventional suburban households: $\text{Miles} = 65.3 + 3.8 * \text{HHSize} + 2.5 * \text{NVehicles}$ (See NCDOT Report No. 2003-13 for more details)

As shown in Table H-1, compared to the 2002 baseline scenario, the TND scenario has a lower vehicle trip rate and a higher pedestrian trip rate. We use the equation below to calculate the potential travel reduction effect of TND designs:

$$\# \text{ of reduced automobile trips} = (\text{TND trip rate difference}) * (\# \text{ of TND-transformable households})$$

Based on the equation, 0.6 fewer vehicle trips per household per day translate to 13,042 fewer automobile trips per day for the Jacksonville case ($0.6 \text{ trips} * 21,736 \text{ households} = 13,042$).

Khattak, Roupail et al. (2005) provided a graph shown in Figure H-7 for calculating urban area traffic volumes based on NCDOT traffic count data.

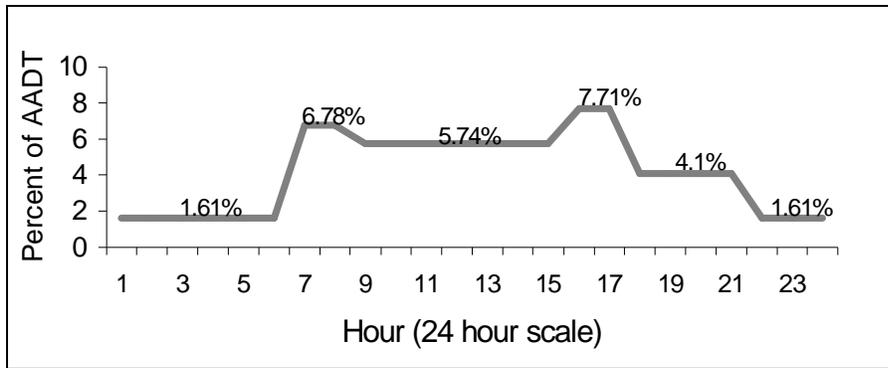


Figure H-7: Urban Traffic Volume Distribution by Time of Day

If we assume that 6.8% of the traffic will occur during the a.m. peak period, and 7.7% in the p.m. peak period, then this will imply 887 fewer a.m. peak period auto trips ($13,042 \times 0.068 = 887$) and 1,004 fewer p.m. peak period auto trips ($13,042 \times 0.077 = 1,004$). Given that roadway capacity is approximately 2,000 passenger cars per hour per lane and assuming that all 1,891 trips are made in single-occupant vehicles ($887 + 1,004 = 1,891$), a fair amount of network impact of TND designs can occur.

Likewise, 21 fewer person miles traveled per household per day translate to 357,862 fewer vehicle miles traveled per day for the selected Jacksonville areas that are readily transformable to TNDs ($21,736$ households * 21 miles * 78.4% auto mode share). Given that the emission factors for an average passenger car¹ are 2.9 grams per mile for hydrocarbons, 22 grams per mile for Carbon Monoxide, 1.5 grams per mile for Nitrogen Oxide, 0.8 pounds per mile for Carbon Dioxide, the travel reduction impact of TND designs in Jacksonville can be associated with a significant positive impact on air quality—2,286 fewer pounds of hydrocarbons, 17,341 fewer pounds of carbon monoxide, 1,182 fewer pounds of nitrogen oxides, and 286,290 fewer pounds of carbon dioxide per day. See the detailed calculations in Table H-3 below.

Table H-3. Reduced Emissions by TND Designs

Pollutant	Problem	Emission factor ¹	Reduced emissions ²
Hydrocarbons	Urban ozone (smog)	2.9 grams per mile	2,286 pounds
Carbon monoxide	Hazardous gas	22 grams per mile	17,341 pounds
Nitrogen oxides	Urban ozone (smog), acid rain	1.5 grams per mile	1,182 pounds
Carbon dioxide	Global warming	0.8 pounds per mile	286,290 pounds

Note:

¹ The emission factors used here come from standard EPA emission models. They assume an "average" properly maintained car on the road in 1997, operating on typical gasoline on a summer day (72-96°F). Emissions may be higher in very hot or very cold weather. Source: <http://www.epa.gov/otaq/consumer/f97037.pdf>

² Reduce emissions = emission factor * vehicle miles saved by TND transformable households

An average passenger car consumes 0.044 gallon gasoline per mile. The 357,862 fewer vehicle miles associated with TND designs suggests that Jacksonville residents may consume 15,746 fewer gallons of gasoline per day by incorporating TND designs into their neighborhoods. At the same time, the TND scenario is associated with more daily walking trips. In addition, TND households on average make one more pedestrian trip per household per day than current Jacksonville households. This suggests the beneficial impact of TND on public health, in addition to TND's travel reduction impact and the associated positive impact on air quality. Table H-4 summarized the possible impacts of the TND growth scenario on peak traffic conditions, vehicle miles traveled (VMT), air quality, and fuel consumption.

Table H-4. Possible Impacts of TND Scenario

	Possible daily impacts of TND growth scenario
Peak traffic conditions	887 fewer a.m. peak period auto trips; 1,004 fewer p.m. peak period auto trips.
VMT	357,862 fewer vehicle miles traveled
Air quality	2,286 fewer pounds of hydrocarbons; 17,341 fewer pounds of carbon monoxide; 1,182 fewer pounds of nitrogen oxides; 286,290 fewer pounds of carbon dioxide.
Fuel consumption	15,746 fewer gallons of gasoline per day

This exercise shows that consideration of a TND growth alternative can be helpful in terms of reducing traffic congestion, improving air quality, and saving energy resources. Clearly, the TND scenario presented here is for demonstration purposes only and in reality only a small subset of the area will be transformable to TNDs. Some of the existing developments may be transformable in terms of adding sidewalks and transit services. As Jacksonville is experiencing growth challenges and is exposed to the negative impacts of urban growth, such TND designs should be considered as options for both new suburban developments and re-developments and infill developments in urban areas.

However, implementing TND designs can be practically difficult. First, although several municipalities in North Carolina have adopted or amended zoning and planning codes to promote TND designs, the vast majority of municipalities do not specifically focus on TND and many zoning codes restrict it. Second, the American dream of owning a large home on a big lot on a safe street where kids can play away from big-city noise, pollution and traffic is still has not changed much. The majority of Americans, voting with their dollars, still choose the typical suburban subdivision over a TND community. For instance, although people who attended the open community meetings in Jacksonville's master planning process clearly stated that residential areas need sidewalks, they pointed out that they do not like narrow streets and inadequate parking spaces in the downtown area.

Closure

To conclude, TND designs encourage residents to substitute driving trips with alternative modes, which can bring significant transportation and environment benefits including reduced traffic congestion, reduced fuel consumption, and reduced car emissions to growing communities such as Jacksonville. The TND scenario described is for demonstration purposes only. We recommend that planners in Jacksonville consider TND as a growth alternative, with the caveat that there may be several challenges in planning for and implementing TND designs.

References:

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