Final Report
Contract BDV24-977-15

EVALUATING THE BENEFITS OF MULTI-MODAL INVESTMENTS ON PROMOTING TRAVEL MOBILITY IN CENTRAL FLORIDA

Sponsoring Agency: Florida Department of Transportation, Systems Planning Office
Project Manager: Jeremy Dilmore
Systems Traffic Models Manager: Thomas Hill

Naveen Eluru, Ph.D.
Shamsunnahar Yasmin, Ph.D.
Moshiur Rahman, M.Sc.
Tanmoy Bhowmik, M.Sc.
Mohamed Abdel-Aty, Ph.D., P.E.

University of Central Florida
Department of Civil, Environmental & Construction Engineering
Orlando, FL 32816-2450

August 2018

Disclaimer

Metric Conversion Chart

SYMBOL	WHEN YOU KNOW	MULTIPLY BY	TO FIND	SYMBOL
LENGTH				
in	inches	25.4	millimeters	mm
ft	feet	0.305	meters	m
yd	yards	0.914	meters	m
mi	miles	1.61	kilometers	km
AREA				
in^2	square inches	645.2	square millimeters	mm^2
ft^2	square feet	0.093	square meters	m^2
yd^2	square yard	0.836	square meters	m^2
ac	acres	0.405	hectares	ha
mi^2	square miles	2.59	square kilometers	km^2
VOLUME				
fl oz	fluid ounces	29.57	milliliters	mL
gal	gallons	3.785	liters	L
ft^3	cubic feet	0.028	cubic meters	m^3
yd^3	cubic yards	0.765	cubic meters	m^3
NOTE: volumes greater than 1000 L shall be shown in m^3				
MASS				
oz	ounces	28.35	grams	g
lb	pounds	0.454	kilograms	kg
T	short tons (2000 lb)	0.907	megagrams (or "metric ton")	Mg (or "t")

Technical Report Documentation Page

1. Report No.

2. Government Accession No.

3. Recipient's Catalog No.

4. Title and Subtitle
Evaluating the Benefits of Multi-Modal Investments on Promoting Travel Mobility in Central Florida

5. Report Date
May 2018

6. Performing Organization Code

7. Author(s)
Naveen Eluru, Shamsunnahar Yasmin, Moshiur Rahman, Tanmoy Bhowmik, Mohamed Abdel-Aty

8. Performing Organization Report No.

9. Performing Organization Name and Address
Department of Civil, Environmental & Construction Engineering
University of Central Florida,
Orlando, FL 32816
naveen.eluru@ucf.edu

10. Work Unit No. (TRAIS)

11. Contract or Grant No.
BDV24-977-15

12. Sponsoring Agency Name and Address
Florida Department of Transportation
605 Suwannee Street, MS 30
Tallahassee, FL 32399

13. Type of Report and Period Covered
Final Report
Jan 2016 to August 2018

14. Sponsoring Agency Code

15. Supplementary Notes

16. Abstract
In this research effort, a trip-based approach is employed to study the benefits of investments on public transit and non-motorized transportation in the Central Florida region. Florida trip-based method is geared toward auto-oriented mobility analysis. With growing emphasis in Florida's urban regions on non-auto mobility – public transit, pedestrian, and bicyclist modes – it is useful to develop methods that accommodate the potential adoption of non-auto modes within the mobility planning process. Toward this end, the proposed research effort employs an existing regional model framework to study multi-modal mobility. The study effort provides frameworks to estimate transit and non-motorized mode demand and identify policies to alleviate auto-related travel burden while enhancing non-auto mobility. The analyses are focused on four major components: (1) mobility component – demand analysis for non-motorists road user groups; (2) safety component – zonal level crash frequency and severity analysis for non-motorists road user groups; (3) ridership analysis – transit demand analysis for Lynx and SunRail systems; and (4) cost-benefit analysis – cost-benefit analysis for SunRail commuter rail system. These components were examined, and the associated models were estimated for the study area defined by the Central Florida Regional Planning Model, Version 6.0. The model estimation efforts were also augmented by validation and policy implication exercises. The overall framework proposed and demonstrated in this research effort provides policy makers a blueprint to begin incorporating non-auto mode choice alternatives within the traditional travel demand framework across various urban regions in Florida.

17. Key Word
Non-motorized Transportation; Mobility; Public Transit; Multi-modal Transportation; Ridership.

18. Distribution Statement
No restrictions.

19. Security Classif. (of this report)
Unclassified.

20. Security Classif. (of this page)
Unclassified.

21. No. of Pages
175

22. Price

Acknowledgement

The authors would like to acknowledge various agencies, including SunRail, Lynx, Florida Department of Revenue, Signal Four Analytics, and Florida Department of Transportation, for helping with data acquisition.

Executive Summary

The increasing auto travel and its adverse environmental impacts have led in the past decade to the serious consideration and implementation of travel demand management strategies (for example, enhancing existing public transportation services, building new services such as light rail transit, and improving non-motorized infrastructure such as bicycle lanes and sidewalk). The main objective of these demand management strategies is to encourage the efficient use of transportation resources by influencing travel behavior. Travel demand management strategies offer flexible solutions that can be tailored to meet the specific requirements of a particular urban region. Travel demand models offer analytical frameworks to evaluate the effectiveness of the aforementioned management strategies. The history of demand modeling for planning projects at various levels (such as local, regional, or state level) has been dominated by the traditional travel demand modeling approach referred to as the four-step, or the trip-based approach. As part of the research effort, the emphasis was on, the emphasis is on employing the trip-based approach to study the benefits of investments on public transit and non-motorized transportation in the Central Florida region.

Travel demand modeling approaches employing traditional trip-based methods are geared predominantly toward auto-oriented mobility analysis. With the growing emphasis in Florida's urban regions on non-auto mobility – public transit, pedestrian, and bicyclist modes – it is useful to develop methods that accommodate the potential adoption of non-auto modes within the mobility planning process. Within the current literature, the cost-benefit analysis of public transit, pedestrian, and bicycle infrastructure investments on non-auto mobility has rarely been quantified. Toward this end, the research employed an existing regional model framework to study multi-modal mobility for the Central Florida region (District 5). Specifically, the study effort provides frameworks to understand transit and non-auto modes demand and to identify policies to alleviate auto-related travel burden while enhancing non-auto mobility. The analysis is focused on four major components, including (1) mobility component – demand analysis for non-motorists road user groups, (2) safety component – zonal level crash frequency and severity analysis for non-motorists road user groups, (3) ridership analysis – transit demand analysis for Lynx and SunRail systems, and (4) cost-benefit analysis – cost-benefit analysis for SunRail commuter rail system. These components were examined and the associated models were estimated for the study area defined by the Central Florida Regional Planning Model, Version 6.0 (CFRPM 6.0).

In terms of the mobility component, we investigated non-motorist demand at a zonal level by using aggregate trip information based on origin and destination locations of trips. Specifically, we developed four non-motorist demand models: (1) pedestrian generator model – based on zonal level pedestrian origin demand; (2) pedestrian attractor model – based on zonal level pedestrian destination demand; (3) bicycle generator model – based on zonal level bicycle origin demand; (4) bicycle attractor model – based on zonal level bicycle destination demand. These aggregate level demand models examine critical factors contributing to non-motorist generators and attractors at a zonal level. The outcome of these studies can be used to devise medium or long-term area-wide planning and investment policies in order to encourage and promote non-motorized activities. For examining the safety component, we estimated both crash frequency and crash severity models in understanding non-motorist safety factors. In terms of the crash frequency model, we estimated two models: (1) zonal level crash count model for examining pedestrian–motor vehicle crash occurrences, and (2) zonal level crash count model for examining bicycle–motor vehicle crash occurrences. With regards to the crash severity model, we estimated four different sets of models: (1) disaggregate-level crash severity model for examining pedestrian crash injury severity outcomes; (2) disaggregate-level crash severity model for examining bicycle crash injury severity outcomes; (3) zonal level crash severity model for examining pedestrian crash injury severity by proportions; and (4) zonal level crash severity model for examining bicycle crash injury severity by proportions. Outcomes of these models, specifically zonal level models, can be used to devise safety-conscious decision support tools to facilitate a proactive approach in assessing medium- and long-term policy-based countermeasures.

With regards to the ridership component, in our research effort, we investigated transit demand for the coverage area of Lynx and SunRail network systems of the Greater Orlando region. We estimated and present four different sets of ridership models: for the Lynx network system – (1) stop level average weekday boarding bus ridership analysis, and (2) stop level average weekday alighting bus ridership analysis; and, for the SunRail network system – (3) daily boarding rail ridership analysis, and (4) daily alighting rail ridership analysis. Finally, we performed a comprehensive cost-benefit analysis for the existing 31-mile SunRail system. With regards to the cost component, the factors we considered included (1) capital costs and (2) operation and maintenance costs. In terms of the benefit component, the factors we considered included (1) personal automobile cost savings, (2) crash cost savings, (3) parking cost savings, (4) energy conservation savings, and (5) assessed property value increase. Further, to ensure model prediction performance accuracy, the proposed models were validated for the base year empirical data prior to deploying them for forecasting. The model estimation and validation exercises are also augmented by demonstrating the implication of the estimated models by conducting policy analysis for several scenarios for each component.

The outcomes of the research effort include pedestrian and bicyclist zonal level origin-destination and total demand tables, transit demand for current and future public transit investment scenarios, countermeasures to improve safe mobility for non-motorists road user group, and anticipated benefits of the SunRail commuter rail system. The overall framework proposed and demonstrated in this research effort provides policy makers a blueprint to begin incorporating non-auto mode choice alternatives within the traditional travel demand framework.

Table of Contents

Disclaimer ii
Metric Conversion Chart iii
Technical Report Documentation Page iv
Acknowledgement v
Executive Summary vi
Table of Contents viii
List of Figures xiii
List of Tables xiv
Abbreviations and Acronyms xvi
CHAPTER I: Introduction 1
1.1 BACKGROUND STATEMENT 1
1.2 RESEARCH CONTEXT 1
1.2.1 Project Objective(s) 2
CHAPTER II: LITeRATURE REVIEW 4
2.1 INTRODUCTION 4
2.2 REVIEW OF URBAN TRANSPORTATION MODELING FRAMEWORKS 4
2.2.1 Overview of Different Travel Demand Models 4
2.2.2 Comparison of Different Modeling Steps 5
2.3 REVIEW OF COST-BENEFIT ANALYSIS STUDIES 16
2.3.1 Non-motorized CBA 16
2.3.2 Public Transit Cost-Benefit Analysis 17
2.3.3 Directions for CFRPM Based Cost-Benefit Analysis 18
2.4 SUMMARY 19
CHAPTER III: DATA ASSEMBLY 20
3.1 INTRODUCTION 20
3.2 STUDY AREA 20
3.3 DATA COMPILATION 21
3.3.1 Sociodemographic Characteristics 23
3.3.2 Socioeconomic Characteristics 23
3.3.3 Built Environment 24

3.3.4 Transit Attributes 24
3.3.5 Bicycle Attributes 24
3.3.6 Pedestrian Attributes 24
3.3.7 Transport Infrastructure 24
3.3.8 Traffic Characteristics 25
3.4. DATA DESCRIPTION 25
3.4.1 Sociodemographic and Socioeconomic Characteristics 25
3.4.2 Neighborhood Attributes 25
3.4.3 Bus Ridership Data 29
3.4.4 SunRail Ridership Data 32
3.4.5 Pedestrian Count Data 35
3.4.6 Pedestrian and Bicycle Crash Data 37
3.5 SUMMARY 39
CHAPTER IV: BASE YEAR MOBILITY ANALYSIS 40
4.1 INTRODUCTION 40
4.2 BASE YEAR MOBILITY 40
4.2.1 Mobility Analysis for Motorist Road Users 40
4.2.2 Mobility Analysis for Non-motorist Road Users 44
4.3 SUMMARY 56
CHAPTER V: BASE YEAR Non-motorists Safety ANALYSIS 58
5.1 INTRODUCTION 58
5.2 CRASH FREQUENCY ANALYSIS 59
5.2.1 Model Framework 59
5.2.2 Dependent Variable and Data Description 60
5.2.3 Estimation Results 62
5.3 DISAGGREGATE-LEVEL CRASH SEVERITY ANALYSIS 64
5.3.1 Model Framework 65
5.3.2 Data Description 66
5.3.3 Sample Formation and Description 66
5.3.4 Estimation Results 69
5.4 ZONAL-LEVEL CRASH SEVERITY ANALYSIS 73
5.4.1 Model Framework 73

5.4.2 Model Structure 74
5.4.3 Dependent Variable and Data Description 75
5.3.4 Estimation Results 78
5.5 SUMMARY 79
CHAPTER VI: BASE YEAR PUBLIC TRANSIT RIDERSHIP ANALYSIS 81
6.1 INTRODUCTION 81
6.2 AN OVERVIEW OF PUBLIC TRANSIT SYSTEM 81
6.3 RIDERSHIP ANALYSIS OF PUBLIC TRANSIT 82
6.4 PROXIMITY ANALYSIS FOR LYNX AND SUNRAIL SYSTEMS 83
6.5 RIDERSHIP ANALYSIS FOR LYNX NETWORK SYSTEM 86
6.5.1 Model Framework 87
6.5.2 Data Description 88
6.5.3 Estimation Results 89
6.6 RIDERSHIP ANALYSIS FOR SUNRAIL NETWORK SYSTEM 94
6.6.1 Model Framework 95
6.6.2 Data Description 96
6.6.3 Variable Considered 96
6.7 CATCHMENT AREA OF SUNRAIL STATIONS 101
6.7.1 Catchment Area of SunRail Stations for Walk Mode 101
6.7.2 Catchment Area of SunRail Stations for Bike Mode 102
6.7.3 Catchment Area of SunRail Stations for Transit Mode 103
6.7.4 Catchment Area of SunRail Stations for Drive Mode 104
6.8 SUMMARY 106
CHAPTER VII: VALIDATION OF THE ESTIMATED MODELS 107
7.1 INTRODUCTION 107
7.2 MOBILITY COMPONENT 107
7.2.1 Validation Results of Mobility Component 107
7.3 SAFETY COMPONENT 108
7.3.1 Validation Results of Crash Count Models 108
7.3.2 Validation Exercise of Crash Proportion Models 110
7.4 RIDERSHIP COMPONENT 111
7.4.1 Validation Exercise of Lynx Ridership Models 111

7.4.2 Validation Exercise of SunRail Ridership Models ... 111
7.5 SUMMARY ... 112
CHAPTER VIII: POLICY ANALYSIS ... 113
8.1 INTRODUCTION ... 113
8.2 MOBILITY AND SAFETY COMPONENTS ... 113
8.2.1 Policy Analysis for Non-Motorist Demand ... 115
8.2.2 Policy Analysis for Non-Motorist Crash Frequency ... 116
8.2.3 Policy Analysis for Non-Motorist Crash Severity Proportions ... 117
8.3 RIDERSHIP COMPONENTS ... 119
8.3.1 Policy Analysis for Lynx System ... 120
8.3.2 Policy Analysis for SunRail System ... 123
8.4 IMPACT OF I-4 CONSTRUCTION ON BUS RIDERSHIP ... 125
8.5 SUMMARY ... 128
CHAPTER IX: COST-BENEFIT ANALYSIS ... 129
9.1 INTRODUCTION ... 129
9.2 COST-BENEFIT ANALYSIS FOR SUNRAIL ... 129
9.2.1 Factors Considered ... 129
9.2.2 Demand Attributes ... 130
9.3 COST FACTORS ... 133
9.4 BENEFIT FACTORS ... 133
9.4.1 Personal Automobile Cost Savings ... 133
9.4.2 Crash Cost Savings ... 134
9.4.3 Emission Cost Savings ... 135
9.4.4 Parking Cost Savings ... 135
9.4.5 Energy Conservation Savings ... 136
9.4.6 Assessed Property Value Increase ... 136
9.5 RESULT OF COST-BENEFIT ANALYSIS ... 146
9.6 SUMMARY ... 151
CHAPTER X: Conclusion ... 152
10.1 MOBILITY COMPONENT ... 152
10.2 SAFETY COMPONENT ... 153
10.3 RIDERSHIP COMPONENT ... 153

10.4 COST-BENEFIT ANALYSIS COMPONENT 154
10.5 SUMMARY 155
References 156

List of Figures

Figure 1-1: Study Area and Research Concept Framework 3
Figure 3-2: Study Area Along with County Boundaries 21
Figure 3-3: Traffic Analysis Zones (TAZ) 26
Figure 3-4: Lynx Bus Stop and Route Locations... 30
Figure 3-5: Distribution of Headway... 31
Figure 3-6: SunRail Line and Station Location 32
Figure 3-7: SunRail Ridership for Different Time Periods of Day 35
Figure 3-8: SunRail Ridership for Different Day-of-Week.. 35
Figure 3-9: Intersection Locations of Pedestrian Count Data.. 36
Figure 3-10: Distribution of Pedestrian Count.. 37
Figure 3-11: Location of Pedestrian and Bicycle Crashes for the Year 2010 38
Figure 3-12: Spatial Distribution of Fatal, Injury, and Non-Injury Crashes of Pedestrian and Bicycle Crashes for the Year 2010 38
Figure 4-13: CUBE Interface of Input Files for Trip Generation Process.................................... 41
Figure 4-14: Trip Generation Summary Report.. 42
Figure 4-15: CUBE Interface of Input and Output Files for Trip Distribution Process 43
Figure 4-16: CUBE Interface of Input and Output Files for Mode Choice Models 44
Figure 4-17: Zones with Pedestrian and Bicycle OD Demand... 49
Figure 5-18: Total Number of Pedestrian and Bicycle Crashes for the Year 2010 60
Figure 5-19: Zones with Fatal Pedestrian and Bicycle Crashes for the Year 2010 75
Figure 6-20: Public Transit System (LYNX and SUNRAIL) of Greater Orlando 82
Figure 6-21: Location of Connector Lynx Bus Stops for Different SunRail Stations.................. 83
Figure 6-22: Total Bus Ridership Trend... 86
Figure 6-23: Total Number of Bicycle Boarding in SUNRAIL 95
Figure 6-24: Catchment Area of SUNRAIL Stations for Walk Mode 102
Figure 6-25: Catchment Area of SunRail Stations for Bike Mode 103
Figure 6-26: Catchment Area of SUNRAIL Stations for Transit Mode..................................... 104
Figure 6-27: Catchment Area of SUNRAIL Stations for Drive Mode....................................... 105
Figure 7-28: Crash Count Model Predictions 109
Figure 8-29: Considered Central Business District (CBD) Locations....................................... 115
Figure 8-30: Policy Analysis of SunRail 124
Figure 8-31: Impact Area of I-4 Expansion Project.. 126
Figure 8-32: Average Daily LYNX Ridership.. 127
Figure 9-33: Land Use Types within SunRail Influence Area for 2011 and 2016 138
Figure 9-34: Property Values within SunRail Influence Area for 2011 and 2016 140
Figure 9-35: Station-level Property Value per Acre for Different Land Use Types 143

List of Tables

Table 2-1: Overview of Selected Travel Demand Models for Different Regions 6
Table 2-2: Trip Generation 9
Table 2-3: Trip Distribution 11
Table 2-4: Mode Choice 13
Table 2-5: Trip Assignment 15
Table 2-6: Benefits and Costs Factors for CFRPM-Based Cost-Benefit Analysis 19
Table 3-7: Candidate Variables List 22
Table 3-8: Summary Characteristics for Sociodemographic and Socioeconomic Characteristics 26
Table 3-9: Summary Statistics for Neighbourhood Characteristics 27
Table 3-10: Summary Statistics for Lynx Bus Ridership (August 2013 to April 2015) 31
Table 3-11: Monthly SunRail Ridership from July 2014 through June 2015............................. 34
Table 3-12: Pedestrian Count Data for 726 Intersections 36
Table 3-13: Summary Characteristics of Pedestrian and Bicycle Crashes for the Year 2010...... 39
Table 4-14: Average Congested Trip Length by Trip Purpose.. 43
Table 4-15: HBW Highway Trips Summary 44
Table 4-16: Summary Characteristics for Trip Counts 48
Table 4-17: Summary Characteristics for Exogenous Variables 50
Table 4-18: Fit Measures of the Estimated Demand Models 51
Table 4-19: Estimation Results of Pedestrian Demand Models 52
Table 4-19 (continued): Estimation Results of Pedestrian Demand Models 53
Table 4-20: Estimation Results of Bicycle Demand Models 54
Table 4-21: Trip Demand Matrices by County Level 56
Table 5-22: Sample Characteristics for Crash Frequency Models 61
Table 5-23: Estimation Results of Negative Binomial Models 63
Table 5-24: Distributions of Pedestrian and Bicycle Injury Severity 67
Table 5-25: Summary Statistics of Explanatory Variables for Pedestrian Crashes 67
Table 5-26: Summary Statistics of Explanatory Variables for Bicycle Crashes 69
Table 5-27: OL Model Estimates of Pedestrian Injury Severity Outcomes 71
Table 5-28: OL Model Estimates of Bicycle Injury Severity Outcomes 72
Table 5-29: Severity Proportions 76
Table 5-30: Summary Characteristics for Zonal-level Crash Severity Models 77
Table 5-31: Estimation Results of Ordered Probit Fraction Split Models 78
Table 6-32: Summary Statistics of Lynx Bus Ridership for Different Bins 88
Table 6-33: Summary Statistics for Lynx Ridership Analysis 90
Table 6-34: Lynx Ridership Analysis Results 93
Table 6-35: Summary Statistics for SunRail Average Daily Ridership (January 2015 to October 2015) 97
Table 6-36: Descriptive Statistics of Exogenous Variables for SunRail Ridership...................... 98
Table 6-37: SunRail Ridership Model Estimation Results 100
Table 7-38: Predictive Performance Evaluation 108

Table 7-39: Predictive Performance Evaluation ... 109
Table 7-40: Predictive Performance Evaluation ... 110
Table 7-41: Predictive Performance Evaluation ... 111
Table 7-42: Predictive Performance Evaluation for SUNRAIL Ridership ... 112
Table 8-43: Elasticity Effects for Non-Motorist Total Zonal Demand ... 116
Table 8-44: Elasticity Effects for Non-Motorists Crash Frequency ... 117
Table 8-45: Elasticity Effects for Non-motorists Crash Severity Proportions ... 117
Table 8-46: Policy Analysis of Lynx ... 121
Table 8-47: Expansion Project and Change in Ridership ... 127
Table 9-48: Summary Statistics for SunRail Average Daily Ridership (January 2015 to October 2015) ... 130
Table 9-49: Passenger Miles Travelled Calculations for SunRail ... 131
Table 9-50: Personal Automobile Cost Savings ... 134
Table 9-51: Crash Cost Savings ... 134
Table 9-52: Emission Cost Savings ... 135
Table 9-53: Parking Cost Savings ... 135
Table 9-54: Energy Conservation Savings ... 136
Table 9-55: Computed Property Value Increase for Base Year ... 146
Table 9-56: Scenarios of Cost-Benefit Analysis ... 148
Table 9-57: Cost-Benefits Analysis of SunRail over 30 Years ... 150

Abbreviations and Acronyms

AADT	Annual average daily traffic
ACS	American Community Survey
AIC	Akaike information criterion
BIC	Bayesian information criterion
BRT	Bus Rapid Transit
CARS	Crash Analysis Reporting System
CBA	Cost-benefit analysis
CBD	Central Business District
CF	Crash frequency
CFRPM 6.0	Central Florida Regional Planning Model version 6.0
CFRPM	Central Florida Regional Planning Model
CS	Crash severity
EI	External-to-internal
EPA	Environmental Protection Agency
FDOT	Florida Department of Transportation
FGDL	Florida Geographic Data Library
FL	Florida
GHG	Greenhouse gas
GIS	Geographical Information System
GROL	Grouped Ordered Logit
HBO	Home-based other
HBSH	Home-based shopping
HBSR	Home-based social recreational
HBW	Home-based work
HH	Households
HNB	Hurdle-Negative Binomial
HP	Hurdle Poisson
HTK	Heavy truck
LR	Linear regression

Abbreviations and Acronyms (Continued)

LTK	Light truck
MAD	Mean absolute deviation
MAPE	Mean absolute percentage error
MPB	Mean prediction bias
MPO	Metropolitan planning organization
NB	Negative Binomial
NHB	Non-home-based
NHTS	National Household Travel Survey
OD	Origin destination
OL	Ordered logit
OPFS	Ordered probit fractional split
PAC	Personal automobile cost
RMSE	Root mean square error
S4A	Signal Four Analytics
TAZ	Traffic Analysis Zone
TDM	Travel demand modeling
TOD	Transit Oriented Developments
TPO	Transportation planning organization
U.S	United States of America
VMT	Vehicle miles travelled

CHAPTER I: INTRODUCTION

1.1 BACKGROUND STATEMENT

In the United States (U.S.), a significant number of individuals depend on the auto mode of transportation. This dependency on the auto mode can be attributed to high auto ownership affordability, inadequate public transportation facilities (in many cities), and excess suburban land use developments. For instance, the 2009 National Household Travel Survey (NHTS) data shows that about 91% of the U.S. households owned at least one motor vehicle in 2009 (compared to about 80% in the early 1970s; see Pucher and Renne, 2003). The high auto dependency, in turn, results in high auto travel demand on highways. At the same time, the ability to build additional infrastructure is limited by high capital costs, real-estate constraints, and environmental considerations. The net result has been that traffic congestion levels in metropolitan areas of the U.S. have risen substantially over the past decade (see Schrank and Lomax, 2005). The increase in traffic congestion levels not only causes increased travel delays and impacts stress levels of drivers, but also adversely affects the environment as a result of rising air pollution and greenhouse gas emissions. In fact, in many urban regions, the quantity of emissions is very close to the threshold or beyond the threshold of the Environmental Protection Agency (EPA) conformity levels. Of course, these mobile-source emissions in the environment also contribute to global warming (Greene and Shafer, 2003).

The increasing auto travel, and its adverse environmental impacts, has led, in the past decade, to the serious consideration and implementation of travel demand management strategies (for example, enhancing existing public transportation services, building new services such as light rail transit, and improving non-motorized infrastructure such as bicycle lanes and sidewalk). The main objective of these demand management strategies is to encourage the efficient use of transportation resources by influencing travel behavior. Travel demand management strategies offer flexible solutions that can be tailored to meet the specific requirements of a particular urban region. Travel demand models offer analytical frameworks to evaluate the effectiveness of the aforementioned management strategies. The history of demand modeling for various planning level projects (such as local, regional or state level) have been dominated by the traditional travel demand modeling approach referred to as the four-step approach or the trip-based approach. As part of the research effort, the emphasis was on employing the trip-based approach to study the benefits of investments on public transit and non-motorized transportation in Central Florida region.

1.2 RESEARCH CONTEXT

Travel demand modeling approaches employing traditional trip-based methods are geared predominantly toward auto-oriented mobility analysis. With growing emphasis in Florida's urban regions on non-auto mobility – public transit, pedestrian, and bicyclist modes – it is useful to develop methods that accommodate the potential adoption of non-auto modes within the mobility planning process. Within the current literature, the cost-benefit analysis of public transit, pedestrian and bicycle infrastructure investments on non-auto mobility has rarely been quantified. Toward this end, this research employed an existing regional model framework to study multi-modal mobility for the Central Florida region (District 5). The model can predict the tendency for transit and non-auto mode choice by individual citizens, and the resulting increase in mobility, based on the level of transit and non-motorized investments to help improve travel forecasting accuracy. Further, to ensure model prediction performance accuracy, the proposed models was validated for the base year empirical data prior to deploying them for forecasting.

1.2.1 Project Objective(s)

The research is geared towards enhancing the urban transportation infrastructure to increase non-auto mobility and to improve transit ridership. The current research provides frameworks to understand transit and non-auto modes demand and identifying policies to alleviate auto related travel burden while enhancing non-auto mobility. The specific objectives of the research are described below:

Objective 1: Non-motorized Mobility Analysis - The research was focused on examining current pedestrian and bicyclist mobility trends and identify urban neighborhoods appropriate for pedestrian and bicyclist travel investments. The research was also examined the potential increase in bicycling and pedestrian mobility as a result of changes to land use and urban density, and infrastructure investments (such as separated bicycle lanes, cycle tracks, customized signalization for bicyclists).

Objective 2: Non-motorized Safety Analysis - With increased adoption of pedestrian and bicyclist travel, it is likely that the number of conflicts between vehicle and non-motorized road users increase. The proposed research effort was suggested and evaluated pro-active solutions to prevent such increased conflicts and resulting consequences.

Objective 3: Public Transit Mobility Analysis - The research team was studied current transit mobility profiles for the various transit systems in the Greater Orlando Region and develop a quantitative framework to undertake scenario analysis of future transit mobility patterns.

Expected Research Outcomes – The research outcomes of the proposed framework was:

1. Pedestrian and bicyclist O/D tables similar to ITE trip rates
2. Transit ridership for current and future public transit investment scenarios
3. Identification of non-motorized infrastructure improvements to improve safe mobility
4. Identification of anticipated benefits of SunRail commuter rail system.

The study area along with the research concept framework is shown in Figure 1-1.

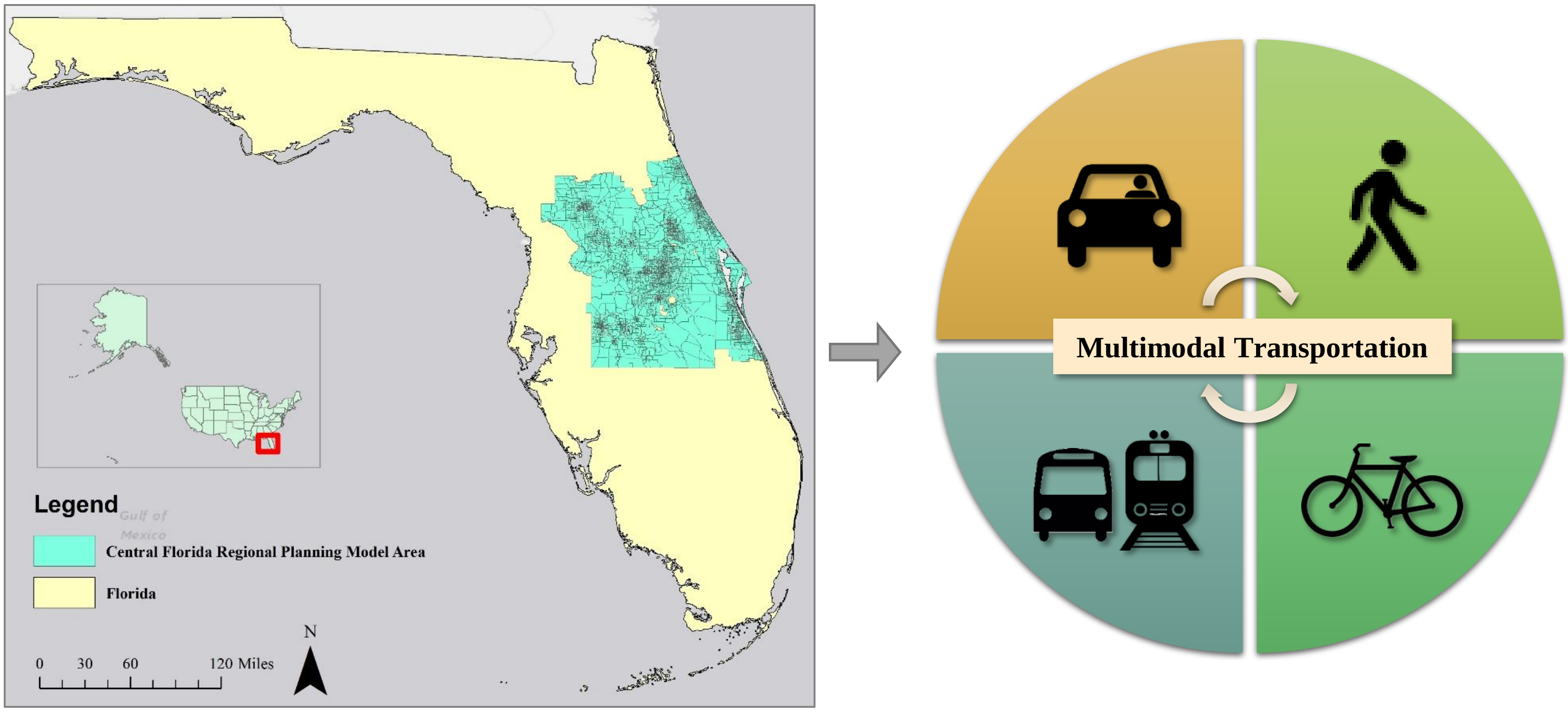


Figure 1-1: Study Area and Research Concept Framework

CHAPTER II: LITERATURE REVIEW

2.1 INTRODUCTION

In the Central Florida region the trip-based model employed is labeled as "Central Florida Regional Planning Model (CFRPM)". As is expected for a traditional trip-based approach, the CFRPM modeling framework is predominantly focused on auto mode and public transit. The modeling approach does not consider the non-motorized mode in detail. However, with greater emphasis on improving mobility in the Florida region, there is growing awareness and effort to enhance non-motorized (pedestrian and bicyclist) mobility. To evaluate the effectiveness of these strategies it is useful to develop methods that accommodate the potential adoption of non-motorized modes within the mobility planning process. To that extent, the current chapter has two objectives. First, the report focuses on reviewing the travel demand modeling frameworks for five urban regions of the US and compare that with the CFRPM approach. The literature review was enable for the research team to propose potential updates to the CFRPM on incorporating pedestrian, bicyclist and public transit modes effectively in the planning model. Specifically, it provided insight on understanding how land use and accessibility attributes can be better incorporated in the model framework for analyzing non-motorized and public transit alternatives within existing modeling framework. Second, the chapter provides a review of cost-benefit analysis conducted for public transit and non-motorized mode investments. The review were allowed for the identification of different dimensions of the CFRPM model to be targeted in undertaking the cost benefit analysis.

The remaining chapter is organized as follows: The next section describes the review of model frameworks from multiple cities selected. The subsequent section focuses on the review of cost benefit analysis studies. The final section describes summary of the chapter.

2.2 REVIEW OF URBAN TRANSPORTATION MODELING FRAMEWORKS

The purpose of the literature review is to identify the non-motorized and public transit components of the travel demand modeling for different urban regions in the US. In this chapter, we provide an overview of the four regional planning models along with the overview of CFRPM to provide an overview of the state-of-the-art efforts for modeling transport demand. Further, we identify and discuss different non-motorized and transit components explored in these models with specific focus on comparing and contrasting these components with the CFRPM model components. For each model component, we provide recommendations on how to enhance the CFRPM framework for accommodating non-motorized and public transit alternatives.

2.2.1 Overview of Different Travel Demand Models

The broad area of travel demand modeling approaches can be classified into two major groups: (1) trip based modeling approaches and (2) activity based modeling approaches (also includes tour based models). The traditional trip-based models focus on individual trips and employ a sequential approach of statistical planning with the following four steps - trip generation, trip distribution, mode choice and trip assignment. On the other hand, activity based models are focused on individual level activity participation resulting in computationally intensive yet behaviorally rich frameworks. In the US, both approaches are widely applied. Unlike the trip-based model, the basic element of activity travel pattern is a tour. The models is more disaggregate in nature accommodating for a finer resolution for demographics, space and time dimensions. While activity-based models are likely to improve sensitivity to policy changes; developing these models are expensive, time consuming and technically skill intensive. Therefore, to date, trip-based model with various enhancement of four-step approach still remain the most commonly employed framework for transportation planning in urban metropolitan regions. Further, as the CFRPM model is a trip-based model, the literature review is also primarily focused on trip-based approaches.

For the purpose of the review, we have selected five regional planning models developed for Atlanta, Tampa Bay, San Diego, Northern New Jersey and North Florida to compare and contrast with the CFRPM model. An overview of these models providing details of the modeling approach, base year and modeling components is presented in Table 2-1. From Table 2-1, we can see that the common forecasting package employed across the frameworks is the CUBE Voyager framework (also used in CFRPM). In terms of modeling approach, we can see that trip-based method with traditional four-step platform is used for modeling travel demand in most regions (four out of five along with CFRPM). The table also indicates the presence of activity based model developed for North Florida region (Jacksonville, FL).

With respect to modeling components, from Table 2-1, we can see that the traditional four-step modeling process is enhanced with different supplemental model steps. The inclusions of these enhancements have evolved with new transportation planning needs for different regions and are inspired by advanced computational and forecasting techniques. On the other hand, the activity-based model for North Florida region employs a fundamentally different structure for travel demand modeling with focus on individual level than on the zonal level.

2.2.2 Comparison of Different Modeling Steps

As activity based models are fundamentally different, a comparison with CFRPM would not be very useful. Hence, the comparison of different travel demand models is restricted only to the trip based model identified in Table 2-1. Further, as we discussed in previous section, the conventional four-step modeling approach has been enhanced with different supplemental modeling steps. However, these enhancements are not uniform across different regions. Hence, it is beyond the scope of this report to compare these various enhancements with steps in CFRPM. Therefore, to keep the discussion relevant to CFRPM, we compare and contrast the basic four-steps (trip generation, trip distribution, mode choice and trip assignment) of trip-based demand models with an emphasis on non-motorized and transit components.

Table 2-1: Overview of Selected Travel Demand Models for Different Regions

Area	Model	Modeling tool	Modeling approach	Base year	Modeling components
Central Florida (Flemming, 2010; CFRPM v5.6, 2012)	Central Florida Regional Planning Model	CUBE Voyager	Trip-based	2005	• External trips • Trip generation • Highway network • Highway path • Trip distribution • Transit network • Mode choice • Highway assignment • Transit assignment
Atlanta (ARC, 2011)	Atlanta Regional Commission (ARC) travel demand model	ALOGIT	Trip-based	2005	• Trip generation • Trip distribution • Mode choice • External/internal model • Commercial vehicle and truck models • Airport passenger model • Assignment model • Networks
Tampa Bay (TBRPM v7.0, 2010)	Tampa Bay Regional Planning Model (TBRPM)	CUBE Voyager, TP+ for transit modeling	Trip-based	2006	• External trips • Trip generation • Highway Network and Path • Trip distribution • Transit network • Transit path • Mode choice • Highway assignment • Transit assignment

Table 2-1 (Continued): Overview of Selected Travel Demand Models for Different Regions

Area	Model	Modeling tool	Modeling approach	Base year	Modeling components
San Diego (SANDAG, 2011)	San Diego Regional Travel Demand Model	TransCAD, ArcInfo	Trip-based	2008	• Trip generation • Path building and skimming • Trip distribution • Mode choice • Truck model • Highway assignment • Transit assignment
Northern New Jersey (NJRTME, 2008)	North Jersey Regional Transportation Model	CUBE Voyager	Trip-based	2000	• Trip generation • Trip distribution • Mode choice • Time of day trip allocation • Highway assignment • Transit assignment
North Florida (NERPM-AB v.1.0, 2015)	Northeast Regional Planning Model: Activity-Based (NERPM-AB)	DaySim, Cube Voyager	Activity-based	2010	• Population synthesis • Usual location choice model • Usual school location sub-model • Auto ownership model • Day pattern models • Non-Mandatory Tour Destination Choice • Tour Mode Choice • Time-of-Day Choice Model • Highway assignment • Auxiliary Demand • Transit assignment

2.2.2.1 Trip Generation
A summary of trip generation component of the selected travel demand models are presented in Table 2-2. The information provided in Table 2-2 include unit of geography, flow unit of daily trip, explanatory variables employed and trip purpose. From Table 2-2 we can see that for all models, trips are aggregated at spatial geography unit of Traffic Analysis Zone (TAZ). In terms of flow unit, the estimated number of trips is considered by mode (both motorized and non-motorized mode) in all models other than the models for Central Florida and Tampa Bay. Further, the model for San Diego also considered transit trips separately from motorized trips. With respect to trip purpose, it is evident from Table 2-2 that CFRPM considers the fewest number of trip purposes compared to other demand models presented. From Table 2-2 we can also see that CFRPM employs only the zonal characteristics in trip generation. Unlike other models, household attributes, roadway characteristics or accessibility measures were not explored.

<u>*Recommendations:*</u> Recommendations from the review of trip generation step that are relevant to the CFRPM model enhancements are summarized below.

- ➢ Trip generation can be enhanced by considering exogenous variables such as household attributes, roadway characteristics and accessibility measures (relevant to non-motorized and transit modes). This will allow trip generation to be sensitive to non-motorized and transit infrastructure changes.
- ➢ Different trip purposes exhibit different sensitivity to non-motorized and transit infrastructure. Hence, considering additional trip purposes in the CFRPM framework would enhance the trip generation resolution.

2.2.2.2 Trip Distribution
A summary of trip distribution step for the selected demand models are presented from the perspective of methodology, impedance variables, input and output of trip distribution step in Table 2-3. In terms of methodology, from Table 2-3 we can see that Gravity model is employed for trip distribution step in all of our selected travel demand models. Due to the simple formulation of Gravity model, it is easy to estimate and calibrate. The term impedance is a measure of the cost of travel between two zones. With respect to impedance variables, it is evident from Table 2-3 that the models for Central Florida and Tampa Bay have considered level-of-service variables (time, distance and cost) related to auto mode only to calculate impedance measures for the input in the trip distribution step. Composite impedance measures (combination of impedance measures for both motorized and non-motorized modes) are not explored in the models for these areas. From the input column of Table 2-3, we can see that, in general, the input for trip distribution step include trip production and attraction by zones, impedances and friction factors. In order to adjust trip distribution patterns of zones, some of the models (Tampa Bay, San Diego, and Northern New Jersey) have also used k-factor (also known as balancing factor). However, k-factor might interfere with future travel prediction ability of demand models, and hence are recommended to be employed cautiously. In general, the output of trip distribution step is production-attraction zonal trips by purpose.

Table 2-2: Trip Generation

Area	Unit of geography	Flow unit of daily trip	Explanatory variables	Trip purpose
Central Florida	TAZ	Person trip	Population classified by single family and multi-family, dwelling units classified by single family and multi-family, number of apartments, mobile homes, recreational vehicle spaces, hotel/motel/timeshares, number of employees by type, and school location/enrollment totals, external trips, spatial trip generator	Home-based work Home-based shopping Home-based social recreational Home-based other Non-home-based
Atlanta	TAZ	Person trip including walking and bicycling trips	Household (HH) size, HH income group, number of workers, number of children, number of autos, highway accessibility measure, transit accessibility measure, density of household, distance access measure, transit accessibility, total employment, employment class	Home based work Home based shopping Home based grade school Home based university Home based other Non-home based
Tampa Bay	TAZ	Vehicle trips	Population, dwelling units, vacancy rates, lifestyle by auto ownership, and hotel/motel units, employment, school enrollment, trucks, and parking costs, average auto occupancies by trip end type, area type, retired households, working households without children, working households, external trips	Home based work Home based shopping Home based strategic Home based other Home based school Non-home based work Non-home based other Light truck Heavy truck Taxi Airport College/University

Table 2-2 (Continued): Trip Generation

Area	Unit of geography	Flow unit of daily trip	Explanatory variables	Trip purpose
San Diego	TAZ	Person trips including automobiles, light-duty trucks, taxicabs, motorcycles, public transits, bicycling and walking	Dwelling unit by structure type, population by age category, land use acres by land use type, employment by land use type, unique generator trips, external trips, trip rates, regional control variables	Home based work Home based college Home based shopping Home based other Work based other Other-other Serve passenger Visitor Regional airport
Northern New Jersey	TAZ	Person trips including motorized and non-motorized modes	Life Cycle, income, household size, number of workers, area type, population/employment density, intersection/network density, pedestrian restrictive network, availability of autos to the traveler, street network connectivity	Home-based Work Direct Home-based Work Strategic Home-based Shop Home-based Other Home-based University Work-based Other Non-Home Non-Work Airport Truck trip

Table 2-3: Trip Distribution

Area	Methodology	Impedance variables	Input	Output
Central Florida	Gravity model	In-vehicle travel time, prohibited movements, penalized movements, toll cost, toll service time	Trip productions and attractions by TAZ, travel impedance is travel time, terminal time and toll cost are also considered as additional travel impedance, trip length frequency (represented by friction factors)	Production-attraction zonal trip tables by purpose
Atlanta	Gravity model	Transit travel time, auto travel time	Composite impedance (auto and transit), trip production and attraction by zone and trip purpose, friction factor	Production-attraction zonal trip tables by purpose and by market groups (combination of car ownership and income)
Tampa Bay	Gravity model	Travel time, turn penalties, toll equivalent time, and acceleration/deceleration delay time, terminal time, parking cost	Highway impedance (auto), trip production and attraction by zone and trip purpose, friction factor, k-factor	Production-attraction zonal trip tables by purpose
San Diego	Gravity model	Auto impedances (travel time, travel distance, toll cost), transit impedances (number of transfers, cash fare, first wait time, transfer wait time, transfer walk time, in-vehicle travel time, main mode indicator), non-motorized mode impedance (travel distance, elevation, walkability factor)	Trip production and attraction by zone and trip purpose, composite impedances (auto, transit and non-motorized) for peak and off-peak conditions, friction factors, Balancing factor for zones	Production-attraction zonal trip tables by purpose
Northern New Jersey	Gravity model	Auto travel time, toll cost, in-vehicle travel time (in-vehicle and drive access) for transit, out-of-vehicle time (walk and wait) for transit, transit fare, park and ride cost	Composite impedance (auto and transit), zonal trip ends (productions and attractions), friction factors, and The specific zone-to-zone adjustment factor (k-factor)	Production-attraction zonal trip tables by purpose and income group combination

Recommendations: Recommendations from the review of trip distribution step that are relevant to the CFRPM model enhancements are summarized below.

- Enhance the impedance computation by allowing for transit and non-motorized components thus developing a multi-modal impedance measure for CFRPM model. The improved measure will enhance the sensitivity of the model to proposed transit and non-motorized infrastructure changes.

2.2.2.3 Mode Choice

A summary of mode choice step for the selected travel demand models is presented in Table 2-4. The information provided in Table 2-4 includes modes considered, modeling framework, explanatory variables, and output of mode choice step. With respect to mode considered, it is evident from Table 2-4 that non-motorized modes (pedestrian and bicycle) are considered in the mode choice models for San Diego and North New Jersey only. However, auto (reflecting occupancy levels) and transit (reflecting transit access mode and transit ride mode) modes are considered in all models. In terms of modeling framework, mode choice models are estimated by using a nested logit model in all regional models considered in our literature review.

From Table 2-4, it is evident that level-of-service variables (travel time, travel distance, and travel cost for available modes) are the most commonly used explanatory variables in developing mode choice models. Trip maker attributes, household characteristics, land-use variables, roadway network characteristics, and infrastructure for transit/non-motorist are rarely considered. For example, household and transit infrastructure characteristics are considered in the model for Atlanta, while land-use variables are considered in the model for San Diego. In general, the output of the mode choice step of a travel demand model is a set of person-trip tables by available mode and trip purposes explored. However, mode choice trip tables are also quantified by different time periods (peak and off-peak periods) in the models for different areas (Central Florida and San Diego). Quantifying mode choice separately by different time periods reflects the quality of service provided by different available modes across different time periods.

Recommendations: Recommendations from the review of mode choice step that are relevant to the CFRPM model enhancements are summarized below.

- In the CFRPM model choice model, non-motorized alternatives should be added. In order to retain the existing structure of the framework, the addition of non-motorized modes can be undertaken only for specific zonal pairs. To elaborate, zonal pairs which are within the walking distance need to be considered. Similarly, for adding bicycling mode, only zonal pairs within bicycling distance need be considered. The incremental process will allow us to retain the original mode choice model with minor modifications to enhance the CFRPM framework.
- The mode choice model can be further enhanced by considering individual and household socio-demographics, roadway network characteristics, transit infrastructure, and non-motorized accessibility measures.

Table 2-4: Mode Choice

Area	Modes considered	Modeling framework	Explanatory variables	Output
Central Florida	• Drive alone • 2 person shared ride • 3 + shared ride • Walk to transit • Park and ride • Kiss and ride • Local bus • Express bus • Urban rail • Commuter rail	Nested logit model	Transit walk time, highway terminal time, transit auto access time, transit run time, highway run time, transit wait time, transit transfer time, transit number of transfers, transit fare, highway auto operating costs, highway parking costs, HOV time difference	Mode choice for two time periods (peak and off-peak hours) and trip purposes
Atlanta	• Drive alone • 2 person shared ride • 3 person shared ride • 4+ person shared ride • Walk to transit • Drive to transit • Non-premium trips • Premium trips • Park and ride • Kiss and ride	Nested logit model	Auto ownership, number of workers in household, initial wait time, walk time, drive time, in-vehicle time, transfer time, block per square mile	Mode choice by trip purpose and market groups (combination of car ownership and income)
Tampa Bay	• Drive Alone • Share Ride • Transit	Nested logit model	Transit system station information, highway toll plaza characteristics, terminal time, walk time, terminal time, interzonal time, drive cost, drive distance, drive time	Mode choice by trip purpose

Table 2-4 (Continued): Mode Choice

Area	Modes considered	Modeling framework	Explanatory variables	Output
San Diego	• Drive alone non-toll trip • Drive alone toll trip • Two person shared-ride non-toll non-high occupancy vehicle (HOV) trip • Two person shared-ride non-toll HOV trip • Two person shared-ride toll HOV trip • 3+ person shared-ride non-toll non-HOV trip • 3+ person shared-ride non-toll HOV trip • 3+ person shared-ride toll HOV trip • Bicycle trip • Pedestrian trip • Walk to transit • Drive to transit • Drop off at transit station • Local bus • Express bus • BRT/rapid bus • Light rail/street car • Commuter rail	Nested logit model	Trip distance, auto travel time, transit travel time, highway tolls, non-motorized distance, transit fares, auto operating cost, parking cost, terminal time, transit transfer time, wait time, land use density, employment density, intersection density	Mode choice for two time periods (peak and off-peak hours), three income levels (low income, middle income and high income) and six trip purposes
Northern New Jersey	• Drive alone • 2 person shared ride • 3 person shared ride • 4+ person shared ride • Walk to transit • Drive to transit • Rail • PATH system • Bus • Ferry • LRT • LDF	Nested logit model	In-vehicle travel time for auto and transit, walk time, bike time, drive access time, drive cost, transit fare, transit distance, use of subway, distance between different transit mode	Mode choice by trip purpose

2.2.2.4 Trip Assignment

A summary of trip assignment across the models is presented in Table 2-5. The information provided in Table 2-5 include step components, model structure, input and output of trip assignment. From Table 2-5, we can see that for all regions (other than Atlanta), this step includes two components: highway and transit assignment components. User equilibrium assignment process is mostly used (other than San Diego) for trip assignment. The output from the assignment process is the daily traffic volume associated with highway assignment process and daily ridership of transit from transit assignment process. The current research effort is primarily geared towards the first three steps of the trip based model and hence we do not intend to modify the CFRPM trip assignment framework. We provide recommendations for future research consideration.

<u>*Recommendations:*</u> Recommendations from the review of trip assignment step that are relevant to the CFRPM model enhancements are summarized below.

- The trip assignment step of CFRPM might be improved by employing multiple class assignment algorithm based on generalized cost.

Table 2-5: Trip Assignment

Area	Components	Model structure	Input	Output
Central Florida	Highway assignment Transit assignment	User equilibrium assignment process	Vehicle trips, volume delay function, highway network	Daily traffic volume Daily boardings of transit
Atlanta	Highway assignment	Standard equilibrium technique	Vehicle trips by mode, volume delay function, value of time factors, highway network	Daily traffic volume by facility types
Tampa Bay	Highway assignment Transit assignment	Equilibrium assignment procedure	Trip table, highway network attributes, transit network attributes	Daily traffic volume Peak and off-peak hour boardings of transit
San Diego	Highway assignment Transit assignment	Multi-modal multi-class assignment	Vehicle trips between zones, highway network, volume-delay function, traffic counts	Daily and peak hour traffic volume Daily and peak hour boardings of transit
Northern New Jersey	Highway assignment Transit assignment	User equilibrium assignment process	Vehicle trips between zones, highway network, volume-delay function, traffic counts	Daily traffic volume Weekday boardings of transit

2.3 REVIEW OF COST-BENEFIT ANALYSIS STUDIES

Given the limited financial resources for urban transportation planning organizations it is important to quantitatively analyze the impacts of transportation investments in an effort to maximize the resource allocation efficiency across different transport needs. Cost-benefit analysis (CBA) is considered to be one of the most appropriate tools in evaluating transportation policies and projects (Litman, 2001). A comprehensive CBA would allow analysts to predict several direct and/or indirect impacts of improvements in existing system or proposed new infrastructures. In terms of investments for transport infrastructure; spending money for pedestrian, bicycle and transit infrastructures are often a low priority compared with investments on roads, improvements to traffic flow and other government expenditure. However, more recently investments in pedestrian, bicycle and transit infrastructures have gained traction from transport authorities as a measure of reducing negative externalities of increasing private auto mode usage. To be sure, increasing walking and bicycling will also provide health benefits to the urban residents. A comprehensive CBA of public transit and non-motorized mode investments would assist the planners and policy makers to evaluate the "real" benefit of these investments and provide evidence to justify allocation of more funding for improving/building pedestrian, bicycle and public transit infrastructures. The current research report focuses on reviewing existing literature of CBA for pedestrian, bicycle and transit infrastructure investments. The literature review will enable the research team to identify several factors that are generally considered in different components of CBA and thus aid in developing a template for CBA for the Central Florida region. The purpose of the literature review is to identify several factors that are generally considered as cost and benefit components of CBA for pedestrian, bicycle and public transit infrastructure investments. Hence we focus our review on relevant studies that evaluated cost and/or benefit components for non-motorized and public transit modes of transport.

2.3.1 Non-motorized CBA

In terms of non-motorized modes, most of the earlier studies were focused on bicycle infrastructure investments evaluations. Very few studies have focused on investments on pedestrian infrastructure investments. Litman (2013) presented a comprehensive method for evaluating cost and benefits of non-motorized transport modes. The author argued that the benefit components of non-motorized mode should include: user benefits, option values (value of available transport options), equity benefits, physical fitness and health, vehicle savings, reduced chauffeuring burdens, congestion reduction, barrier effects, roadway cost savings, parking cost savings, traffic safety impacts, security impacts, energy conservations, pollution reductions, land use impacts and economic developments. On the other hand, the cost component should include: facility cost, vehicle traffic impacts, equipment cost and user travel time cost. The author concluded that conventional economic evaluation studies usually tend to undermine active transport, thus a comprehensive economic evaluation would provide true benefits of this mode, which would further encourage more investments for improving and promoting active transport.

Krizec (2007) evaluated the economic benefits of bicycle facilities. Guided by 25 previous studies, the study documented six core benefits, belonging to direct (mobility, health and safety) and indirect (decreased externalities, liveability and fiscal) benefits, of municipal and regional bicycle facilities. Gotschi (2011) performed a CBA of Portland's past and planned investments in bicycle infrastructures in terms of health benefits and fuel savings. They found that benefit-cost ratios for health care and fuel savings are between 3.8 and 1.2 to 1, respectively. Sælensminde (2004) presented CBA of walking and bicycling track networks of three Norwegian cities (Hokksund, Hamar and Trondheim). In the benefit component, the author considered the benefits of reduced insecurity, safety, health cost, cost of transport, noise, pollution and parking cost. Capital, maintenance and tax costs were considered in cost component of the study. The study found that the benefits of investments in walking and cycling networks is at least 4-5 times the costs. Some of the studies have also evaluated CBA for a specific investment project. For instance, Korve and Niemeier (2002) developed a CBA framework for an added bicycle phase at an existing signalized intersection. The components included in the analysis were construction cost, operating cost, delay, safety, vehicle capacity and emission. From the evaluation, the authors argued that benefits associated with bicycle safety due to improved bicycle infrastructure outweigh all considered costs.

2.3.2 Public Transit Cost-Benefit Analysis

Several studies have evaluated CBA in terms of transit infrastructure investments. Weisbrod et al. (2014) performed an economic impact analysis of public transportation investments. From the long term impact analysis, the study concluded that increased transit investments have potential for significant economic gain as well as societal benefits. They showed that a programme of enhanced public transit investment over twenty years will lead to an increase in income that is equivalent to approximately 50,000 additional jobs per $1 billion invested. Litman (2004) provided a framework for evaluating CBA of a particular transit service or improvements. The author pointed out that the conventional transport evaluation model is usually developed based on financial cost to government, vehicle operating cost, travel speed, crash risk and project construction environmental impacts. These studies overlook many benefits factors; such as downstream congestion impact, parking cost, environmental impacts, strategic land use impact, equity impact, public health and transportation diversity value.

Godavarthy et al. (2014) have documented and quantified benefits of small urban and rural transit systems in the US by employing CBA. The authors categorized transit benefits in three components: transit cost savings benefits (vehicle ownership and operation expenses, chauffeuring cost savings, taxi trip cost savings, travel time cost savings, crash cost savings and emission cost savings), low-cost mobility benefits and economic impact benefits. Cost component included capital, operation and maintenance costs. From the extensive analysis results, the authors concluded that the benefits (benefit-cost ratio greater than 1) provided by transit services in rural and small urban areas are greater than the costs of these services. With respect to rail transit system, Gordon and Kolesar (2011), in an effort to perform CBA for rail transit system in modern American cities, also considered non-user benefit in the benefits component other than conventional benefit measures. The non-user benefits included was number of auto trips avoided by any new-to-transit passengers. Based on the analysis, the authors found that rail transit system into modern American cities cannot be justified on economic ground even after accounting for non-user benefits in the assessments.

Bus Rapid Transit (BRT) has emerged as an attractive public transit system to enhance level of accessibility, mobility and system capacity. Some of the studies have conducted CBA for BRT system as well. Ang-Olson and Mahendra (2011) discussed a methodology of CBA for evaluating the potential benefits of converting a mixed traffic lane to an exclusive BRT lane at a corridor, local and regional level. The costs quantified in the analysis were capital cost, operation and maintenance costs. The benefits component included change in crash cost, travel time change cost, travel cost savings, emission and noise reduction costs and indirect social benefits (land development impacts, savings in parking costs, accessibility impacts and system reliability impacts). From the analysis of a hypothetical project, the authors showed that converting an arterial traffic lane for BRT can result in positive net benefits if the arterial has high person throughput and relatively high pre-project transit mode share. Blonn et al. (2006) analyzed costs and benefits of implementing a BRT system in the greater Madison metropolitan area. The analysis was conducted by considering several costs (raising local revenue, capital cost, operations and maintenance costs) and benefits (reduced travel time, reduced vehicle user cost, reduced emission and reduced crash cost). Based on the CBA, the authors concluded that implementing a BRT system in the greater Madison metropolitan area would return negative net benefits and hence would not be justified to implement on efficiency grounds.

2.3.3 Directions for CFRPM Based Cost-Benefit Analysis

CBA is an essential component that can assist decision makers to implement the most efficient solutions for travel demand management. In order to evaluate the implications of several alternative solutions, it is important to consider all the costs and benefits factors entailed by the project. To that extent, in this section we identify and present several factors, in light of the literature review, that might be considered for CFRPM based CBA for pedestrian, bicycle and public transit investments. A list of the proposed benefits and costs factors along with the measure definition and generation mechanism is presented in Table 2-6. The dimensions identified in Table 2-6 will be adopted for CBA in Chapter IX.

Table 2-6: Benefits and Costs Factors for CFRPM-Based Cost-Benefit Analysis

Factors	Measure definition	Generation Mechanism
	BENEFIT COMPONENTS	
Auto user benefits	Reduced expenditures on motorized travel, vehicle ownership and operation cost savings – includes congestion reduction, gas and energy savings and pollution reduction	CFRPM Mode choice and Traffic Assignment
Non-motorized user benefits	Increased adoption of non-motorized mode	CFRPM Mode choice model
Traffic Safety Benefits	Reduced non-motorized crash rates	Estimated using models developed in future tasks
Transit ridership	Increase in transit revenue	Estimated using models developed in future tasks
Increased property value	Effects of walking, cycling and transit infrastructure improvements on nearby property values	Predefined values for different land-use type
Physical Fitness and Health	Increase in physical activity and the consequent health benefits	Estimated using models developed in future tasks
	COST COMPONENTS	
Capital costs	Costs of infrastructure improvement	To be obtained from FDOT
Operation costs	Costs of fuel and employer salaries of transit agencies, Incremental costs to users of shoes and bicycles	To be obtained from FDOT
Maintenance costs	Travel time unit costs for different modes	To be obtained from FDOT

2.4 SUMMARY

This chapter summarized the modeling procedure of the travel demand modeling frameworks for four urban regions of the US and compared that with the CFRPM approach. For the purpose of the review, we selected five regional planning models developed for Atlanta, Tampa Bay, San Diego, Northern New Jersey and North Florida to compare and contrast with the CFRPM model. Based on the review, we provided recommendations for potential updates to the CFRPM in terms of trip generation, trip distribution, mode choice and trip assignment steps of travel demand model. Further, in this chapter, we also provided a review of cost-benefit analysis conducted for public transit and non-motorized mode investments. Based on the review, we identified and documented different dimensions of the CFRPM model to be targeted in undertaking the cost-benefit analysis.

CHAPTER III: DATA ASSEMBLY

3.1 INTRODUCTION

The research of evaluating multi-modal mobility for the Central Florida region (District 5) was targeted towards predicting the tendency for auto vs. non-auto mode choice by individual citizens, and the resulting increase in mobility, by employing an existing regional model framework and based on the level of transit and non-motorized investments. The objective of the study was to update the District 5 travel forecasting framework. Incorporating non-auto mode accessibility within the travel demand forecasting process involves acquiring and compiling data from multiple sources. This chapter documents the data compilation and data preparation procedures along with summary statistics for attributes that are used by analysts at different stages of analysis in evaluating the multi-modal investments on promoting integrated travel mobility in Central Florida.

The chapter summarizes several sociodemographic, socioeconomic, and built environment characteristics. These attributes serve as indicators of overall travel behaviour and travel demand of a community. In order to represent the supply side of the transportation network in terms of auto and public transit modes, several attributes representing transportation infrastructure, traffic characteristics, and transit facilities were also compiled. For identifying public transit demand, public transit ridership data is also collected and documented. Finally, to evaluate the demand of non-auto (pedestrian and bicycle) modes, to examine the effectiveness of enhanced non-motorized mobility, and to identify safety-related issues of non-motorists, we also compiled a number of attributes representing pedestrian and bicycle facilities, pedestrian counts, and crash records of pedestrians and bicycles for the study area. The chapter contains a detailed description of the data sources and methodologies to calculate each of the aforementioned attributes.

The remainder of the chapter is organized as follows. The next section describes the data along with the study area. The subsequent section focuses on data compilation procedures followed by data description and summary of the chapter.

3.2 STUDY AREA

The study area includes the TAZ defined for Central Florida Regional Planning Model version 6.0 (CFRPM 6.0). CFRPM 6.0 includes a total of 5,350 TAZs; among these, 4,747 TAZs are internal zones, and 603 TAZs are external zones. The boundary of the study area encompasses nine counties (Brevard, Flagler, Lake, Marion, Orange, Osceola, Seminole, Sumter, and Volusia) within FDOT District 5, Polk County within FDOT District 1, and part of Indian River County in FDOT District 4. Further, the component of public transit ridership evaluation of the research effort is mainly focused on the coverage area of Lynx and SunRail network systems. Lynx is a public bus system that is operated in the city of Orlando with the connection between Orange, Seminole, and Osceola counties along with limited service in Polk County. The bus transit system serves approximately 2,500 square miles with a population more than 1.8 million. SunRail, a commuter rail system, started its service in greater Orlando on May 1, 2014. It comprises 31 miles of rail line along with 12 active stations that connect Volusia and Orange Counties. The County boundaries along with the TAZ outlines, SunRail station, SunRail line, and Lynx bus route of the study area are presented in Figure 3-2.

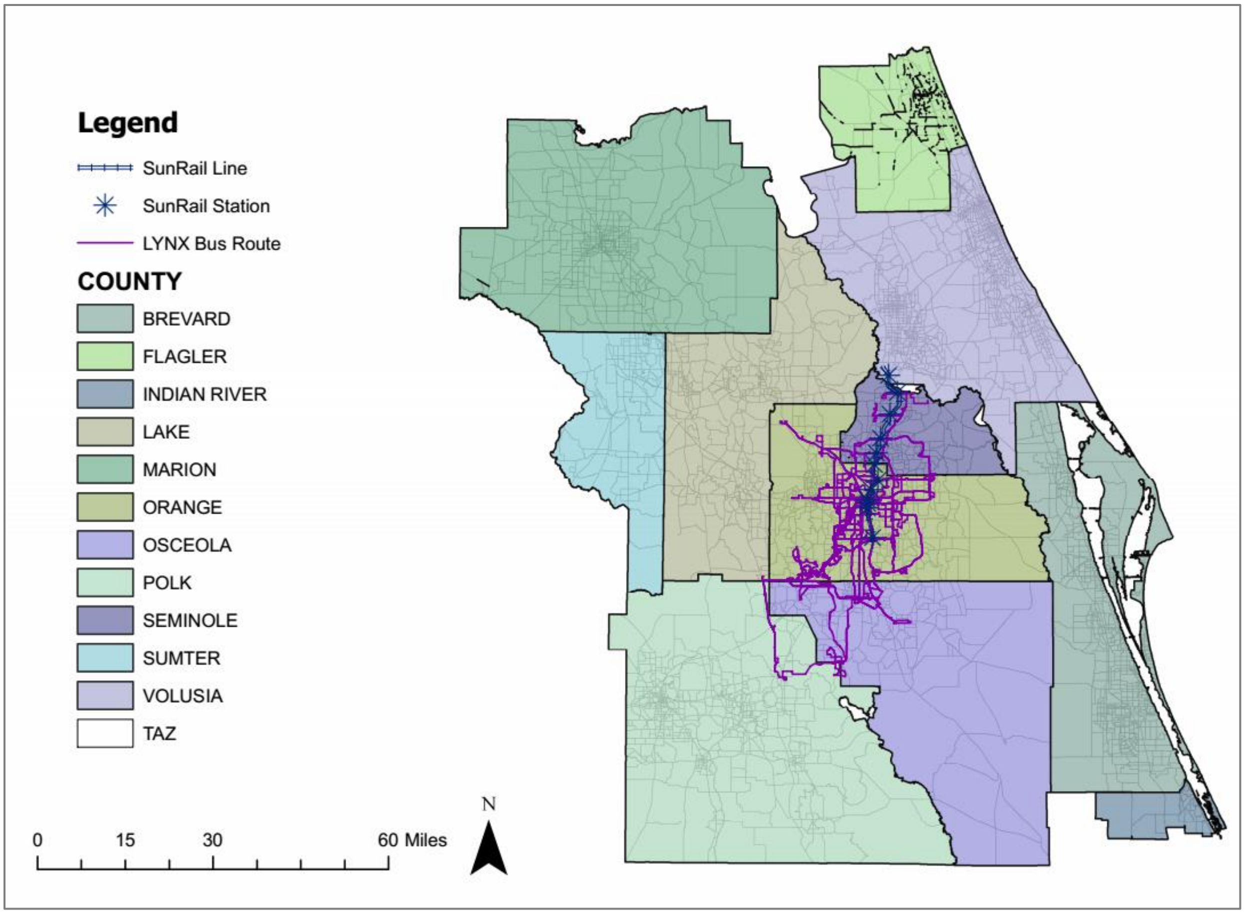


Figure 3-2: Study Area Along with County Boundaries

3.3 DATA COMPILATION

For different levels of analysis, we have assembled variables from eight broad categories: Sociodemographic characteristics, Socioeconomic characteristics, Built environment, Transit attributes, Bicycle attributes, Pedestrian attributes, Transportation infrastructure and Traffic characteristics. These variables are collected from different data sources including: 2010 US census data, 2010 American Community Survey (ACS), Florida Geographic Data Library (FGDL), Florida Department of Transportation (FDOT), Lynx, SunRail management and Signal Four Analytics (S4A). Table 3-7 represents the list of these variables along with the data sources. In the following section, we present the description of these variables.

Table 3-7: Candidate Variables List

Variables Descriptions	Data Source
Sociodemographic Characteristics	
Total population	CFRPM 6.0
Total population by gender	2010 US Census
Total population by age	2010 US Census
Total population by race	2010 US Census
Total number of HH	CFRPM 6.0
HH by family structure	CFRPM 6.0
Total number of owner/tenure occupied HH	2010 US Census
HH year built	2010 ACS
Socioeconomic Characteristics	
HHs by poverty status	2010 ACS
Population by educational attainment	2010 ACS
Number of commuters by commute mode	2010 ACS
Population by school enrollment	2010 ACS
Population by poverty status	2010 ACS
Population by income level	2010 ACS
Number of HH by vehicle ownership	CFRPM 6.0
Number of Jobs	CFRPM 6.0
Jobs by Employment Type	CFRPM 6.0
Built Environment	
General land use types	FGDL
Urban area	FGDL
Number of law enforcement offices	FGDL
Number of hospitals	FDOT
Number of restaurants	FDOT
Number of shopping center	FDOT
Number of Night Clubs, Bars, and Cocktail Lounges	FGDL
Number of park and recreational center	FDOT
Number of educational institution	FDOT
Transit Attributes	
Number of bus stops	Lynx
Length of bus route	Lynx
Presence of bus stop shelter	Lynx
Bus ridership	Lynx
SunRail station	ArcGiS online
SunRail line	ArcGiS online
SunRail ridership	FDOT and SunRail Management
Bicycle Attributes	
Bike lane length	FGDL
Bike slots	FGDL
Bicycle crash records	S4A

Table 3-7 (Continued): Candidate Variables List

Variables Descriptions	Data Source
Pedestrian Attributes	
Sidewalk barrier length	FDOT
Sidewalk width and separation feature	FGDL
Pedestrian count	FDOT
Pedestrian crash records	S4A
Transport Infrastructure	
Major Highways length	FDOT
Secondary Highways Length	FDOT
Streets/Local road length	FDOT
Rail road length	FDOT
Number of intersections	FDOT
Inside shoulder type	FDOT
Inside shoulder width	FDOT
Median type	FDOT
Median width	FDOT
Outside shoulder type	FDOT
Outside shoulder width	FDOT
Road surface width	FDOT
Rail crossing	FDOT
Number of traffic signals	FDOT
Number of transportation hubs	FDOT
Number of lanes	FDOT
Traffic Characteristics	
Average speed limit	FDOT
Access control type	FDOT
AADT	FDOT
Truck AADT	FDOT

3.3.1 Sociodemographic Characteristics

Sociodemographic characteristics includes total population, total population by gender, total population by age, total population by race, total number of households (HH), HH structure, total number of owner/tenure occupied HH and HH built year. The source of total population, total HHs and HH by family structure variables is collected from CFRPM 6.0 input files, which are available at the TAZ level. Other variables, within this broad category, are compiled from 2010 US census and 2010 ACS databases and are computed at the TAZ level.

3.3.2 Socioeconomic Characteristics

Socioeconomic characteristics includes HHs by poverty status, population by educational attainment, number of commuters by commute mode, population by school enrollment, population by poverty status, population by income level, number of HH by vehicle ownership, number of jobs and jobs by employment type. Amon these variables, HH by vehicle ownership, number of jobs and jobs by employment type are collected from CFRPM 6.0 TAZ level data; rest of the variables are gathered from 2010 ACS database at the TAZ level.

3.3.3 Built Environment

The variables that are compiled within built environment category includes general land use types, number of law enforcement offices, number of hospitals, number of restaurants, number of shopping center, number of educational institution, number of night clubs/bars/cocktail lounges and number of park/recreational center. These variables are gathered in Geographical Information System (GIS) shape file format. Four of the variables (general land use types, urban area, number of law enforcement offices and number of night clubs/bars/cocktail lounges) within built environment category are downloaded from FGDL database and the rest are gathered from FDOT.

3.3.4 Transit Attributes

The variables within broad category representing transit attributes include number of bus stops, length of bus route, presence of bus stop shelter, SunRail station, SunRail line, bus ridership and SunRail ridership. All the transit infrastructure variables are downloaded as GIS shape file either from Lynx website or from ArcGis online. The ridership data are collected from Lynx system and FDOT/SunRail management for bus and SunRail ridership, respectively.

3.3.5 Bicycle Attributes

Bike attributes include bike lane length, bike slots and bicycle crash records. These information are downloaded from FGDL database system in GIS shape file format. Bicycle crash records are collected from S4A crash database.

3.3.6 Pedestrian Attributes

The variables that are compiled within pedestrian attributes category include sidewalk barrier length, sidewalk width and separation feature, pedestrian count and pedestrian crash records. Sidewalk barrier length and sidewalk width/separation feature are gathered from FDOT and FGDL databases, respectively in shape file format. The source of the pedestrian count data is the FDOT field data collection for the year 1999 through 2013. Further, pedestrian crash data is compiled for S4A database.

3.3.7 Transport Infrastructure

The variables within broad category representing transport infrastructure include major highways length, secondary highways length, streets/local road length, rail road length, number of intersections, inside shoulder type, inside shoulder width, median type, median width, outside shoulder type, outside shoulder width, road surface width, rail crossing, number of traffic signals, number of transportation hubs and number of lanes. All these variables are collected from FDOT in GIS shape file format.

3.3.8 Traffic Characteristics

The last broad category of variables representing traffic characteristics include average speed limit, access control type, annual average daily traffic (AADT) and truck AADT. These variables are collected from FDOT in shape file format.

3.4. DATA DESCRIPTION

The level of analysis of multi-modal mobility evaluation can be classified in three groups: (1) individual level (for example pedestrian, bicycle and car) (2) micro-level (for example intersection, bus stop, rail station) and (3) macro-level (for example TAZ, census block). The variables that are compiled from different sources, as presented in Section 3.3, are further processed for different level of analyses. To be sure, the major focus of this research effort is on planning level analysis (macro-level representing zones). In this section, we present the data preparation and summary statistics. Specifically, we have presented the data preparation and summary statistics for base year, for neighbourhood attributes and for bus ridership. Further, we have also presented the summary statistics of SunRail ridership, pedestrian count and pedestrian/bicycle crash data. In the following sections we have presented the data preparation summary statistics for these components.

3.4.1 Sociodemographic and Socioeconomic Characteristics

3.4.1.1 Data Preparation

2010 is considered as base year for this research purpose. Therefore, to reflect the base year demographic and economic characteristics of the analysis zone, the sociodemographic and socioeconomic characteristics are generated for the year 2010. These attributes are compiled from input file of CFRPM 6.0 model, where the variables are available at the TAZ level. Figure 3-3 represents the TAZs of the study area.

3.4.1.2 Summary Statistics

Summary characteristics of sociodemographic and socioeconomic characteristics for 4,747 TAZs are presented in Table 3-8. In Table 3-8 we have presented the minimum, maximum and mean values for different attributes.

3.4.2 Neighborhood Attributes

3.4.2.1 Data Preparation

With respect to transportation planning, a neighbourhood is usually characterized by land use diversity, design of the built environment, access to destinations, pedestrian facilities, bicycle facilities and transportation infrastructures. To that extent, the research team has also generated several variables reflecting built environment, pedestrian attributes, bicycle attributes, transportation infrastructure and traffic characteristics. We have generated these variables for each zone by using ArcGis tool and the attributes are further aggregated at the zonal level to reflect density, diversity and destination attributes of zones related to travel behaviour. The attributes are computed for all 4,747 TAZs.

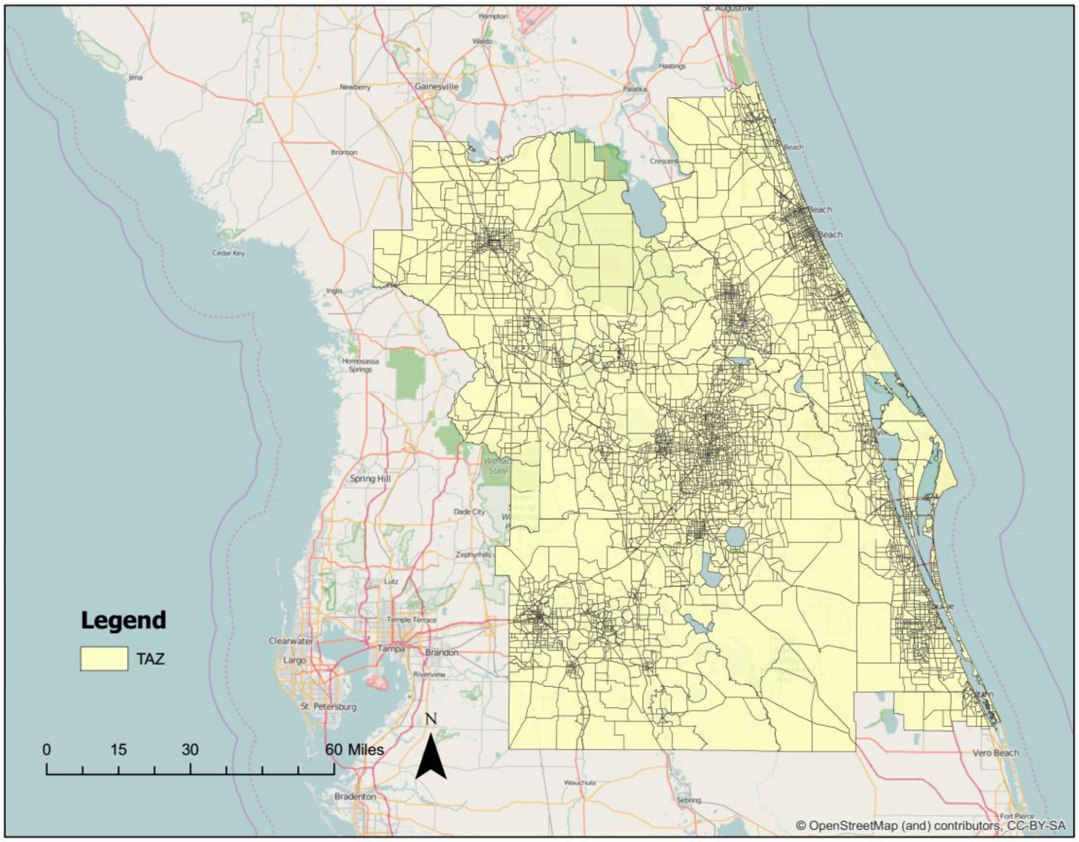


Figure 3-3: Traffic Analysis Zones (TAZ)

Table 3-8: Summary Characteristics for Sociodemographic and Socioeconomic Characteristics

Variables	Minimum	Maximum	Mean
Sociodemographic Characteristics			
Single family HH	0.000	5,763.000	310.699
Multifamily HH	0.000	4,990.000	120.685
Single family population	0.000	15,701.000	724.142
Multifamily population	0.000	12,248.000	206.946
Hotel/motel units	0.000	10,597.000	44.538
Total population in hotel/motel	0.000	22,521.000	90.715
Socioeconomic Characteristics			
Proportion of Single family HH with 0 car ownership	0.000	50.000	4.994
Proportion of Single family HH with 1 car ownership	0.000	98.000	40.982
Proportion of Single family HH with 2 and more car ownership	0.000	100.000	49.307
Proportion of Multifamily HH with 0 car ownership	0.000	57.000	7.202
Proportion of Multifamily HH with 1 car ownership	0.000	100.000	42.730
Proportion of Multifamily HH with 2 and more car ownership	0.000	100.000	44.433
Industrial employment	0.000	6,500.000	63.631
Commercial employment	0.000	5,781.000	114.994
Service employment	0.000	17,905.000	274.377
Total employment	0.000	20,401.000	453.002

3.4.2.2 Summary Statistics

Summary characteristics of neighbourhood attributes for 4,747 TAZs are presented in Table 3-9. In presenting neighbourhood characteristics, we have categorized variables as built environment, bicycle attributes, pedestrian attributes, transportation infrastructures and traffic characteristics. We have also generated transit attributes (specifically for Lynx and SunRail systems), however, those are presented in separate sections of this chapter.

Table 3-9: Summary Statistics for Neighbourhood Characteristics

Variables	Minimum	Maximum	Mean
Built Environment			
TAZ area (sq.Km)	0.011	441.100	6.080
Urban area (sq.Km)	0.000	19.720	1.157
Land use area acreage with zoned for agriculture (sq.Km)	0.000	111.301	0.281
Land use area agriculture (sq.Km)	0.000	333.545	2.244
Land use area industrial (sq.Km)	0.000	2.501	0.038
Land use area institutional (sq.Km)	0.000	4.743	0.035
Land use area mining (sq.Km)	0.000	61.300	0.080
Land use area other land use (sq.Km)	0.000	126.100	0.593
Land use area public or semipublic (sq.Km)	0.000	157.732	0.803
Land use area recreational (sq.Km)	0.000	74.042	0.172
Land use area residential in meter sq	0.000	13.640	0.654
Land use area retail/office (sq.Km)	0.000	2.980	0.088
Land use area vacant non-residential (sq.Km)	0.000	240.803	0.340
Land use area water (sq.Km)	0.000	7.720	0.025
Land use area vacant residential (sq.Km)	0.000	40.603	0.306
Parking lots and mobile home sale slots area (sq.Km)	0.000	2.444	0.020
Count of Law enforcement office	0.000	3.000	0.055
Count of night club, bar and cocktail lounge	0.000	12.000	0.101
Parking lots and mobile home sale slots count from parcel	0.000	94.000	0.596
Transportation hub	0.000	9.000	0.059
Hospital	0.000	4.000	0.020
Educational institution	0.000	9.000	0.346
Count of park and recreational location	0.000	19.000	0.334
Count of restaurants	0.000	39.000	1.620
Count of shopping center	0.000	109.000	2.297
Bicycle Attributes			
Length of bike lane (Km)	0.000	23.440	0.232
Colored bike lane length (Km)	0.000	0.372	0.000
Designated bike lane length (Km)	0.000	23.440	0.230
Undesignated bike lane length (Km)	0.000	3.480	0.002
Composite road side bike lane length (Km)	0.000	6.437	0.004
Left road side bike lane length (Km)	0.000	11.720	0.114
Right road side bike lane length (Km)	0.000	11.720	0.114
Count of bike slots	0.000	19.000	0.300

Table 3-9 (Continued): Summary Statistics for Neighbourhood Characteristics

Variables	Minimum	Maximum	Mean
Pedestrian Attributes			
Length of sidewalk (Km)	0.000	21.418	0.953
Average width of sidewalk (Km)	0.000	0.035	0.003
Average distance of sidewalk from the outer edge of pavement (Km)	0.000	0.097	0.006
Composite: length of sidewalk by side of the road (Km)	0.000	7.056	0.084
Left: length of sidewalk by side of the road (Km)	0.000	11.492	0.444
Right: length of sidewalk by side of the road (Km)	0.000	10.709	0.425
Length of sidewalk with no barrier (Km)	0.000	21.304	0.665
Length of sidewalk with On-street parking lane (Km)	0.000	2.489	0.015
Length of sidewalk with Row of trees, planters, utility poles, etc. (Km)	0.000	5.654	0.039
Length of sidewalk with Guardrail/traffic railing barrier/swale (Km)	0.000	5.495	0.103
Transport Infrastructure			
Length of divided roadways (Km)	0.000	41.194	1.100
Length of Principal Arterial-Interstate - RURAL roadways (Km)	0.000	8.850	0.036
Length of Principal Arterial-Expressway - RURAL roadways (Km)	0.000	37.849	0.035
Length of Principal Arterial-Other - RURAL roadways (Km)	0.000	33.233	0.174
Length of Minor Arterial - RURAL roadways (Km)	0.000	17.267	0.081
Length of Major Collector - RURAL roadways (Km)	0.000	26.585	0.220
Length of Minor Collector - RURAL roadways (Km)	0.000	16.227	0.170
Length of Local - RURAL roadways (Km)	0.000	21.376	0.084
Length of Principal Arterial-Interstate - URBAN roadways (Km)	0.000	6.577	0.071
Length of Principal Arterial-Freeway and Expressway - URBAN roadways (Km)	0.000	5.715	0.076
Length of Principal Arterial-Other - URBAN roadways (Km)	0.000	8.478	0.389
Length of Minor Arterial - URBAN roadways (Km)	0.000	10.042	0.338
Length of Major Collector - URBAN roadways (Km)	0.000	13.217	0.605
Length of Minor Collector (Fed Aid) - URBAN roadways (Km)	0.000	18.182	0.260
Length of Local - URBA roadways (Km)	0.000	5.386	0.082
Length of rail line (Km)	0.000	38.893	0.282
Number of intersections	0.000	107.000	9.801
Flashing Beacon count	0.000	2.000	0.008
Traffic signal count	0.000	7.000	0.376
Mid-block pedestrian control count	0.000	1.000	0.003
Emergency signal count	0.000	1.000	0.005
School signal count	0.000	1.000	0.001
Other type of signal count	0.000	5.000	0.063
Average surface width of roadway (ft)	0.000	55.250	20.116

Table 3-9 (Continued): Summary Statistics for Neighbourhood Characteristics

Variables	Minimum	Maximum	Mean
Traffic Characteristics			
Average maximum speed (miles/hour)	0.000	70.000	36.535
Length of full controlled road (Km)	0.000	37.849	0.219
Length of partial controlled road (Km)	0.000	3.537	0.009
Length of no control road (Km)	0.000	45.800	2.376
Vehicle miles travelled (per 1000)	0.000	819.101	23.666
Truck vehicle miles travelled (per 1000)	0.000	101.887	2.082

3.4.3 Bus Ridership Data

3.4.3.1 Data Preparation

As of January 2016, there were a total of 4,401 active Lynx bus stops. Figure 3-4 presents the location of these bus stops. Bus ridership was examined in order to identify the demand of bus transit at stop level and to evaluate the influence of SunRail on bus ridership. Towards that end, we prepared a dataset at the stop level.

3.4.3.2 Summary Statistics

For our analysis, average daily weekday boarding and alighting ridership data were considered from 2013 to 2016 for the following eleven time periods: (1) May through August 2013, (2) September through December 2013, (3) January through April 2014, (4) May through August 2014, (5) September through December 2014, (6) January through April 2015, (7) May through August 2015, (8) September through December 2015, (9) January through April 2016, (10) May through August 2016, and (11) September through December 2016. The number of bus stops considered for analysis included 3,444 stops. The final sample consisted of 37,884 records (3,444 stops × 11 quarters). The average daily stop-level boarding (alighting) was around 18.84 (18.70) with a minimum of 0 (0) and maximum of 6,135 (5,943). A summary of the system-level ridership (boarding and alighting) were provided in Table 3-10. The standard deviation was large as the ridership is varied widely across different bus stops in our analysis. We have also calculated headways for different bus stops from the headway data of each bus route. The main source the route's headway was the Lynx website. Frequency distribution of stops across different headway categories is presented in Figure 3-5.

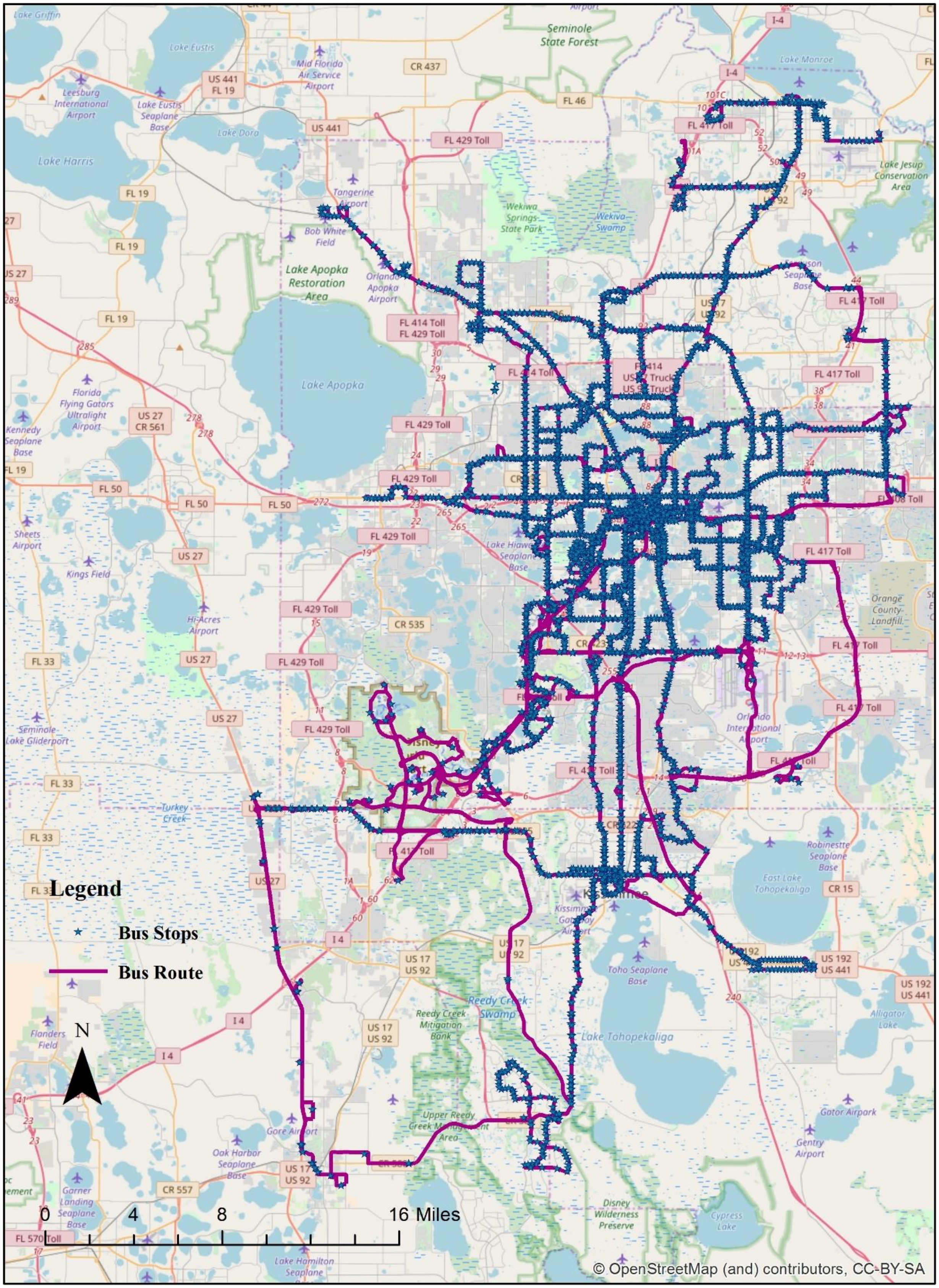


Figure 3-4: Lynx Bus Stop and Route Locations

Table 3-10: Summary Statistics for Lynx Bus Ridership (August 2013 to April 2015)

Time-period	Quarter Name	Boarding		Alighting	
		Mean	Standard Deviation	Mean	Standard Deviation
1	August-13	19.91	140.54	19.63	132.67
2	December-13	19.17	135.70	19.04	129.16
3	April-14	19.03	142.17	18.88	137.42
4	August-14	19.66	144.18	19.50	136.68
5	December-14	18.51	132.80	18.45	128.70
6	April-15	18.81	138.54	18.89	133.20
7	August-15	18.79	138.63	18.77	132.55
8	December-15	18.55	131.09	18.43	129.42
9	April-16	17.84	127.10	17.83	126.67
10	August-16	18.64	131.77	18.50	130.15
11	December-16	18.29	129.38	17.84	124.80

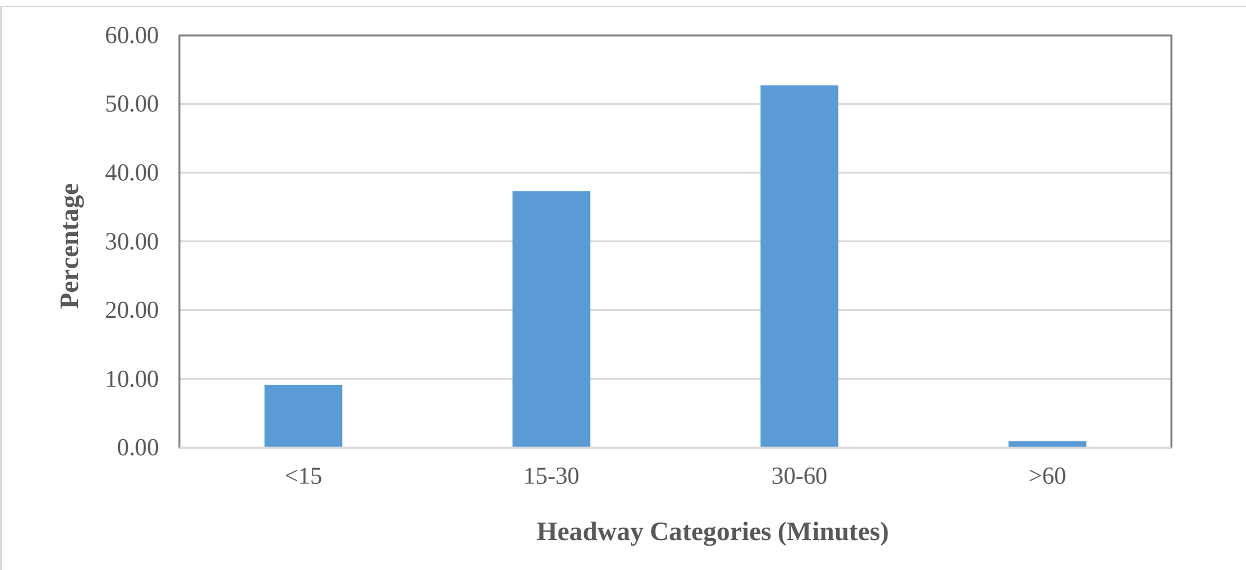


Figure 3-5: Distribution of Headway

3.4.4 SunRail Ridership Data

3.4.4.1 Data Preparation

SunRail, a commuter rail system, is in operation since May, 2014 in greater Orlando. SunRail comprises of 31-mile rail length along with 12 active stations. The location of SunRail stations along with the rail route is presented in Figure 3-6. For the study, SunRail ridership data is collected from FDOT and SunRail management. We have monthly ridership data from July 2014 through June 2015. Also, we have daily ridership data from November 2014 to October 2015 across different stations.

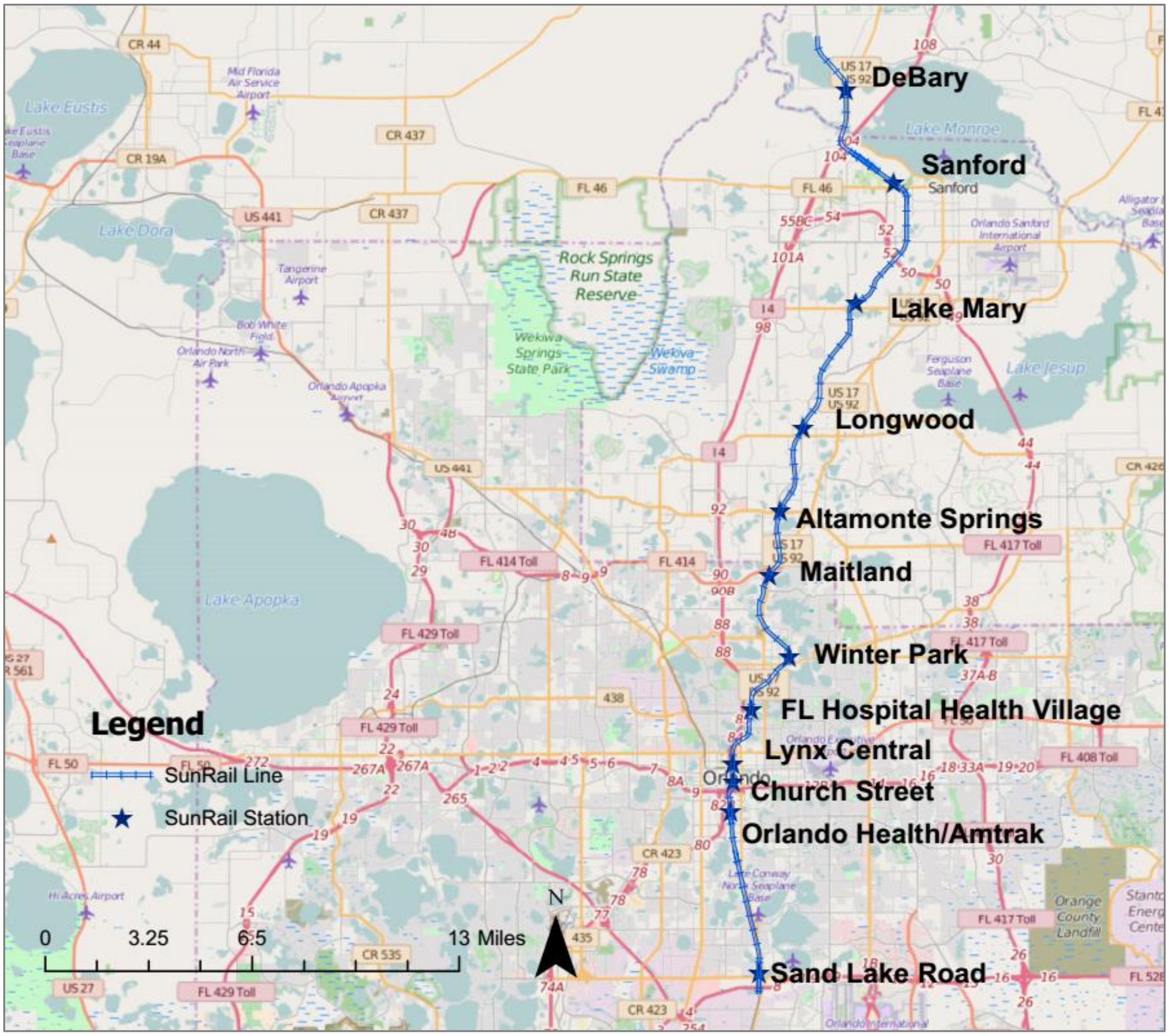


Figure 3-6: SunRail Line and Station Location

3.4.4.2 Summary Statistics

For analysis, we have compiled SunRail monthly ridership data for twelve months from July 2014 through June 2015 and daily ridership data for twelve months from November 2014 through October 2015. Table 3-11 offers summary statistics of monthly SunRail ridership for Southbound

(Debary to Sand Lake Road) and Northbound (Sand Lake Road to Debary) directions across different months. From Table 3-11, we can see that monthly mean ridership between two bounds does not vary much across different months. However, the ridership along Southbound direction is higher than Northbound direction for all months. Overall, highest ridership is observed for July 2014 followed by March 2015 along Southbound direction.

In Figure 3-7 and 3-8, we present some temporal characteristics from the daily SunRail ridership data. Figure 3-7 represents the variation of ridership for different time periods across twelve months. The time periods considered are: AM – Peak (5 to 8 am), PM - Peak (3 pm to 6 pm) and Off-Peak periods. From Figure 3-7 we can see that total ridership has decreased after July 2015. Overall, PM-Peak period ridership is higher than AM-Peak and Off-Peak period ridership. Figure 3-8 offers SunRail ridership for different day of week across twelve months. From Figure 3-7 we can observe that overall Friday has the highest ridership for most of the months. For 2014, Thursday has the lowest ridership compared to other day-of-week. On the other hand, for 2015, Monday has the lowest ridership in 6 months compared to other day-of-week.

Table 3-11: Monthly SunRail Ridership from July 2014 through June 2015

BOUNDS	SOUTHBOUND: Debary to Sand Lake Road						NORTHBOUND: Sand Lake Road to Debary				
Months	**N**	**Minimum**	**Maximum**	**Sum**	**Mean**	**Standard Deviation**	**Minimum**	**Maximum**	**Sum**	**Mean**	**Standard Deviation**
July_2014	12	0	12,750.00	47,107.00	3,925.58	3,716.16	0	12,150.00	44,859.00	3,738.25	3,925.92
August_2014	12	0	10,225.00	38,601.00	3,216.75	2,980.10	0	9,702.00	37,524.00	3,127.00	3,176.12
September_2014	12	0	7,964.00	32,383.00	2,698.58	2,370.48	0	7,932.00	31,508.00	2,625.67	2,675.32
October_2014	12	0	9,120.00	38,099.00	3,174.92	2,752.62	0	9,206.00	36,026.00	3,002.17	3,030.30
November_2014	12	0	7,267.00	30,600.00	2,550.00	2,176.99	0	7,556.00	29,907.00	2,492.25	2,526.99
December_2014	12	0	9,797.00	40,512.00	3,376.00	3,002.53	0	9,523.00	39,346.00	3,278.83	3,486.83
January_2015	12	0	9,346.00	38,367.00	3,197.25	2,780.94	0	9,204.00	37,450.00	3,120.83	3,273.87
February_2015	12	0	8,798.00	35,830.00	2,985.83	2,606.61	0	8,521.00	35,393.00	2,949.42	3,001.92
March_2015	12	0	10,861.00	45,494.00	3,791.17	3,260.48	0	10,358.00	43,401.00	3,616.75	3,679.24
April_2015	12	0	9,854.00	42,666.00	3,555.50	2,978.70	0	9,172.00	40,352.00	3,362.67	3,381.24
May_2015	12	0	8,675.00	36,856.00	3,071.33	2,555.52	0	8,689.00	35,872.00	2,989.33	2,969.72
June_2015	12	0	10,032.00	43,092.00	3,591.00	3,038.65	0	10,499.00	41,485.00	3,457.08	3,448.99

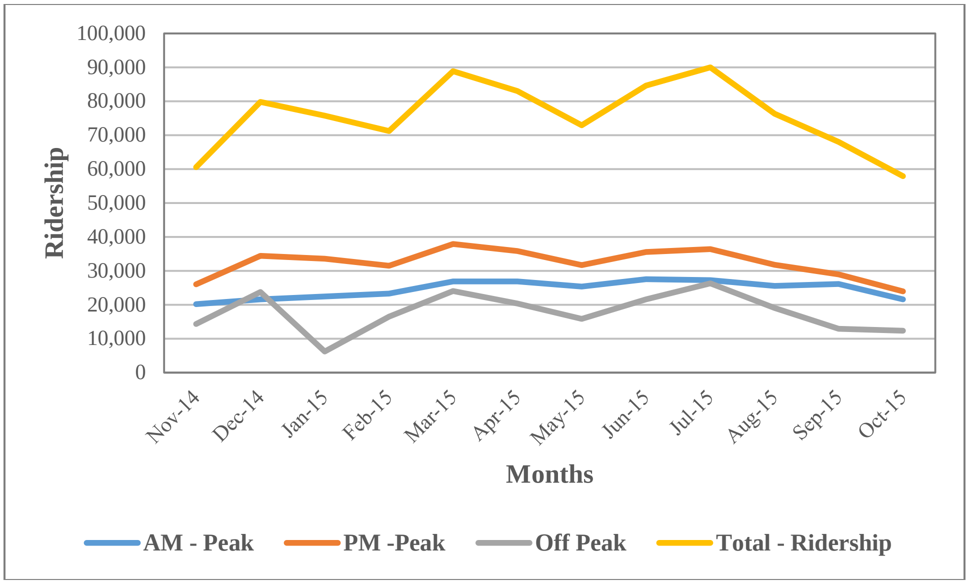


Figure 3-7: SunRail Ridership for Different Time Periods of Day

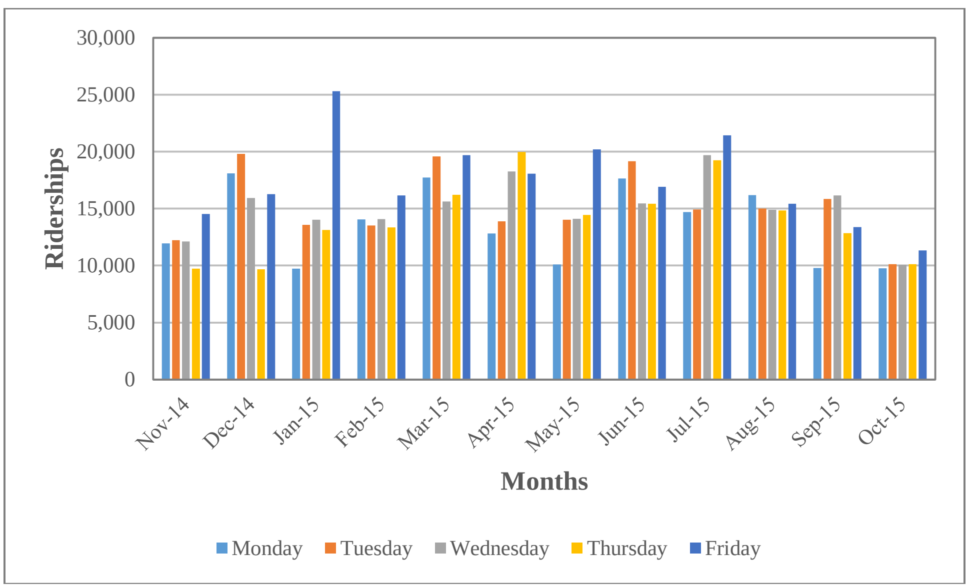


Figure 3-8: SunRail Ridership for Different Day-of-Week

3.4.5 Pedestrian Count Data

3.4.5.1 Data Preparation

For analysis of pedestrian activity, we compiled pedestrian count data from 726 intersections of Orange and Seminole counties. The source of the pedestrian count data is FDOT field data collection from the year 1999 through 2013. Figure 3-9 represents the intersection locations of pedestrian count data that has been compiled by the research team.

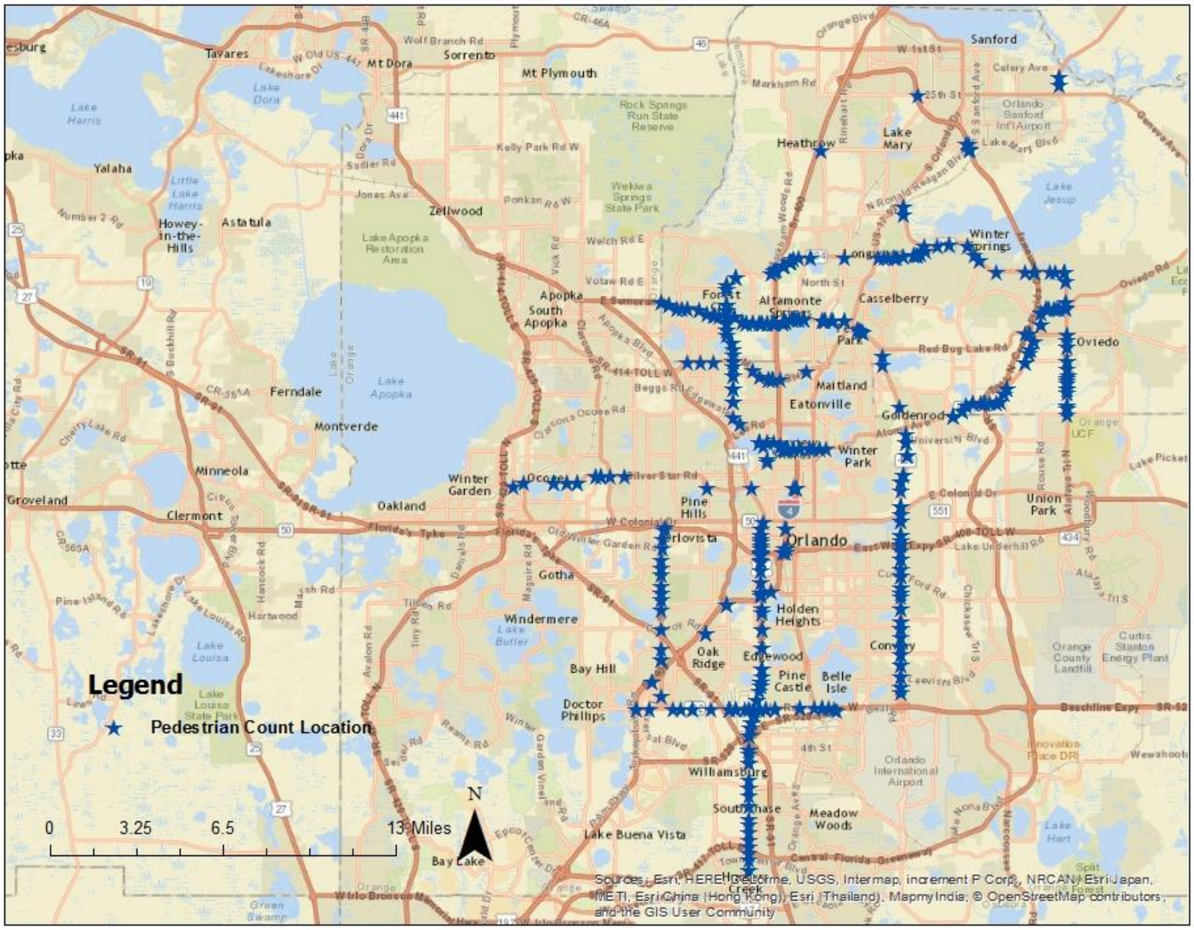


Figure 3-9: Intersection Locations of Pedestrian Count Data

3.4.5.2 Summary Statistics

Among 726 intersections, 396 intersections are in Orange County and the rest are in Seminole county. Table 3-12 offers summary characteristics of pedestrian count data for the recorded intersections. Further, Figure 3-10 represents the distribution of pedestrian counts. From Figure 3-10 we can see that among 726 intersections, 252 intersections have zero pedestrian counts.

Table 3-12: Pedestrian Count Data for 726 Intersections

	N	Minimum	Maximum	Sum	Mean	Standard Deviation
Pedestrian Count	726	0	599	404,68	55.74	64.655

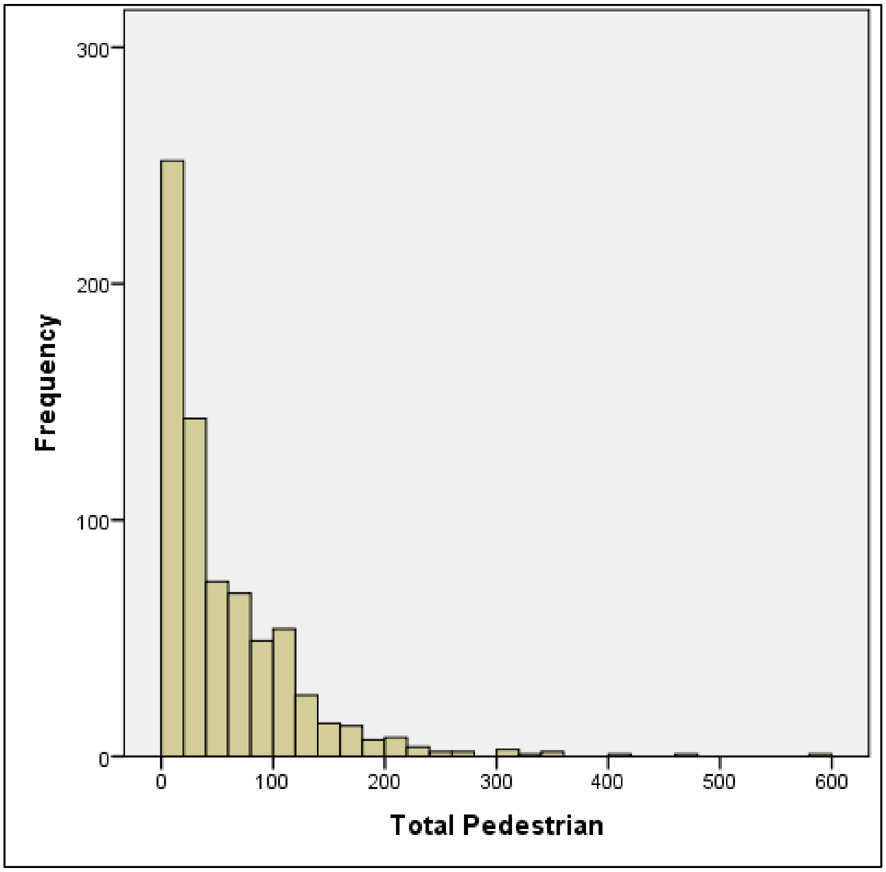


Figure 3-10: Distribution of Pedestrian Count

3.4.6 Pedestrian and Bicycle Crash Data

3.4.6.1 Data Preparation

For increasing the adoption of active transportation, there is a need to reduce the risk to pedestrian and bicycle crashes on roadways. To that extent, we will also examine the risk of pedestrian and bicycle crashes in order to evaluate the safety situation, which would allow us to identify effective countermeasures in reducing the risk of these crashes. Therefore, we also collected pedestrian and bicycle crash data for the year 2010 (base year). The pedestrian and bicycle crash records are collected and compiled from Florida Department of Transportation CARS (Crash Analysis Reporting System) and Signal Four Analytics (S4A) databases. Florida Department of Transportation CARS and S4A are long and short forms of crash reports in the State of Florida, respectively. The long form crash report includes finer resolution of injury severity level or crash related to criminal activities (such as hit-and-run or Driving Under Influence). Crash data records from short and long form databases are compiled in order to have complete information on road crashes and hence is compiled for the purpose of analysis. For this report, we have summarized the pedestrian and bicycle crashes for the year 2010 to reflect the base year situation in terms of non-motorized safety. The location of pedestrian and bicycle crashes of the year 2010 for the study area is shown in Figure 3-11. Further, we also presented the spatial distribution of fatal, injury and non-injury crashes for the non-motorized road user group in Figure 3-12.

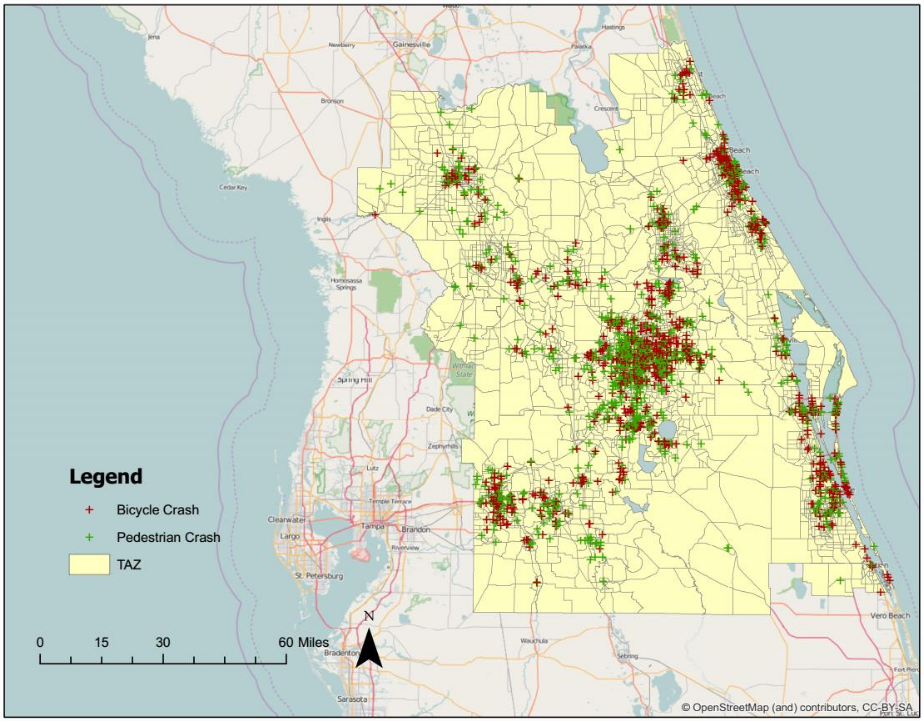


Figure 3-11: Location of Pedestrian and Bicycle Crashes for the Year 2010

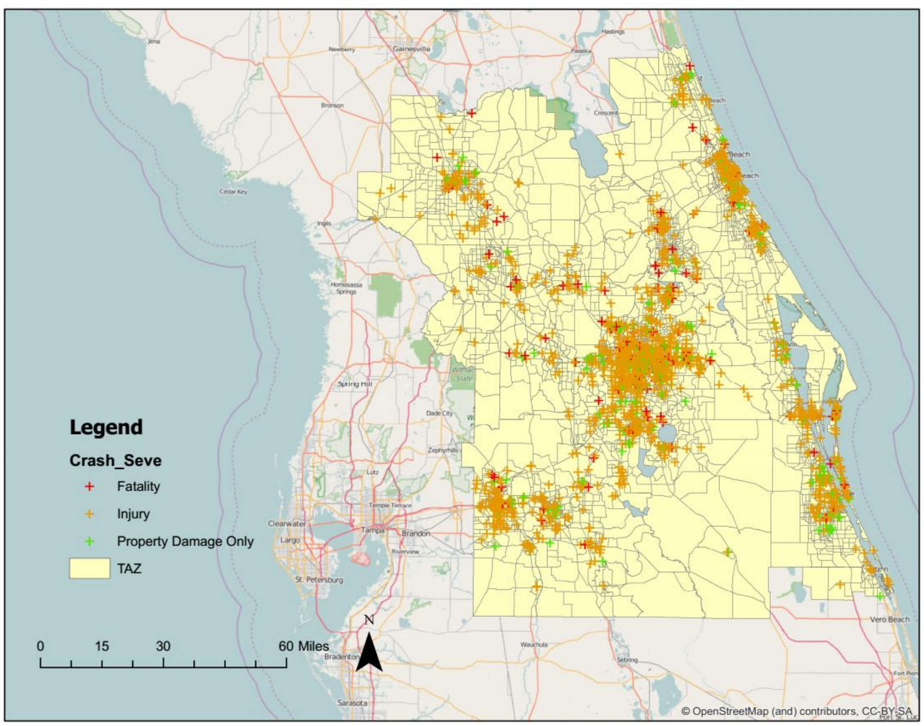


Figure 3-12: Spatial Distribution of Fatal, Injury, and Non-Injury Crashes of Pedestrian and Bicycle Crashes for the Year 2010

3.4.6.2 Summary Statistics

For this report, we have aggregated the pedestrian and bicycle crash records at the TAZ level. During 2010, total 2,050 number of pedestrian and bicycle crashes were recorded for the study area. Among these crashes, pedestrian was involved in 1,145 number of crashes and 910 crashes were recorded as bicycle involved crashes. These crashes resulted in 103 fatalities and 1,839 injuries to non-motorized road user groups. 9.6% and 1.3% of these non-motorized involved crashes were recorded to be alcohol and drug related, respectively. Table 3-13 offers the summary characteristics of these crashes for the year 2010. From Table 3-13, we can see that overall the mean number of pedestrian crashes is higher than bicycle crashes at the zonal level.

Table 3-13: Summary Characteristics of Pedestrian and Bicycle Crashes for the Year 2010

Road User	Number of Zones	Minimum	Maximum	Mean
Pedestrian crash	4,747	0.000	7.000	0.252
Bicycle crash		0.000	6.000	0.193

3.5 SUMMARY

The chapter summarized data that will used by the research team for different stages of analysis of the multi-modal mobility study for the Central Florida Region. The data compiled was presented as eight broad categories: Sociodemographic characteristics, Socioeconomic characteristics, Built environment, Transit attributes, Bicycle attributes, Pedestrian attributes, Transportation infrastructure and Traffic characteristics. Further, we presented the data preparation and summary statistics for base year (2010), for neighbourhood attributes and for bus ridership data. We also presented the summary statistics for SunRail ridership, pedestrian count and pedestrian/bicycle crash data.

CHAPTER IV: BASE YEAR MOBILITY ANALYSIS

4.1 INTRODUCTION

The objective of this chapter is to document and present the base year mobility analysis in evaluating the benefits of multi-modal investments on promoting travel mobility for the Central Florida Region. In current research effort, we presented base year mobility analysis for motorists and non-motorists road user groups separately. The mobility component analysis for motorist road user group (auto and public transit) is presented based on CFRPM version 6.0. Specifically, we present the model estimation procedures and model results for trip generation, trip distribution and mode choice components in an effort to understand the base year mobility treads of Central Florida Region for the motorist road user group. Further, the mobility component analysis for non-motorists road user group, including pedestrian and bicyclist, is presented based on aggregate level demand analysis. Specifically, we investigate non-motorists demand at a zonal level by using aggregate trip information based on origin and destination locations of trips. Specifically, we develop four non-motorists demand models: (1) <u>Pedestrian generator model</u> – based on zonal level pedestrian origin demand, (2) <u>Pedestrian attractor model</u> – based on zonal level pedestrian destination demand, (3) <u>Bicycle generator model</u> – based on zonal level bicycle origin demand, (4) <u>Bicycle attractor model</u> – based on zonal level bicycle destination demand. The demand model would allow us to identify number of non-motorists at a zonal level. These models are estimated for the study are defined by CFRPM 6.0 area 2010 is considered as the base year.

The remaining chapter is organized as follows: The next section describes the base year mobility for motorist road user group. The subsequent section focuses on base year mobility analysis for the non-motorist road user group. The final section describes summary of the chapter.

4.2 BASE YEAR MOBILITY

Travel demand modeling (TDM) is an important analytical tool to support and develop long-range transportation plans. The overall methodology for TDM comprises of two broad components: (1) developing base year mobility models and (2) forecasting future travel demand trends. For developing a trip-based four-step TDM, an initial step is the development of base year mobility models. Mobility trends for base year is usually estimated for each 4-steps (trip generation, trip distribution, modal split and trip assignment) by using demographic and economic data from existing source and travel behaviour of the corresponding base year. In current research effort, we presented base year mobility analysis for motorists and non-motorists road user groups separately. The mobility component analysis for motorized road user group (auto and public transit) is presented based on CFRPM version 6.0. The mobility component analysis for non-motorists road user group, including pedestrian and bicyclist, is presented based on aggregate level demand analysis.

4.2.1 Mobility Analysis for Motorist Road Users

In terms of modeling approach, CFRPM model is developed based on trip-based method with traditional four-step platform. CFRPM version 6.0 (CFRPM 6.0) is the most recent version of

TDM for Central Florida available to the research team. The CFRPM 6.0 model is developed by using CUBE Voyager forecasting package. The base year for CFRPM 6.0 is 2010. The research team has familiarized themselves with model estimation procedures of CFRPM 6.0 for the base year. This section documents the model estimation procedures and model results for trip generation, trip distribution and mode choice components in an effort to understand the base year mobility treads of Central Florida region. To be sure, the input and output of these components are same as presented in CFRPM 6.0 developed by FDOT. To be sure, the existing CFRPM modeling framework is predominantly focused on motorized road user group including auto mode and public transit mode.

4.2.1.1 Trip Generation

Trip Generation is the second step in the CFRPM model followed by External trips step. This step determines the number of trip productions and trip attractions within each TAZ. Trip generation for each TAZ is based on cross classification tables and a function of socioeconomic data such as household and employment. It converts socioeconomic data into person-trip productions and attractions, by trip purpose, and by TAZ. The input datasets of trip generation step are: trip production variables (Zdata 1), trip attraction variables (Zdata 2), special generators (Zdata 3) and external-to-internal (EI) trip percentage by external station (Zdata 4). The CUBE interface of input file component for trip generation model is shown in Figure 4-13.

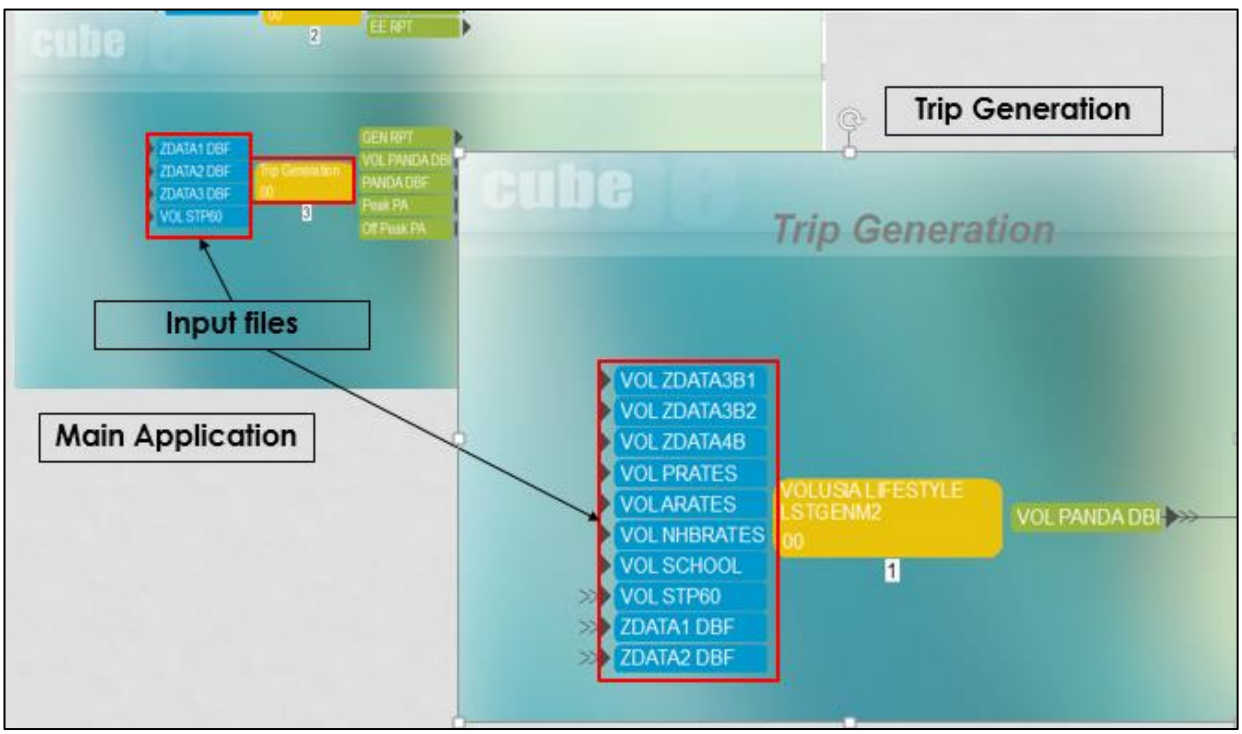


Figure 4-13: CUBE Interface of Input Files for Trip Generation Process

Trip production variables considered are: population classified by single family and multi-family, dwelling units classified by single family and multi-family, percent of vacant and seasonal dwelling units and hotel/motel classified by population and dwelling units. Further, trip attraction variables considered are: employment classified by commercial, service and industrial; and school enrollment for kindergarten to 12th and college. Trip purposes analyzed are: home-based work (HBW), home-based shopping (HBSH), home-based social recreational (HBSR), home-based other (HBO), non-home-based (NHB), light truck (LTK), heavy truck (HTK), taxi and external-to-internal (EI) trip purposes. The summary report for production and attraction of trip generation process by trip purpose and counties are shown in Figure 4-14 below.

Trip Generation Summary Report

CFRPM STANDARD TRIP GENERATION SUMMARY												
Trip Purpose	Seminole	Orange	Osceola	Lake	Volusia	Brevard	Marion	Sumter	Flagler	Polk	Indian River	Total
PRODUCTIONS												
HBW	229,520	602,530	152,400	127,551	239,946	256,388	133,551	29,602	44,131	453,787	23,874	**2,293,280**
HBSH	127,214	511,033	106,428	85,838	145,832	148,452	83,825	26,659	32,634	173,698	15,138	**1,456,751**
HBSR	99,613	450,320	200,703	68,141	190,182	90,976	57,209	16,432	24,809	166,693	11,256	**1,376,334**
HBO	342,230	1,049,852	263,985	223,442	363,442	394,730	224,808	63,051	80,748	478,116	39,010	**3,523,414**
NHB	472,436	1,721,729	202,685	257,134	439,179	483,222	243,964	57,934	55,398	489,600	33,303	**4,456,584**
LTK	122,656	422,899	101,426	79,662	175,301	160,571	86,871	23,929	22,861	106,012	11,278	**1,313,466**
HTK	30,814	103,862	18,833	20,236	24,143	35,620	21,721	6,291	3,796	31,413	3,698	**300,427**
TAXI	1,495	4,964	1,145	985	1,632	1,821	1,014	288	246	905	151	**14,646**
EI	0	0	20,547	0	4,084	0	90,429	46,720	59,290	199,400	59,216	**479,686**
TOTAL	1,425,978	4,867,189	1,068,152	862,989	1,583,741	1,571,780	943,392	270,906	323,913	2,099,624	196,924	**15,214,588**
ATTRACTIONS												
HBW	163,505	816,455	69,708	124,970	185,746	254,097	140,017	32,587	34,793	380,233	18,156	**2,220,269**
HBSH	91,311	605,115	42,175	80,518	155,131	144,979	84,076	19,191	21,415	170,041	10,921	**1,424,873**
HBSR	97,766	611,900	59,858	90,574	190,721	109,144	89,831	29,903	19,965	204,988	6,150	**1,510,801**
HBO	315,314	1,171,213	136,876	210,534	389,242	386,689	221,580	42,922	63,266	439,295	25,268	**3,402,199**
NHB	457,475	1,701,329	211,936	271,948	438,710	496,259	257,289	58,896	56,545	484,759	33,849	**4,468,995**
LTK	122,656	422,899	101,426	79,662	175,301	160,571	86,871	23,929	22,861	106,012	11,278	**1,313,466**
HTK	30,814	103,862	18,833	20,236	24,143	35,620	21,721	6,291	3,796	31,413	3,698	**300,427**
TAXI	1,495	4,964	1,145	985	1,632	1,821	1,014	288	246	905	151	**14,646**
EI	12,675	25,518	23,330	25,985	34,755	22,134	97,059	39,582	786,921	927,755	45,505	**2,041,219**
TOTAL	1,293,012	5,463,256	665,288	905,413	1,595,382	1,611,314	999,458	253,589	1,009,808	2,745,401	154,976	**16,696,896**

Figure 4-14: Trip Generation Summary Report

4.2.1.2 Trip Distribution

Another important module in the CFRPM 6.0 model chain is trip distribution. The trip distribution step involves the conversion of productions and attractions by zone to person trip tables. This trip distribution is based on the gravity model that assesses the attractiveness of two TAZs based on the number of productions and attractions in those zones as well as the relative generalized cost between them. The major input to the trip distribution module is a series of friction factor tables for each trip purpose. The CUBE interface of input and output file components for trip distribution process is shown in Figure 4-15.

Overall, trip distribution process is performed by using the criteria: using Gravity model, by performing preliminary mode choice and trip assignment, using friction factors and finally by using both congested and uncongested trip length distribution. Congested average trip lengths by trip purpose, an excerpt from trip distribution process outputs, for the CFRPM 6.0 is presented in the Table 4-14.

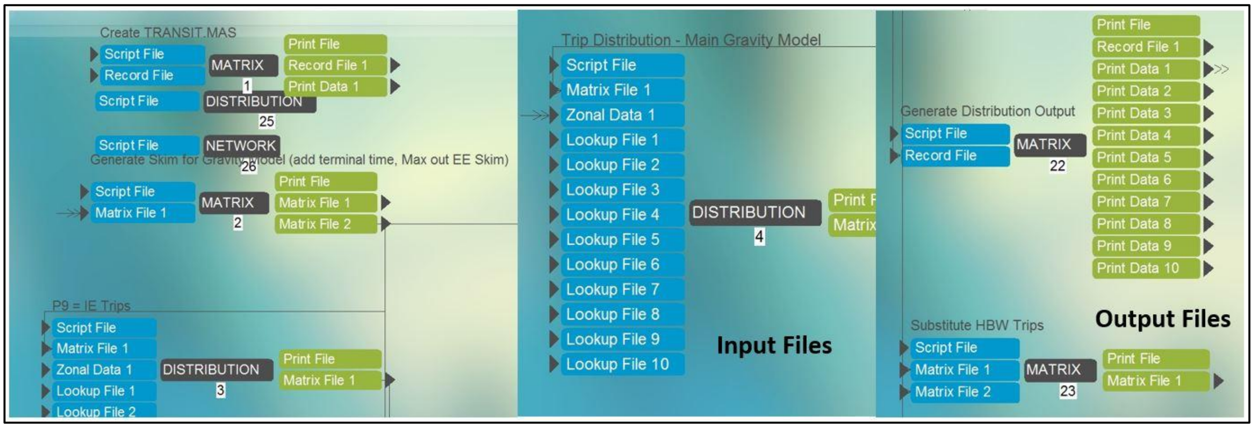


Figure 4-15: CUBE Interface of Input and Output Files for Trip Distribution Process

Table 4-14: Average Congested Trip Length by Trip Purpose

Trip Purpose	Total Trips	Trip-Minutes	Average Minutes	Trip-Miles	Average Miles
HBW	2,293,252	66,053,517	28.803	31,376,158	13.682
HBSH	1,456,719	30,632,488	21.028	14,089,649	9.672
HBSR	1,376,295	38,177,560	27.739	18,185,659	13.213
HBO	3,523,399	76,214,003	21.631	34,993,990	9.932
NHB	4,457,355	94,247,916	21.144	41,078,060	9.216
LTK	1,313,458	25,314,110	19.273	11,062,457	8.422
HTK	300,381	5,667,444	18.868	2,451,779	8.162
TAXI	14,582	279,790	19.187	119,902	8.223
IE	479,686	16,060,732	33.482	10,896,036	22.715

4.2.1.3 Mode Choice

Mode choice model estimates the probability of using available modes for travelling between each pair of zones. The mode choice model is based on nested logit structures and the modes considered are: drive alone, 2 person shared ride, 3+ shared ride, walk to transit, park and ride, kiss and ride, local bus and premium transits. Mode choice models are developed for three trip purposes (HBW, HBO and NHB) and for two different time periods (peak and off peak periods). The CUBE interface of input and output file components for mode choice model is shown in Figure 4-16.

Table 4-15 presents an example of output from mode choice component representing the highway person trips, highway vehicle trips, total transit trips and the total person trips for each metropolitan planning organization (MPO)/transportation planning organization (TPO) in the CFRPM 6.0 study area for the HBW trip purpose.

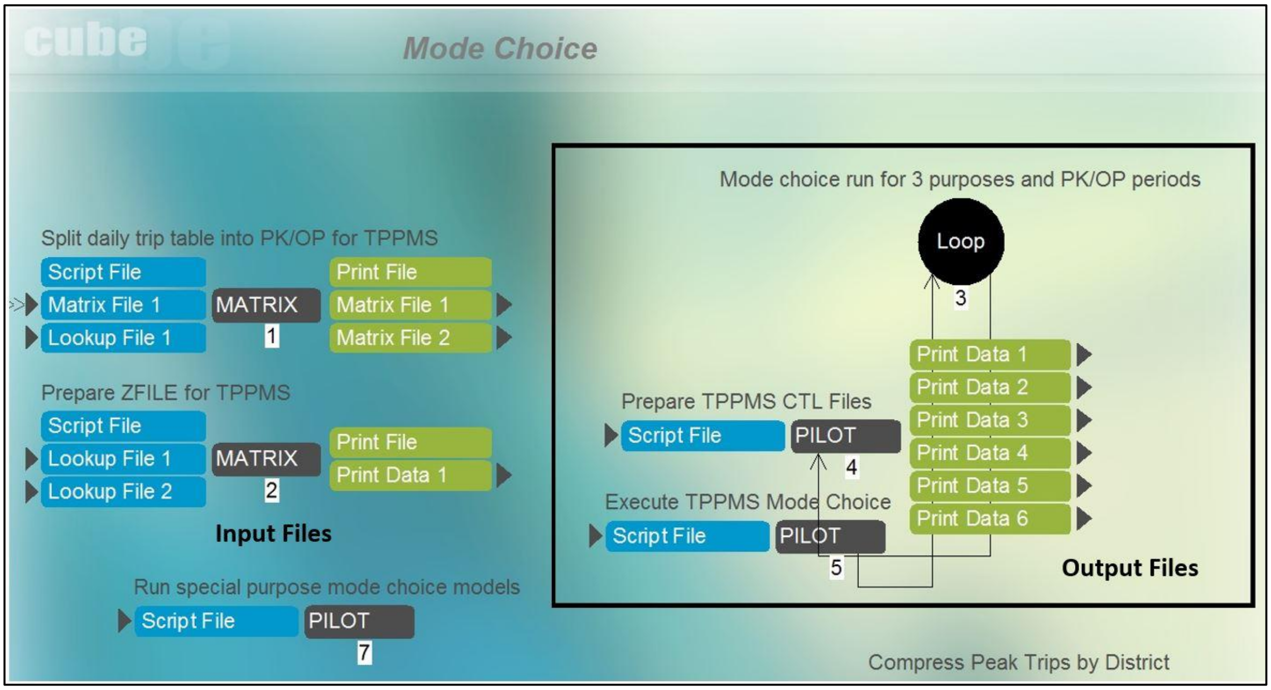


Figure 4-16: CUBE Interface of Input and Output Files for Mode Choice Models

Table 4-15: HBW Highway Trips Summary

	Highway Person Trips				Highway Vehicle Trips					Total	
Urban Area	Drive Alone	Shared Ride 2	Shared Ride 3+	Person Total	Drive Alone	Shared Ride 2	Shared Ride 3+	Vehicle Total	Auto Occ.	Transit Trips	Person Trips
METROPLAN	2,149,352	1,302,712	653,367	4,105,431	2,149,352	654,082	193,576	2,997,011	1.370	24,510	4,129,941
Volusia/Flagler	400,956	238,548	166,783	806,287	400,956	120,220	49,363	570,539	1.413	4,166	810,453
Brevard	393,925	223,839	130,388	748,152	393,925	112,399	38,658	544,982	1.373	1,503	749,654
Ocala/Marion	194,431	115,228	62,253	371,912	194,431	57,842	18,441	270,714	1.374	488	372,400
Lake/Sumter	246,015	151,320	81,133	478,468	246,015	76,012	24,017	346,043	1.383	505	478,973
Total	3,384,679	2,031,647	1,093,924	6,510,250	3,384,679	1,020,554	324,055	4,729,289	1.377	31,171	6,541,421

4.2.2 Mobility Analysis for Non-motorist Road Users

As is evident, the existing CFRPM modeling framework is predominantly focused on auto mode and public transit mode. The modeling approach does not consider non-motorized modes in detail. However, with growing emphasis on improving mobility in Florida region there is increasing awareness and targeted efforts to enhance non-motorized (pedestrian and bicyclist) mobility. To evaluate the effectiveness of these strategies, it is useful to develop methods that accommodate the potential adoption of non-motorized modes within the mobility planning process.

In order to assess the benefit of investments in non-motorized infrastructure, it is important to evaluate and document demand of non-motorized road users. Analysts often develop non-motorist demand model at different local levels, such as regional level, corridor or sub-area level, and household/individual level. Among these models, analyses are widely conducted to evaluate non-motorist travel at a zonal level. Several high resolution modeling frameworks, such as activity-based or trip-based approach, could be pursued for evaluating planning level non-motorists demand. However, it is worthwhile to mention here that high resolution disaggregate level data of non-motorist activity are still unavailable or available only for few locations at a corridor level. Extrapolating planning level non-motorist demand from few corridor level exposure data would require several assumptions along with a higher level of computational burden. Another approach to generating planning level non-motorist demand model is to estimate origin-destination (OD) demand at an aggregate level.

The aggregate level demand models examine critical factors contributing to non-motorist generators and attractors at a zonal level. Outcomes of these studies can be used to devise medium-and-long-term area-wide planning and investment policies in order to encourage and promote non-motorized activities. Moreover, these models can be used as a tool for evaluating non-motorized transportation pilot projects. To that extent, in our current study, we investigated non-motorist demand at a zonal level by using aggregate trip information based on origin and destination locations of trips. Specifically, we developed four non-motorist demand models: (1) <u>Pedestrian generator model</u> – based on zonal level pedestrian origin demand, (2) <u>Pedestrian attractor model</u> – based on zonal level pedestrian destination demand, (3) <u>Bicycle generator model</u> – based on zonal level bicycle origin demand, (4) <u>Bicycle attractor model</u> – based on zonal level bicycle destination demand. The demand model allowed us to identify the number of non-motorist at a zonal level. These models were estimated for the study area defined by CFRPM 6.0 area by using trip records from 2009 National Household Travel Survey (NHTS) database. In the following section, we have presented and discussed estimation results of these models along with data compilation procedures.

4.2.2.1 Data Source

For developing non-motorists demand models, the data is sourced from 2009 NHTS database conducted in the US. The database provides useful information on home-based trip making. It includes information on modes taken by trip makers for each trip, trip purpose, trip location along with trip maker's characteristics, household characteristics and trip characteristics. The 2009 NHTS collected detailed information on more than one million trips undertaken by 320,000 individuals from 150,000 households sampled from all over the country. The 2009 NHTS database from FDOT with add-ons allowed us to identify trips which were recorded for the Central Florida Region. In the 2009 NHTS, there were 2,749 households surveyed in the Central Florida region. It included a total of 5,090 individuals and 22,359 trips. Among these trips, walk and bike trips were 8.8 % and 1.3 %, respectively. In the current study context, we incorporate "person-trip weight" – as defined in NHTS database – in order to extrapolate representative number of trips for the whole Central Florida region.

4.2.2.2 Empirical Analysis

Non-motorists travel demand models are estimated at zonal level based on information of trip origin and destination. Specifically, we estimate four different models: (1) Pedestrian generator model, (2) Pedestrian attractor model, (3) Bicycle generator model and (4) Bicycle attractor model. In generator models, we examine daily zonal trip origin count (total number of trip originated at zones) to identify critical factors that are likely to generate non-motorists origin demand. On the other hand, in attractor models, we examine daily zonal trip destination count (total number of trip ended at zones) to identify critical factors that are likely to generate non-motorists destination demand. In the current research effort, we formulated and estimate. The HNB models are estimated at the TAZ level for CFRPM 6.0 area employing a comprehensive set of exogenous variables. Based on the model results we identify important exogenous variables that influence pedestrian and bicycle OD demand.

4.2.2.3 Model Framework

In our current research effort, the non-motorists OD demands are examined by using Hurdle count regression approach. The non-motorists demands are represented as total number of non-motorists trips originated and destined to a zone. Thus, the demands are non-negative integer values. Naturally, these integer counts can be examined by employing count regression approaches, such as Poisson and Negative Binomial (NB) regression approaches. However, for the zonal level non-motorists trip counts, in more than 84% TAZs have zero trip records. The traditional count models (Poisson and NB models) do not account for such over-representation of zero observations in the data. Hurdle model is typically used in the presence of such excess zeroes. Cameron and Trivedi (1998) presented these models as finite mixture models with a degenerate distribution and probability mass concentrated at zeroes. Hurdle approach is generally used for modeling excess sampling zeroes. It is usually interpreted as a two part model (Heilbron, 1994): the first part is a binary response structure modeling the probability of crossing the hurdle of zeroes for the response and the second part is a zero-truncated formulation modeled in the form of standard count models (Poisson or NB). Thus the probability expression for Hurdle model can be expressed as:

$$\Lambda_i[y_i] = \begin{cases} \pi_i & y_i = 0 \\ \dfrac{(1-\pi_i)}{(1-e^{-\mu_i})} P_i(y_i) & y_i > 0 \end{cases} \tag{1}$$

where, i be the index for TAZ ($i = 1,2,3, \dots, N$) and y_i be the index for non-motorists (pedestrian and bicycle) trips occurring daily in a TAZ i. In equation 1, π_i is the probability of zero trip count and is modeled as a binary logit model as follows:

$$\pi = \frac{exp(\gamma \boldsymbol{\eta}_i)}{1 + exp(\gamma \boldsymbol{\eta}_i)} \tag{2}$$

where, $\boldsymbol{\eta}_i$ is a vector of attributes and γ is a conformable parameter vector to be estimated. $P_i(y_i)$ in equation 1 can be presented as Poisson and NB expressions in forming Hurdle Poisson (HP) and HNB regression models, respectively. Given the set up as presented in Equation 1, the probability distribution for Poisson can be written as:

$$P_i(y_i|\mu_i) = \frac{e^{-\mu_i}(\mu_i)^{y_i}}{y_i!}, \mu_i > 0 \tag{3}$$

where μ_i is the expected number of daily trips non-motorists are making in TAZ i. We can express μ_i as a function of explanatory variable $(\boldsymbol{z}_i)$ by using a log-link function as: $\mu_i = E(y_i|\boldsymbol{z}_i) = exp(\delta \boldsymbol{z}_i)$, where δ is a vector of parameters to be estimated. However, one of the most restrictive assumptions of Poisson regression, often being violated, is that the conditional mean is equal to the conditional variance of the dependent variable.

The variance assumption of Poisson regression is relaxed in NB by adding a Gamma distributed disturbance term to Poisson distributed count data (Jang, 2005). Given the above setup, the NB probability expression for $\boldsymbol{y_i}$ can be written as:

$$P_i(y_i|, \mu_{i,}\alpha) = \frac{\Gamma(y_i + \alpha^{-1})}{\Gamma(y_i + 1)\Gamma(\alpha^{-1})}\left(\frac{1}{1 + \alpha\mu_i}\right)^{\frac{1}{\alpha}}\left(1 - \frac{1}{1 + \alpha\mu_i}\right)^{y_i} \tag{4}$$

where, $\boldsymbol{\Gamma}(\cdot)$ is the Gamma function and $\boldsymbol{\alpha}$ is the NB dispersion parameter. Finally, the weighted log-likelihood function for the Hurdle count model can be written as:

$$LL = w_i * \begin{cases} ln(\pi_i) & y_i = 0 \\ \ln\left(\frac{(1 - \pi_i)}{(1 - e^{-\mu_i})}P_i(y_i)\right) & y_i > 0 \end{cases} \tag{5}$$

The daily trip weight at the zonal level is generated by using the following formulation:

$$w_i = \sum_{j=1}^{J} \frac{Yearly\ person\ trip\ weight}{365} \tag{6}$$

where, j $(j = 1,2,3, \ldots J)$ represents the index for trip. The reader would note that in computing the weighting factor we divided the yearly trip factor, as obtained from NHTS data, by 365 in order to convert the yearly trip rate to a daily trip rate. Substitution of $(\boldsymbol{P_i}(\boldsymbol{y_i}))$ by equations 3 and 4 into equation 5 results in HP and HNB models, respectively.

4.2.2.4 Data Description

The non-motorists demand model is focused on non-motorists OD demand at the TAZ level. With respect to origin and destination demand, we examine daily zonal trip origin count and daily zonal trip destination count, respectively. Table 4-16 offers summary characteristics of these daily trip counts for pedestrian and bicycle trip activities based on their trip origin and trip destination along with the number of zones with sample characteristics. From Table 4-16, we can see that number of zones with pedestrian demand is much higher than the number of zones with bicycle demand. Locations of zones with pedestrian and bicycle OD demand are shown in Figure 4-17.

Table 4-16: Summary Characteristics for Trip Counts

Sample characteristics		Frequency (percentage)		
Total number of zones		4,747		
Zones with zero pedestrian origin trip counts		4,007 (84.4011)		
Zones with pedestrian origin trip counts		740 (15.589)		
Zones with zero pedestrian destination trip counts		4,010 (15.53)		
Zones with pedestrian destination trip counts		737 (84.47)		
Zones with zero bicycle origin trip counts		4,574 (3.64)		
Zones with bicycle origin trip counts		173 (96.36)		
Zones with zero bicycle destination trip counts		4,581 (3.50)		
Zones with bicycle destination trip counts		166 (96.50)		
Variable names	**Definition**	**Zonal (weighted)**		
		Minimum	**Maximum**	**Mean**
Dependent variables				
Pedestrian origin trip count	Total daily pedestrian trip origin demand at a zone	0.000	39,232.010	265.450
Pedestrian destination trip count	Total daily pedestrian trip destination demand at a zone	0.000	39,232.010	261.696
Bicycle origin trip count	Total daily bicycle trip origin demand at a zone	0.000	7,012.434	35.022
Bicycle destination trip count	Total daily bicycle trip destination demand at a zone	0.000	7,012.434	34.937

In addition to the trip counts, the explanatory attributes considered in the empirical study are also aggregated at the TAZ level accordingly. For the empirical analysis, the selected explanatory variables can be grouped into four broad categories: sociodemographic characteristics, roadway and traffic attributes, built environment and land use characteristics. The sociodemographic characteristics are compiled from census bureau’s Tiger/line data and American Community Survey database. Moreover, roadway and traffic attributes, built environment and land use characteristics are obtained from FGDL and FDOT data repository. Table 4-17 offers a summary of the sample characteristics of the exogenous variables and the definition of variables considered for final model estimation along with the zonal minimum, maximum and average. In generating the driver demand (as presented in Table 4-17), we add drive production and drive attraction at a zonal level, which were output from trip generation step of CFRPM model.

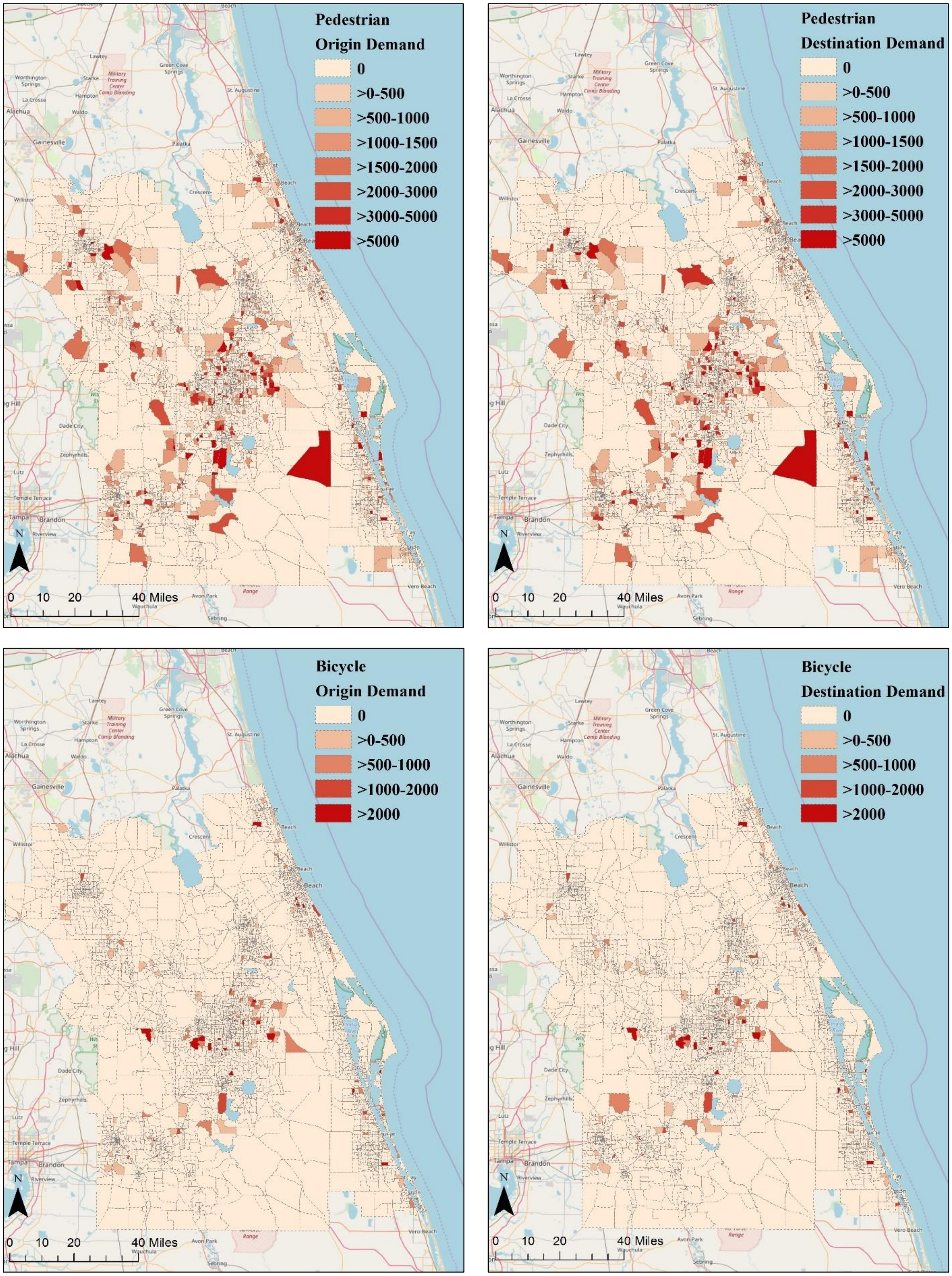


Figure 4-17: Zones with Pedestrian and Bicycle OD Demand

Table 4-17: Summary Characteristics for Exogenous Variables

Variable names	Definition	Zonal		
		Minimum	Maximum	Mean
Built environment				
Number of educational center	Total number of educational center of TAZ	0	5	0.275
Number of financial center	Total number of financial center of TAZ	0	17	0.586
Number of park and recreational center	Total number of park and recreational center of TAZ	0	20	0.245
Number of commercial center	Total number of commercial center of TAZ	0	4	0.087
Number of entertainment center	Total number of entertainment center of TAZ	0	3	0.017
Number of restaurant	Total number of restaurant of TAZ	0	36	1.335
Number of shopping center	Total number of shopping center of TAZ	0	78	1.492
Number of transit hub	Total number of transit hub of TAZ	0	11	0.051
Land-use characteristics				
Institutional area	Ln (Institutional area in a TAZ in acre)	-16.417	7.071	0.785
Residential area	Ln (Residential area in a TAZ in acre)	-12.427	8.014	3.596
Industrial area	Ln (Industrial area in a TAZ in acre)	-12.943	6.709	0.671
Recreational area	Ln (Recreational area in a TAZ in acre)	-13.946	10.04	0.388
Retail/Office area	Ln (Office/Retail area in a TAZ in acre)	-17.312	6.611	1.744
Urban area	Ln (Urban area in a TAZ in acre)	-9.275	8.491	4.291
Land-use mix	Land use mix = $\left[\frac{-\sum_k (p_k(lnp_k))}{lnN}\right]$, where k is the category of land-use, p is the proportion of the developed land area devoted to a specific land-use, N is the number of land-use categories in a TAZ	0	0.929	0.35496

4.2.2.5 Model specification and Overall Measures of Fit

The empirical analysis of non-motorist demand involves the estimation of model using two different econometric frameworks: HP and HNB. Prior to discussing the estimation results, we compare the performance of these models in this section. To compare the performance of estimated models, Bayesian information criterion (BIC) and Akaike information criterion (AIC) measures are used. These measures can be computed as follows:

$$BIC = -2\ln(\mathrm{L}) + \mathrm{K}\ln(\mathrm{Q})$$
$$AIC = 2\mathrm{K} - 2\ln(\mathrm{L}) \tag{7}$$

where $ln(L)$ is the log-likelihood value at convergence, K is the number of parameters and Q is the number of observations. The model with the lower BIC and AIC values is the preferred model. The computed BIC and AIC values along with the log-likelihood at the convergence and number of parameters estimated for all the models are presented in Table 4-18. The BIC (AIC) values for the final specifications of the HP and HNB models clearly indicates that HNB model shows superior fit compared to the HP models for all four models. Therefore, in explaining the effect of exogenous variable, we will restrict ourselves to the discussion of the HNB models.

Table 4-18: Fit Measures of the Estimated Demand Models

Models	Econometric Framework	Log-likelihood at convergence	Number of parameters	BIC	AIC
Pedestrian Generator Model	**HP**	-933,160.513	16	1,866,456.470	1,866,353.026
	HNB	-845,920.147	17	1,691,984.204	1,691,874.294
Pedestrian Attractor Model	**HP**	-924,530.467	21	1,849,238.705	1,849,102.934
	HNB	-835,125.469	22	1,670,437.174	1,670,294.938
Bicycle Generator Model	**HP**	-113,462.794	15	227,052.567	226,955.588
	HNB	-112,380.003	16	224,895.451	224,792.007
Bicycle Attractor Model	**HP**	-109,786.243	21	219,750.256	219,614.485
	HNB	-109,381.323	22	218,948.883	218,806.647

4.2.2.6 Pedestrian Trip Demand Models

Table 4-19 presents the estimation results of the pedestrian generator and attractor models. The pedestrian generator model results are presented in the 2nd and 3rd columns of Table 4-19 and pedestrian attractor model results are presented in the 4th and 5th columns of Table 4-19. In the Hurdle model, the positive (negative) coefficient in the probabilistic component corresponds to increased (decreased) propensity of zero trip events. On the other hand, the positive (negative) coefficient in the count component of the Hurdle model corresponds to increased (decreased) non-zero trip count events. The final specification of the model was based on removing the statistically insignificant variables in a systematic process based on statistical significance (90% significance level) and intuitive coefficient effect. In estimating the models, several functional forms and variable specifications were explored. The functional form that provided the best result was used for the final model specifications and, in Table 4-19, the variable definitions are presented based on these final functional forms of variables. The effects of exogenous variables in model specifications for both pedestrian generator and attractor models are discussed in this section by variable groups.

Probabilistic Component: In the probabilistic component, land-use mix, urban area, and number of households were found to be significant in both pedestrian generator and attractor models. As expected, these variables were positively correlated with the propensity of non-zero pedestrian demand. As these variables served as surrogates for pedestrian activity, it was expected that TAZs with higher levels of these variables were likely to be associated with pedestrian generator and attractor.

Count Component:

Sociodemographic characteristics: With respect to sociodemographic characteristics, from Table 4-19, we can see that the proportion of 65+ aged population was positively associated with pedestrian generator, indicating that TAZs with a higher number of population aged 65+ have higher pedestrian origin demand.

Roadway and Traffic Attributes: Zones with higher average speed limit of roadways are likely to generate less pedestrian origin demand. Annual average daily traffic (AADT) is negatively associated with both pedestrian demand components, indicating lower pedestrian activities in the zones with higher vehicular traffic. From Table 4-19, we can see that zones with a higher proportion of arterial roads are likely to have a higher level of pedestrian activities, both in terms of pedestrian activity generation and attraction. A higher proportion of roadways with 3 or more lanes is negatively associated with zonal level pedestrian activities. As expected, zones with higher sidewalk length are likely to have a higher level of pedestrian activities – both generation and attraction. Drive demand is found to have significant influence in both pedestrian generator and attractor models. Surprisingly, the drive demand variable has positive association with both pedestrian generation and attraction, perhaps is indicating activity exposures for both motorists and non-motorists road user groups.

Table 4-19: Estimation Results of Pedestrian Demand Models

Variable name	**Pedestrian generator model**		**Pedestrian attractor model**	
	Estimates	**t-stat**	**Estimates**	**t-stat**
Probabilistic component				
Constant	2.346	55.583	2.319	54.791
Land-use mix	0.605	8.131	0.539	7.197
Urban area	0.224	37.317	0.215	35.192
Number of Household	0.212	27.328	0.228	29.526
Count component				
Constant	-0.255	-24.579	-0.496	-49.782
Sociodemographic characteristics				
Proportion of 65+ aged population	0.805	62.270	--	--
Roadway and traffic attributes				
Average zonal speed	-0.008	-59.578	--	--
AADT	-0.035	-31.384	-0.047	-40.972
Proportion of arterial road	0.320	53.059	0.256	44.021
Proportion of 3 and more lane road	-0.321	-32.745	-0.425	-40.344
Length of sidewalk	0.048	48.219	0.030	31.874
Drive demand per population	0.011	5.849	0.024	11.165
Built environment				
Number of business center	--	--	0.148	10.100
Number of entertainment center	--	--	0.193	14.342
Number of financial center	--	--	0.018	15.344

Table 4-20 (continued): Estimation Results of Pedestrian Demand Models

Number of park and recreational center	--	--	0.099	38.022
Number of restaurant	--	--	-0.023	-28.174
Number of shopping center	--	--	0.032	46.317
Number of transit hub	--	--	-0.056	-10.579
Land-use characteristics				
Industrial area	-0.029	-22.716	-0.055	-41.630
Recreational area	0.070	70.345	0.043	39.171
Residential area	0.064	50.883	0.070	52.586
Retail/office area	0.047	36.634	0.034	22.899
Institutional area	0.127	110.639	0.148	124.294
Overdispersion parameter	0.916	116.460	0.826	110.499
Log-Likelihood Value	-845901.159		-835059.011	

<u>*Built Environment:*</u> Built environment attributes are considered only in pedestrian attractor models as these attributes are more likely to attract pedestrians. With respect to built environment, we find that higher numbers of business centers, entertainment centers, financial centers, park/recreational centers and restaurants are positively associated with pedestrian attraction demand. On the other hand, higher numbers of shopping centers and transit hubs are found to be negatively associated with pedestrian destination demand at the zonal level.

<u>*Land-use Characteristics:*</u> Land-use characteristics are found to have significant influence in both pedestrian generator and attractor demand models. Among different land-use categories, industrial area is found to be negatively associated with both pedestrian origin and destination demands. All other land-use categories (recreational, residential, retail/office and institutional area) are likely to generate higher levels of pedestrian demands.

4.2.2.7 Bicycle Trip Demand Model

Table 4-20 presents the estimation results of the bicycle generator and attractor models. The bicycle generator model results are presented in 2nd and 3rd columns of Table 4-20 and bicycle attractor model results are presented in 4th and 5th columns of Table 4-20. In Hurdle model, the positive (negative) coefficient in the probabilistic component corresponds to increased (decreased) propensity of zero trip events. On the other hand, the positive (negative) coefficient in the count component of the Hurdle model corresponds to increased (decreased) non-zero trip count events. The final specification of the model was based on removing the statistically insignificant variables in a systematic process based on statistical significance (90% significance level) and intuitive coefficient effect. In estimating the models, several functional forms and variable specifications are explored. The functional form that provided the best result is used for the final model specifications and, in Table 4-20, the variable definitions are presented based on these final functional form of variables. The effects of exogenous variables in model specifications for both bicycle generator and attractor models are discussed in this section by variable groups.

Probabilistic Component: In the probabilistic component, land-use mix, urban area and number of households are found to be significant in both bicycle generator and attractor models. As expected, these variables are positively correlated with the propensity of non-zero bicycle demand. As these variables serve as surrogates for bicycle activity, it is expected that TAZs with higher levels of these variables are likely to be associated with bicycle generator and attractor.

Table 4-21: Estimation Results of Bicycle Demand Models

Variable Name	Bicycle generator model		Bicycle attractor model	
	Estimates	t-stat	Estimates	t-stat
PROBABILISTIC COMPONENT				
Constant	-0.197	-3.641	-0.341	-6.240
Land-use mix	0.597	8.182	0.721	9.840
Urban area	0.305	38.231	0.300	36.626
Number of household	0.286	25.058	0.304	26.490
COUNT COMPONENT				
Constant	-2.755	-59.179	-1.444	-40.014
Sociodemographic characteristics				
Proportion of 65+ aged population	-0.545	-12.618	--	--
Roadway and traffic attributes				
AADT	-0.034	-10.234	--	--
Proportion of arterial road	0.108	7.779	0.054	4.250
Proportion of 3 and more lane road	-0.732	-33.463	-1.260	-56.179
Length of sidewalk	0.055	17.816	0.046	14.894
Drive demand per population	0.103	13.549	-0.168	-21.049
Built environment				
Number of commercial center	--	--	-0.394	-27.211
Number of educational center	--	--	0.119	22.598
Number of entertainment center	--	--	2.888	22.876
Number of financial center	--	--	-0.149	-43.853
Number of park and recreational center	--	--	0.337	53.979
Number of restaurant	--	--	0.236	74.553
Number of shopping center	--	--	-0.101	-37.045
Number of transit hub	--	--	0.329	27.745
Land-use characteristics				
Industrial area	0.097	33.236	0.045	14.692
Recreational area	0.008	3.313	-0.054	-21.718
Residential area	0.491	73.216	0.297	53.479
Retail/office area	-0.145	-42.512	-0.164	-42.773
Institutional area	0.036	10.899	0.037	11.206
Overdispersion parameter	3.112	26.604	5.223	21.465
Log-likelihood Value	-112,288.861		-109,152.043	

Count Component:

Sociodemographic characteristics: With respect to sociodemographic characteristics, from Table 4-20 we can see that proportion of 65+ aged population is negatively associated with bicycle generator, indicating that TAZs with a higher number of population aged 65+ have lower bicycle origin demand.

Roadway and Traffic Attributes: AADT is negatively associated with bicycle generator demand component, indicating lower bicycle origin demand in the zones with higher vehicular traffic. From Table 4-20, we can see that zones with a higher proportion of arterial roads are likely to have higher level of zonal-level bicycle activities, both in terms of bicycle activity generation and attraction. A higher proportion of roadways with 3 or more lanes is negatively associated with zonal-level bicycle activities. Zones with higher sidewalk lengths are likely to have higher levels of bicycle activities – both generation and attraction, perhaps indicating that in Central Florida bicyclists use sidewalks as well as roads for biking. Drive demand has a positive impact on bicycle origin demand, but the variable is negatively associated with bicycle destination demand.

Built Environment: Built environment attributes are considered only in bicycle attractor models as these attributes are more likely to attract bicyclists. With respect to built environment, we find that higher numbers of education centers, entertainment centers, park/recreational centers, restaurants and transit hubs are positively associated with bicycle attraction demand. On the other hand, higher numbers of commercial centers, financial centers and shopping centers are found to be negatively associated with bicycle destination demand at the zonal level.

Land-use characteristics: Land-use characteristics are found to have significant influence in both bicycle generator and attractor demand models. Among different land-use categories, industrial, residential and institutional area are found to be positive associated with both bicycle origin and destination demands. Retail/office and institutional area is likely to generate lower levels of bicycle demands. Recreational area has a positive impact on bicycle generation, while the variable has negative impact in bicycle attraction model.

4.2.2.8 Non-motorists Exposure Matrices

In evaluating non-motorist exposure, we also generate different zonal-level trip exposure matrices with the number of daily trip origins and daily trip destinations at the zonal level for both the pedestrian and bicycle modes. Specifically, three different zonal-level exposure matrices are generated: 1) trip origin demand matrices, 2) trip destination demand matrices and 3) total trip demand matrices. These matrices are generated for pedestrian and bicycle modes separately for the 4,747 TAZs in the area defined by the Central Florida region. The procedure for generating these matrices along with the summary reports are discussed in this section.

Trip origin demand matrices: Zonal-level trip origin demand matrices are computed by using predictions from non-motorist generator models, which are further used to generate the trip origin matrices for the pedestrian and bicycle trip modes. Thus, the dimensions of the generated trip origin demand matrices are $[4{,}747 \times 1]$ with origin trip counts across different rows. The origin demand matrices are generated for the pedestrian and bicycle modes separately.

Trip destination demand matrices: Zonal-level trip destination demand matrices are computed by using predictions from non-motorist attractor models, which are further used to generate the trip destination matrices for the pedestrian and bicycle trip modes. Thus, the dimension of the generated trip destination demand matrices are $[4{,}747 \times 1]$ with destination trip counts across different rows. The destination demand matrices are generated for the pedestrian and bicycle modes separately.

Total trip demand matrices: Finally, zonal-level total trip demand matrices are generated by combining the trip origin and destination demand matrices across different zones (total trip demand = trip origin demand + trip destination demand). Thus, the dimensions of the generated total trip demand matrices are $[4{,}747 \times 1]$ with total trip counts across different rows. The total trip demand matrices are generated for the pedestrian and bicycle modes separately.

Summary report: For representation purposes, the summary report for trip origin, destination and total trip demands are presented at the county level. In Table 4-21 we present the county-level trip origin, trip destination and total trip demand matrices for the pedestrian and bicycle modes. From Table 4-21, we can see that the Orange County has the highest total demand for both pedestrian and bicyclist group.

Table 4-22: Trip Demand Matrices by County Level

County	No. of TAZs	Pedestrian			Bicycle		
		Trip origin demand	Trip destination demand	Total trip demand	Trip origin demand	Trip destination demand	Total trip demand
Brevard	692	154,936.5	149,804.8	304,741.3	21,663.5	23,172.9	44,836.4
Flagler	141	26,241.4	23,153.6	49,395.1	2,940.3	2,634.0	5,574.3
Indian River	37	12,066.7	11,826.1	23,892.9	1,735.2	999.4	2,734.7
Lake	350	67,309.2	66,545.8	133,855.2	10,784.2	9,977.6	20,761.9
Marion	422	95,199.8	89,602.9	184,802.8	5,238.2	4,226.2	9,464.5
Orange	781	348,163.9	355,169.8	703,333.7	57,661.9	64,084.7	121,746.7
Osceola	250	67,651.6	65,181.7	132,833.3	4,026.1	3,875.6	7,901.7
Polk	621	185,959.9	195,543.4	381,503.4	10,931.1	10,687.6	21,618.8
Seminole	230	75,690.1	79,212.1	154,902.3	12,179.3	11,558.8	23,738.2
Sumter	147	32,272.7	26,598.9	58,871.6	553.0	817.9	1,370.9
Volusia	1076	18,9987.7	174,051.2	364,038.8	37,957.9	39,924.8	77,882.8
Total	4,747	1,255,480.0	1,236,691.0	2492171.0	165,671.4	171,960.0	337,631.3

4.3 SUMMARY

The chapter summarized base year mobility trends for Central Florida. Specifically, we presented base year mobility analysis for motorists and non-motorists road user groups separately. The mobility component analysis for motorist road user group (auto and public transit) was presented based on CFRPM version 6.0. Further, the mobility component analysis for non-motorists road user group, including pedestrian and bicyclist, was presented based on aggregate level demand analysis. We investigate non-motorists demand at a zonal level by using aggregate trip information based on origin and destination locations of trips. We develop four non-motorists demand models: (1) Pedestrian generator model, (2) Pedestrian attractor model, (3) Bicycle generator model, and (4) Bicycle attractor model. These model were estimated by using HNB model framework. Based on the predictions from these demand models, we also generated zonal level demand matrices for pedestrian and bicyclists, separately. The generated demand matrices will be used as exposure measures in exploring zonal level non-motorists safety for Central Florida Region.

CHAPTER V: BASE YEAR NON-MOTORISTS SAFETY ANALYSIS

5.1 INTRODUCTION

Among the different modes of transportation, active forms such as walking and bicycling are the most sustainable, leaving the lowest carbon footprint on the environment. These modes also contribute to improving the physical health of non-motorists. However, non-motorist safety is a global health concern, and Florida is no exception. The safety risk posed to active transportation users in Florida is exacerbated compared to active transportation users in the US. While the national average for pedestrian (bicyclist) fatalities per 100,000 population is 1.50 (2.35), the corresponding number for the state of Florida is 2.56 (6.80), which present a clear picture of the challenge faced in Florida. For increasing the adoption of active transportation, there is a need to reduce the risk to pedestrians and bicyclists on roadways. Any effort to reduce the social burden of these crashes and enhance non-motorists safety would necessitate the examination of factors that contribute significantly to crash likelihood and/or injury severity in the event of a crash and the implementation of policies that enhance safety for pedestrians and bicyclists. An important tool for identifying and evaluating road safety policies is forecasting and policy evaluation which are predominantly devised through evidence-based and data-driven safety analysis.

Traditionally, the transportation safety analysis by using crash records has evolved along two major streams: crash frequency (CF) analysis and crash severity (CS) analysis. Crash frequency or crash prediction analysis is focused on identifying attributes that result in traffic crashes and propose effective countermeasure to improve the roadway design and operational attributes (see Lord and Mannering (2010) for a review of these studies). The crash frequency models study aggregate information; such as total number of crashes at an intersection or at a spatial aggregation level (zone or tract level) and are developed by using non-crash-specific data. On the other hand, crash severity analysis is focused on examining crash events, identifying factors that impact the crash outcome and providing recommendations to reduce the consequences in the unfortunate event (injuries and fatalities) of a traffic crash (see Savolainen et al. (2011) and Yasmin et al. (2013) for a review). The crash severity models are developed by using detailed post-crash data and are quite disaggregate in nature because these consider every crash as a record for model development. In evaluating impact of a safety measure, CF analysis forecasts the change in crash occurrences, whereas CS analysis forecasts the change in crash consequences (injuries and fatalities).

To that extent, in this research effort, we estimate both crash frequency and crash severity models in understanding non-motorists safety factors. In terms of crash frequency model, we estimate two models: (1) zonal-level crash count model for examining pedestrian–motor vehicle crash occurrences, and (2) zonal-level crash count model for examining bicycle–motor vehicle crash occurrences. With regards to crash severity model, we estimate four different sets of models: (1) disaggregate-level crash severity model for examining pedestrian crash injury severity outcomes, (2) disaggregate-level crash severity model for examining bicycle crash injury severity outcomes, (3) zonal-level crash severity model for examining pedestrian crash injury severity by proportions and (4) zonal-level crash severity model for examining bicycle crash injury severity by proportions. The objective of this chapter is to document and present the base year non-motorists safety trends analysis in evaluating the benefits of multi-modal investments on promoting travel mobility for Central Florida. These models are estimated for the study area defined by CFRPM 6.0 by using crash records of the base year 2010. In the following sections, we present the outcomes of these models.

The remaining chapter is organized as follows: The next section describes the crash frequency analysis. The subsequent section focuses on disaggregate-level followed by zonal-level crash severity analysis. The final section describes summary of the chapter.

5.2 CRASH FREQUENCY ANALYSIS

A regional or zonal level safety planning tool can be devised by using macro-level study and hence are useful not only for the planners but also for the decision-makers. Therefore, it is important to investigate zonal level pedestrian and bicycle crashes to identify critical factors and propose implications to facilitate proactive safety-conscious planning. In this current research effort, we formulate and estimate count models for examining pedestrian and bicycle crash risks. The count models are estimated at the TAZ level for CFRPM 6.0 area employing a comprehensive set of exogenous variables. Based on the model results we identify important exogenous variables that influence pedestrian and bicycle crash counts. The NB model, which offers a closed form expression while relaxing the mean variance equality constraint of Poisson regression, serves as the workhorse for crash count modeling. Therefore, crash count models for examining pedestrian and bicycle crash events are developed in this study by using NB modeling approach.

5.2.1 Model Framework

The focus of our study is to model pedestrian crash frequency and bicycle crash frequency at zonal level by employing NB modeling framework. The econometric framework for the NB model is presented in this section.

Let i be the index for TAZ ($i = 1,2,3, \ldots, N$) and $\boldsymbol{y_i}$ be the index for crashes occurring over a period of time in a TAZ $\boldsymbol{i}$. The NB probability expression for random variable $\boldsymbol{y_i}$ can be written as:

$$P_i(y_i|\mu_i, \alpha) = \frac{\Gamma\left(y_i + \frac{1}{\alpha}\right)}{\Gamma(y_i + 1)\Gamma\left(\frac{1}{\alpha}\right)} \left(\frac{1}{1 + \frac{\mu_i}{\alpha}}\right)^{\frac{1}{\alpha}} \left(1 - \frac{1}{1 + \frac{\mu_i}{\alpha}}\right)^{y_i} \tag{1}$$

where, $\boldsymbol{\Gamma}(\cdot)$ is the Gamma function, $\boldsymbol{\alpha}$ is the NB dispersion parameter and $\boldsymbol{\mu_i}$ is the expected number of crashes occurring in TAZ $\boldsymbol{i}$ over a given period of time. We can express $\boldsymbol{\mu_i}$ as a function of explanatory variable $(\boldsymbol{x_i})$ by using a log-link function as: $\boldsymbol{\mu_i = E(y_i|x_i) = exp(\beta x_i)}$, where $\boldsymbol{\beta}$ is a vector of parameters to be estimated. Finally, the log-likelihood function for the NB model can be written as:

$$LL = \sum_{i=1}^{N} log(P_i) \tag{2}$$

The parameters to be estimated in the model of equation 2 are: $\boldsymbol{\beta}$ and $\boldsymbol{\alpha}$. The parameters are estimated using maximum likelihood approaches.

5.2.2 Dependent Variable and Data Description

The crash frequency analysis is focused on pedestrian and bicycle crashes at the TAZ level for 4,747 TAZs in the area defined by the CFRPM 6.0 area. For this research effort, we have examined the pedestrian and bicycle crash count events for the year 2010 to reflect the base year situation in terms of non-motorized safety. For the year 2010, 1,474 (with 0, 9 and 0.31 zonal minimum, maximum and average, respectively) and 1,012 (with 0, 8 and 0.21 zonal minimum, maximum and average, respectively) crashes were reported involving pedestrians and bicycles, respectively. Spatial representation of these crashes at the zonal level is shown in Figure 5-18.

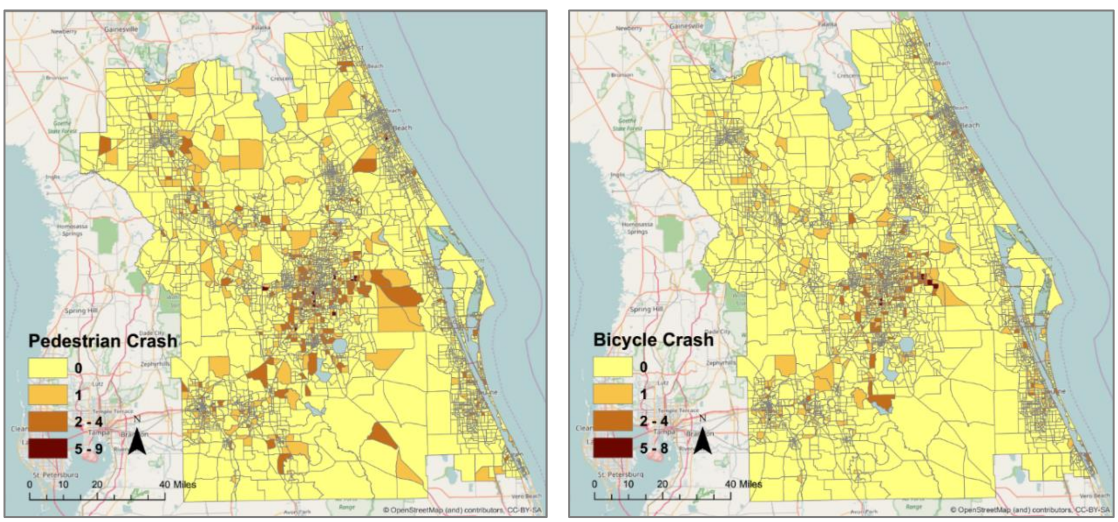


Figure 5-18: Total Number of Pedestrian and Bicycle Crashes for the Year 2010

In addition to the crash database, the explanatory attributes considered in the empirical study are also aggregated at the TAZ level accordingly. To reflect the base year characteristics of the analysis zone, all attributes are generated for the year 2010. For the empirical analysis, the selected explanatory variables can be grouped into five broad categories: sociodemographic characteristics, roadway and traffic attributes, built environment, land use characteristics and exposure measures. Table 5-22 offers a summary of the sample characteristics of the exogenous variables and the definition of variables considered for final model estimation along with the zonal minimum, maximum and average.

Table 5-23: Sample Characteristics for Crash Frequency Models

Variable name	Description	Zonal		
		Minimum	Maximum	Mean
Sociodemographic characteristics				
Population density	Total number of Population of TAZ/ Area of TAZ in acre	0.000	19.956	2.366
Proportion of people aged 65+	Total number of people above 65 years old of TAZ/ Total number of Population of TAZ	0.000	0.899	0.182
Roadway and traffic attributes				
Traffic signal density	Total number of Traffic signal in TAZ	0.000	8.000	0.379
Proportion of arterial road	Total length of arterial road of TAZ/Total roadway length of TAZ	0.000	1.000	0.459
Proportion of local road	Total length of local road of TAZ/Total roadway length of TAZ	0.000	1.000	0.040
Length of sidewalk	Total sidewalk length in meter of TAZ	0.000	36.346	0.280
Length of bike lane	Total bike lane length in meter of TAZ	0.000	58.525	0.421
Length of bus lane	Total bus lane length in kilometer of TAZ	0.000	31.161	0.888
AADT	Total Annual Average Daily Traffic (AADT) of TAZ/10000	0.000	27.550	0.931
Truck AADT	Total Truck AADT of TAZ/10000	0.000	2.747	0.083
Drive Demand per family	Ln of [(Total drive demand/total number of family) +1), in a TAZ	0.000	21.055	3.353
Built environment				
Number of commercial center	Total number of commercial center of TAZ	0.000	4.000	0.087
Number of financial center	Total number of financial center of TAZ	0.000	17.000	0.586
Number of educational center	Total number of educational center of TAZ	0.000	5.000	0.275
Number of transit hub	Total number of transit hub of TAZ	0.000	11.000	0.051
Number of restaurant	Total number of restaurant of TAZ	0.000	36.000	1.335
Number of park and recreational center	Total number of park and recreational center of TAZ	0.000	20.000	0.245
Number of hospital	Total number of hospital of TAZ	0.000	2.000	0.017
Land-use characteristics				
Urban area	Ln (Urban area in a TAZ in acre)	-9.275	8.491	4.291
Residential area	Ln (Residential area in a TAZ in acre)	-12.427	8.014	3.596
Recreational area	Ln (Recreational area in a TAZ in acre)	-13.946	10.040	0.388
Land-use mix	Land use mix = [(-∑k(Pk (lnPk)))/lnN], , where k is the category of land-use, p is the proportion of the developed land area devoted to a specific land-use, N is the number of land-use categories in a TAZ	0.000	0.929	0.355

Table 5-22 (Continued): Sample characteristics for crash frequency models

Variable name	Description	Zonal		
		Minimum	Maximum	Mean
Exposure measures				
Total pedestrian trip demand per household	Total pedestrian daily trip demand in a TAZ/(Total number of household in a TAZ*100)	0.000	948.164	0.321
Total bicycle trip demand	Ln(Total bicycle daily trip demand in a TAZ)	0.000	9.549	0.259

5.2.3 Estimation Results

In this research effort, we estimate two different NB models: one model for pedestrian crash count events at the zonal level and another model for bicycle crash count events at the zonal level. Table 5-23 presents the estimation results of the NB models. The pedestrian crash count model results are presented in 2nd and 3rd columns of Table 5-23, and the bicycle crash count model results are presented in the 4th and 5th columns. The effects of exogenous variables in model specifications for both pedestrian and bicycle crash count models are discussed in this section by variable groups.

In NB models, the positive (negative) coefficient corresponds to increased (decreased) crash risk. The final specification of the model was based on removing the statistically insignificant variables in a systematic process based on statistical significance (90% significance level) and intuitive coefficient effect. In estimating the models, several functional forms and variable specifications are explored. The functional form that provided the best result is used for the final model specifications and, in Table 5-23, the variable definitions are presented based on these final functional forms of variables.

Sociodemographic characteristics: With respect to sociodemographic characteristics, the estimates indicate that both pedestrian and bicycle crashes are positively associated with population density. At the same time, the results in Table 5-23 indicate a reduced crash propensity for both pedestrians and bicyclists with a higher proportion of population aged 65 and over.

Roadway and traffic attributes: Several roadway and traffic attributes are found to be significant determinants of pedestrian and bicycle crashes at the zonal level. The results associated with traffic signal density reveal that an increase in traffic signal density in a zone increases the likelihood of both pedestrian and bicycle crashes. A higher proportion of arterial road results in higher pedestrian and bicycle crash risks. At the same time, a higher proportion of local roads is found to have negative impact on bicycle crash risk. From Table 5-23, we can see that the likelihood of a pedestrian crash is higher in the zone with a higher sidewalk length. It is also surprising to note that TAZs with higher bicycle lane lengths have an increased likelihood of bicycle crashes. The result for length of zonal-level bus lanes reveals an increasing likelihood of bicycle crash. An increase in zonal AADT increases the likelihood of both pedestrian and bicycle crashes at the TAZ level. The result in the bicycle crash model suggests that zones with higher truck AADT have a decreased likelihood of bicycle crashes. As expected, drive demand has positive impact on crash risk on both group of non-motorists.

Table 5-24: Estimation Results of Negative Binomial Models

Variable name	Pedestrian		Bike	
	Estimates	t-stat	Estimates	t-stat
Constant	-3.881	-18.914	-4.437	-19.595
Sociodemographic characteristics				
Population density	0.152	12.318	0.144	10.940
Proportion of people aged 65+	-1.432	-4.375	-0.962	-2.971
Roadway and traffic attributes				
Traffic signal density	0.196	5.493	0.131	3.612
Proportion of arterial road	0.327	3.742	0.338	3.574
Proportion of local road	---	---	-0.855	-2.352
Length of sidewalk	0.023	1.949	---	---
Length of bike lane	---	---	0.015	1.666
Length of bus lane	---	---	0.079	4.512
AADT	0.035	2.401	0.081	2.077
Truck AADT	---	---	-0.932	-2.256
Drive demand per family	0.175	6.439	0.139	4.975
Built environment				
Number of commercial center	---	---	0.159	1.663
Number of financial center	---	---	0.060	3.174
Number of transit hub	0.242	5.252	---	---
Number of restaurant	0.071	7.672	0.042	4.245
Number of park and recreational center	0.122	3.161	---	---
Number of hospital	---	---	0.271	2.697
Land-use characteristics				
Urban area	0.126	4.898	0.167	5.603
Residential area	0.105	4.512	0.129	5.062
Recreational area	---	---	-0.044	-1.967
Land-use mix	0.677	3.965	0.583	3.084
Exposure measures				
Total pedestrian trip demand per household	-0.406	-1.787	---	---
Total bicycle trip demand	---	---	0.041	2.022
Overdispersion parameter	0.955	9.158	0.641	5.642
Log-likelihood Value	-2912.379		-2278.062	

Built environment: With respect to built environment, the estimation results of the pedestrian crash risk model reveal that a higher number of educational centers, transit hubs, restaurants and parks/recreational centers results in a higher pedestrian crash risk at the zonal level. From the results of the bicycle crash risk models, we can see that bicycle crash risk is positively associated with a higher number of commercial centers, financial centers, restaurants and hospitals.

<u>Land-use characteristics:</u> Several land-use characteristics are found to be significant determinants of pedestrian and bicycle crash risks. Pedestrian and bicycle crash risks increase with increasing urbanized and residential areas. In the bicycle crash risk model, recreational area is found to decrease the likelihood of zonal-level bicycle crash risk. TAZs with higher land-use mix have increased propensity for both pedestrian and bicycle crashes.

<u>Exposure measures:</u> The non-motorist exposure measures generated from Chapter 4 are used in evaluating zonal-level pedestrian and bicycle crash risk. Specifically, we use the total daily trip demand of pedestrians and bicyclists as exogenous variables in pedestrian and bicycle crash risk models, respectively. We consider different functional forms of pedestrian and bicycle exposure measures in estimating NB models and the functional form that provides the best fit is considered in the final specifications. With respect to the pedestrian crash risk model, pedestrian exposure measures with any of the functional forms are not found to be significant at a 90% confidence level. However, pedestrian trip demand per household at a zonal level provides the best data fit and hence is considered in our final pedestrian crash risk model. From Table 5-23, we can see that a higher number of pedestrians per household decreases the risk of pedestrian–motor vehicle crashes. With respect to bicycle crash risk model, bicycle exposure measures are found to have a significant impact on zonal-level bicycle-motor vehicle crash risk. The estimation result of exposure measure in the bicycle crash risk model reveals that a higher bicyclist trip demand at a zonal level increases the risk of bicycle crashes.

5.3 DISAGGREGATE-LEVEL CRASH SEVERITY ANALYSIS

In this current research effort, we formulate and estimate disaggregate-level severity models for examining pedestrian and bicycle crash severity outcomes. To be sure, the unit of analysis of the disaggregate-level models are each crash involving at least one non-motorists. Based on the model results we identify critical exogenous variables that influence pedestrian and bicycle crash severity outcomes.

In general, a number of earlier studies have employed the logistic regression model (for example see Sze and Wong, 2007) to identify the contributing factors of non-motorists crash severity outcomes. In traffic crash reporting, injury severity is typically characterized as an ordered variable (for example: no injury, minor injury, serious injury and fatal injury). It is no surprise that the most commonly employed statistical framework in modeling crash injury severity is the ordered outcome models (ordered logit or probit) (Yasmin et al., 2014). Researchers have also employed unordered choice models to study injury severity due to additional flexibility offered by these frameworks. Specifically, the unordered systems allow for the estimation of alternative specific variable impacts while the ordered systems impose a uni-directional impact of the exogenous variable on injury severity alternatives. The most prevalent unordered outcome structure considered is the multinomial logit model (Tay et al. 2011). However, the unordered model does not recognize the inherent ordering of the crash severity outcome and therefore, it neglects vital information present in the data. Therefore, crash severity models for examining pedestrian and bicycle crash severity outcomes are developed by using ordered logit (OL) modeling approach in current research effort.

5.3.1 Model Framework

The focus of our study is to model pedestrian crash severity and bicycle crash severity outcomes by employing OL modeling framework. The econometric framework for the OL model is presented in this section.

In the traditional ordered outcome model, the discrete injury severity levels $(\boldsymbol{y_i})$ are assumed to be associated with an underlying continuous latent variable $(\boldsymbol{y_i^*})$. This latent variable is typically specified as the following linear function:

$$y_i^* = \boldsymbol{X}_i\boldsymbol{\beta} + \varepsilon_i, \textit{for } i = 1,2, \dots \dots \dots, N \tag{3}$$

where,

i $(i = 1,2, \dots \dots \dots, N)$ represents the pedestrian/bicyclist
$\boldsymbol{X}_{\mathrm{i}}$ is a vector of exogenous variables (excluding a constant)
$\boldsymbol{\beta}$ is a vector of unknown parameters to be estimated
ε is the random disturbance term assumed to be standard logistic

Let j $(j = 1,2, \dots \dots \dots, J)$ denotes the injury severity levels and τ_j represents the thresholds associated with these severity levels. These unknown τ_js are assumed to partition the propensity into $J - 1$ intervals. The unobservable latent variable y_i^* is related to the observable ordinal variable y_i by the τ_j with a response mechanism of the following form:

$$y_i = j, \;\; if\; \tau_{j-1} < \; y_i^* < \tau_j, \textit{for } j = 1,2, \dots \dots \dots, J \tag{4}$$

In order to ensure the well-defined intervals and natural ordering of observed severity, the thresholds are assumed to be ascending in order, such that $\tau_0 < \tau_1 < \; \dots \dots \dots < \tau_J$ where $\tau_0 = -\infty$ and $\tau_J = +\infty$. Given these relationships across the different parameters, the resulting probability expressions for individual *i* and alternative *j* for the ordered logit model take the following form:

$$\pi_{ij} = Pr(y_i = j|X_i) = \Lambda(\tau_j - X_i\beta) - \Lambda(\tau_{j-1} - X_i\beta) \tag{5}$$

where $\boldsymbol{\Lambda}(.)$ represents the standard logistic cumulative distribution function. Finally, the log-likelihood function for the OL model can be written as:

$$LL = \sum_{i=1}^{N} log(\pi_{ij}) \tag{6}$$

The parameters are estimated using maximum likelihood approaches.

5.3.2 Data Description

Pedestrian and bicycle crash data of CFRPM 6.0 area were extracted from the FDOT CARS) database for the year 2010. For severity analysis, we did not consider short form crash report of Florida in the current study context. The short form report has few disaggregate level crash information and therefore are less informative for developing disaggregate level severity models. Moreover, the outcome of pedestrian and bicycle crashes is likely to be severe since these groups of road users are unshielded and unprotected. Therefore, examining the outcome variables representing pedestrian and bicycle crash severity by using long form crash records only are likely to result in unbiased estimates.

The crash database is compiled of total 3,418 number of crashes involving at least one non-motorist. These crashes involve 2,063 pedestrians and has a record of 1,355 number of crashes involving bicycle. The severity of road crashes is identified, in the road safety literature, to be influenced by a multitude of factors. Accordingly, a number of crash-related factors were compiled from this database in order to explore the variables that might influence the pedestrian and bicycle crash severity outcomes.

5.3.3 Sample Formation and Description

The disaggregate-level component of severity analysis for pedestrian and bicyclist injury severity outcomes is developed for the area defined by CFRPM 6.0 model. The final datasets, after removing records with missing information for essential attributes, consisted of 1,466 pedestrian and 971 bicycle crash records. The distributions of pedestrian injury severity (upper row panel of Table 5-24) and bicycle injury severity (lower row panel of Table 5-24) for the final model estimation samples are presented in Table 5-24. From the distribution of Table 5-24, it is quite evident that the chance of a pedestrian being fatally injured was recorded to be substantially higher (11.7%) than bicyclists (0.4%) in the event of crashes for the year 2010. However, pedestrian was recorded to evade possible and non-incapacitating injuries more than bicyclist whenever he/she involved in a crash on roadways.

For the empirical analysis, we selected variables that can be grouped into six broad categories: vehicle characteristics, roadway characteristics, environmental characteristics, operational characteristics, non-motorists characteristics and driver characteristics. For pedestrian severity models, <u>vehicle characteristics</u> considered include vehicle type and vehicle use; <u>roadway characteristics</u> considered include roadway location; <u>environmental characteristics</u> considered include day of week, light condition and time of crash; <u>operation attributes</u> considered include traffic control device; pedestrian characteristics include pedestrian age and alcohol/drug impairment of pedestrian; finally, driver characteristics include driver age group. For bicycle severity models, vehicle characteristics considered include vehicle use; roadway characteristics considered include roadway location, influence area and road surface type; environmental characteristics considered include light condition and weather condition; finally, bicyclist's characteristics include biker age group. Table 5-25 and Table 5-26 offer a summary of the sample characteristics of the exogenous factors in the estimation dataset for pedestrian crashes and bicycle crashes, respectively.

Table 5-25: Distributions of Pedestrian and Bicycle Injury Severity

Severity outcomes	Pedestrian		Bicycle	
	Frequency	Percent	Frequency	Percent
No Injury	91	6.2	95	9.8
Possible Injury	329	22.4	303	31.2
Non-incapacitating injury	550	37.5	445	45.8
Incapacitating injury	324	22.1	124	12.8
Fatal	172	11.7	4	0.4
Total	**1,466**	**100.0**	**971**	**100.0**

Table 5-26: Summary Statistics of Explanatory Variables for Pedestrian Crashes

Variable Name	Variable Description	Percentage
Vehicle Characteristics		
Vehicle type		
Truck, Tractor and bus	Truck, Tractor and bus	8.9
Automobile	Automobile	37.9
Other Vehicles	Van, Bike, Motorbike, mopped, slow moving vehicles, Level Terrene vehicle etc.	53.2
Vehicle use		
Public School Bus	Public School Bus	0.3
Private Transportation	Private Transportation	52.4
Other Uses	Cargo van, law enforcement, ambulance, fire, rescue, military, dump, concrete mixer etc.	47.3
Roadway Characteristics		
Roadway location		
Median	On the median	1.6
On Road	On the road	89.8
Shoulder	On shoulder	4.3
Not on road	Outside roadway	3.8
Turn Lane	On turning lanes	0.5
Environmental Characteristics		
Day of week		
Weekend	During the weekends (Saturday-Sunday)	19.8
Weekdays	During the weekdays (Monday-Friday)	80.2

Table 5-25 (Continued): Summary Statistics of Explanatory Variables for Pedestrian Crashes

Variable Name	Variable Description	Percentage
Light condition		
Dark (No street light)	Dark period with no street light	18.6
Daylight	Daylight	47.5
Dark (Street light)	Dark period with street light	27.7
Dusk	Dusk	2.9
Dawn	Dawn	3.2
Time of crash		
PM Peak	Time of day (4 pm-6 pm)	10.2
AM Peak	Time of day (7 am-9 am)	9.2
Off peak	Time of day (9 am-4 pm)	80.6
Operational Attributes		
Traffic control device		
Speed control sign	Speed control sign	40.6
Special speed zone	Special speed zone	0.9
No control	No control	27.2
Traffic signal	Traffic light control system	21.9
Stop sign	Stop sign control system	7.2
School zone	School zone (Special zone)	0.8
No passing Zone	No pedestrian passing zone	0.5
Railroad signal	Railroad crossing/passing signal	0.7
Pedestrian Characteristics		
Pedestrian age		
Senior pedestrian	Pedestrian age (>65 years old)	8.0
Child pedestrian	Pedestrian age (<18 years old)	23.9
Adult pedestrian	Pedestrian age (18-64 years old)	68.1
Alcohol/drugs impairment of pedestrian		
Involvement	Pedestrian impaired by in alcohol/drugs	82.9
No involvement	Pedestrian not impaired by alcohol/drugs	17.1
Driver Characteristics		
Driver Age group		
Teenage driver	Driver age (15-19 years old)	6.6
Adult driver	Driver age (20-64 years old)	82.9
Senior Driver	Senior Driver (<65 years old)	10.4

Table 5-27: Summary Statistics of Explanatory Variables for Bicycle Crashes

Variable Name	Variable Description	Percentage
Vehicle Characteristics		
Vehicle Use		
Public Transportation	Public Transportation	87.6
Other uses	Other uses (school bus, law enforcement, military, Cargo van, PT)	12.4
Roadway Characteristics		
Roadway location		
On road	On the road	85.5
Shoulder	On the Shoulder	4.0
Not on Road	Not on Road	9.3
Median	Median of road	1.2
Influence area		
Not at intersection	Not at intersection/Bridge	14.4
Influenced by intersection	Influenced by intersection	8.0
Driveway access	Driveway access	19.3
Intersection	Intersection	57.5
Exit ramp	Exit Ramp	0.8
Road Surface Type		
Blacktop	Blacktop road surface	91.9
Concrete	Concrete road surface	5.7
Other road surface	Brick/dirt/gravel/slag/stone road surface	2.5
Environmental Characteristics		
Light condition		
Dark (No street light)	Dark period with no street light	4.3
Dark (Street Light)	Dark period with street light	11.4
Daylight	Daylight	80.2
Dusk	Dusk	2.9
Dawn	Dawn	1.1
Weather Condition		
Clear	Clear weather	82.8
Cloudy	Cloudy weather	16.0
Rain	Rainy weather	1.2
Bicyclist’s characteristics		
Biker Age Group		
Children bike rider	Biker age < 18 year	16.5
Adult bike rider	Biker age 18-64 year	78.4
Senior bike rider	Biker age > 64 year	5.1

5.3.4 Estimation Results

We estimated two different OL models: one model for pedestrian crash injury severity outcome and another model for bicycle crash injury severity outcome. Table 5-27 and Table 5-28 present the estimation results of the OL models of pedestrian and bicycle crash injury severity outcomes, respectively. The effects of exogenous variables in model specifications for pedestrian and bicycle crash severity models are discussed in the following sections.

In OL models, the positive (negative) coefficient corresponds to increased (decreased) likelihood of severe crash severity outcome. The final specification of the model was based on removing the statistically insignificant variables in a systematic process based on statistical significance (95% significance level) and intuitive coefficient effect.

5.3.4.1 Pedestrian Crash Severity Model

Table 5-27 presents the OL model results for pedestrian crash injury severity outcomes for base year 2010.

Vehicle Characteristics: Vehicle type and vehicle use are two vehicle characteristics variables that are found to be significant determinants of pedestrian crash injury severity outcomes. The results presented in Table 5-27 indicate that truck, tractor and bus results in severe pedestrian crashes compared to crashes with automobile and other vehicles. The result may be attributed to heavy vehicular mass of truck, tractor and bus. The likelihood of severe pedestrian crash outcome is lower if the vehicle use is related to public school bus relative to private and other vehicular use categories.

Roadway Characteristics: The results of pedestrian crash injury severity outcomes indicate that roadway location affects the injury sustained by a pedestrian in a crash. In particular, crashes on median results in more severe crashes compared to the other roadway location.

Environmental Characteristics: Several environmental characteristics considered are found to be significant determinants of pedestrian crash injury severity outcomes. As is expected, we find that pedestrians are less likely to evade higher severity during weekend relative to crashes during weekdays. Daylight is negatively associated with pedestrian crash injury severity propensity indicating lower likelihood of severity outcome during daylight compared to crashes during other period of the day. With respect to time of day, crashes during PM peak period increases the likelihood of severe pedestrian injury compared to AM peak and off peak periods.

Pedestrian Characteristics: The relevance of pedestrian age has long been recognized as an important contributory factor in pedestrian crash severity studies. The model results reveal a reduction in the risk propensity for child pedestrian group compared to the adult group perhaps because these pedestrian groups are more physically fit compared to other pedestrians. On the other hand, it is found that senior pedestrians are associated with the higher likelihood of severe crashes compared to the adult pedestrian groups. Older pedestrians might be physically weak and they may be medically unfit with problems related to hearing, vision and contrast sensitivity. As is expected, the model result related to alcohol/drug impairment indicates higher injury severity outcome if the pedestrians are impaired by alcohol/drug while involved in crash.

Driver Characteristics: With respect to the driver characteristics, driver age is found to affect pedestrian crash severity outcome. Pedestrians are likely to sustain serious injury when the driver of the motor vehicle is a teenager relative to adult or senior driver groups.

Table 5-28: OL Model Estimates of Pedestrian Injury Severity Outcomes

Variable Name	Estimates	t-stat
Threshold no injury and possible injury	-2.856	-19.901
Threshold possible injury and non-incapacitating injury	-0.918	-8.619
Threshold between non-incapacitating injury and incapacitating injury	0.865	8.124
Threshold between incapacitating injury and fatal injury	2.394	18.904
Vehicle Characteristics		
Vehicle type (Base: Automobile and other vehicles)		
Truck, Tractor & Bus	0.370	2.378
Vehicle use (Base: Private transportation and other uses)		
Public School Bus	-3.697	-3.177
Roadway Characteristics		
Roadway location (Base: Location other than median)		
Median	1.132	3.011
Environmental Characteristics		
Day of week (Base: Weekdays)		
Weekends	0.284	2.351
Light Condition (Base: Non-daylight)		
Daylight	-0.799	-7.045
Time of crash (Base: AM peak and off peak)		
PM Peak	0.621	3.785
Operational Attributes		
Traffic control device (Base: All other traffic control device)		
Speed control sign	0.416	3.971
Special speed zone	-1.742	-3.620
Pedestrian Characteristics		
Pedestrian age (Base: Adult Pedestrian)		
Senior pedestrian	0.704	3.928
Child pedestrian	-0.282	-2.351
Alcohol/drugs impairment of pedestrian (Base: No involvement)		
Involvement	1.161	7.613
Driver Characteristics		
Driver Age group (Base: Adult and senior driver)		
Teenage Driver	0.541	2.82
Number of Observations	1466	
Log likelihood at zero	- 2359.94	
Log likelihood at constant	- 2141.39	
Log likelihood at convergence	- 2003.01	

5.3.4.2 Bicycle Crash Severity Model

Table 5-28 presents the OL model results for bicycle crash injury severity outcomes for base year 2010.

Table 5-29: OL Model Estimates of Bicycle Injury Severity Outcomes

Variable Name	Estimates	t-stat
Threshold no injury and possible injury	-0.860	-2.067
Threshold possible injury and non-incapacitating injury	1.093	2.621
Threshold between non-incapacitating injury and incapacitating injury	3.456	8.089
Threshold between incapacitating injury and fatal injury	7.081	10.854
Vehicle Characteristics		
Vehicle use (Base: Other uses)		
Private transportation	0.633	3.372
Roadway Characteristics		
Roadway location (Base: Roadway location other than shoulder)		
Shoulder	1.023	3.288
Influence area (Base: Not at intersection, intersection and exit ramp)		
Influenced by intersection	-0.548	-2.477
Driveway Access	-0.719	-4.430
Road surface Type (base: Other road surface type)		
Blacktop	1.421	3.966
Concrete	1.521	3.528
Environmental Characteristics		
Light Condition (Base: Other than dark non street light condition)		
Dark (No street light)	0.685	2.355
Weather Condition (Base: Cloudy and rainy)		
Clear	-0.347	-2.148
Bicyclist's characteristics		
Biker Age group (base: Adult and old biker)		
Teenage biker	-0.390	-2.436
Number of Observations	971	
Log likelihood at zero	- 1562.76	
Log likelihood at constant	- 1198.07	
Log likelihood at convergence	- 1162.65	

Vehicle Characteristics: The only vehicle characteristics influencing pedestrian crash injury severity outcome is the vehicle use variable. The indicator variable representing private transportation is likely to increase the likelihood of severe bicycle injury compared to other vehicle usage.

Roadway Characteristics: Several roadway characteristics considered are found to be significant determinants of bicycle crash severity outcomes. Among roadway characteristics, the indicator variable shoulder reveals positive association with bicycle crash injury severity outcome propensity relative to other roadway location. In terms of roadway influence area, intersection influence area and driveway access are likely to result in higher crash severity outcomes relative to other roadway influence area. From Table 5-28, we can also see that bicycle crashes on blacktop and concrete road surface are likely to result in higher crash severity compared to bike crashes on other road surfaces.

Environmental Characteristics: Lighting and weather conditions are environmental characteristics variables that are found to significantly affect bicycle crash injury severity outcomes. From bicycle crash severity model, we find that crashes occurring in the absence of artificial illumination (street-lights) during dark periods increases the likelihood of severe bicycle injury compared to other lighting conditions. Problems associated with darkness at night-time could be attributed to poor visual conditions, higher vehicular speed, fatigue and/or possible negligence. As expected, the propensity of severe bicycle crash is lower for clear weather condition relative to cloudy and rainy weather conditions.

Bicyclist's Characteristics: With respect to the bicyclist's characteristics, age of biker is found to affect bicycle crash severity outcome. Teenager bicyclists are likely to evade serious injury relative to adult or senior biker groups, perhaps indicating higher physical fitness of this group of bikers.

5.4 ZONAL-LEVEL CRASH SEVERITY ANALYSIS

Crash count data are often compiled by injury severity outcomes (for example: no injury, minor injury, major injury and fatal injury crashes). Given the consequences of road traffic crashes, it is important to examine crash frequency by severity level as it would play a significant role in model implications. To that extent, we can develop independent crash prediction models for different injury severity levels. However, for the same observation record, crash frequencies by different severity levels are likely to be dependent. Therefore, it might be beneficial to evaluate the impact of exogenous variables in a framework that directly relates a single exogenous variable to all severity count variables simultaneously, *i.e.*, a framework where the observed propensities for crashes are examined by severity level directly. To that extent, in this current research effort, as opposed to modeling the number of crashes, we adopt a fractional split modeling approach to study the fraction of crashes by each severity level at a TAZ level. Specifically, we formulate and estimate ordered probit fractional split (OPFS) models for examining pedestrian and bicycle crash proportions by severity levels. The fractional split models are estimated at the TAZ level for the CFRPM 6.0 area employing a comprehensive set of exogenous variables. Based on the model results, we identify important exogenous variables that influence pedestrian and bicycle crash severity proportions.

5.4.1 Model Framework

The formulation for the OPFS model for modeling the proportion of crashes by severity is presented in this section. The reader would note that conventional maximum likelihood approaches are not suited for factional proportion models. Hence, we resort to a quasi-likelihood approach. See Yasmin et al. (2016) for detailed description of the modeling approach. Yasmin et al. (2016) developed the ordered outcome fractional split model that allows the analysis of proportion for variables with multiple alternatives while also recognizing the inherent ordering in the severity outcomes.

5.4.2 Model Structure

Let q (q = 1, 2, …, Q) be an index to represent TAZ, and let k (k = 1, 2, 3, …, K) be an index to represent severity category. The latent propensity equation for severity category at the q th zone:

$$y_q^* = \alpha' z_q + \xi_q, \tag{7}$$

This latent propensity y_q^* is mapped to the actual severity category proportion y_{qk} by the ψ thresholds ($\psi_0 = -\infty$ and $\psi_k = \infty$). z_q is an (L x 1) column vector of attributes (not including a constant) that influences the propensity associated with severity category. α is a corresponding (L x 1)-column vector of mean effects. ξ_q is an idiosyncratic random error term assumed to be identically and independently standard normal distributed across zones q.

<u>Model Estimation</u>

The model cannot be estimated using conventional Maximum likelihood approaches. Hence we resort to quasi-likelihood based approach for our methodology. The parameters to be estimated in the Equation (7) are α , and ψ thresholds. To estimate the parameter vector, we assume that

$$E(y_{qk} \mid z_{qk}) = H_{qk}(\alpha,\psi), 0 \le H_{qk} \le 1, \sum_{k=1}^{K} H_{qk} = 1 \tag{8}$$

H_{qk} in our model takes the ordered probit probability (P_{qk}) form for severity category k defined as

$$P_{qk} = \left\{ G\lfloor \psi_k - \alpha_q' z_q \rfloor - G\lfloor \psi_{k-1} - \alpha_q' z_q \ \rfloor \right\} \tag{9}$$

The proposed model ensures that the proportion for each severity category is between 0 and 1 (including the limits). Then, the quasi-likelihood function, for a given value of δ_q vector may be written for site q as:

$$L_q(\alpha,\psi) = \prod_{k=1}^{K} \left\{ G\lfloor \psi_k - \alpha_q' z_q \rfloor - G\lfloor \psi_{k-1} - \alpha_q' z_q \ \rfloor \right\}^{d_{qk}} \tag{10}$$

where G(.) is the cumulative distribution of the standard normal distribution and d_{qk} is the proportion of crashes in severity category k. The model estimation is undertaken using routines programmed in Gauss matrix programming language.

5.4.3 Dependent Variable and Data Description

The crash proportion analysis is focused on pedestrian and bicycle crashes at the TAZ level. There are 4,747 TAZs in the area defined by CFRPM 6.0 model. For this research effort, we have examined the pedestrian and bicycle crash count by severity levels for the year 2010 to reflect the base year situation in terms of non-motorized safety. These crash records are collected and compiled from Signal Four Analytics (S4A) databases. For the year 2010, 1,541 and 984 crashes were reported involving pedestrian and bicycle, respectively. These crashes are classified by injury severity levels as fatal, incapacitating, non-incapacitating, possible injury, and property damage only crashes. Location of zones with fatal pedestrian and bicycle crashes are shown in Figure 5-19. In the case of five severity levels the dependent variable in this research effort is represented as proportions (number of specific crash level/total number of all crashes) as follows: (1) proportion of property damage only crashes, (2) proportion of minor injury crashes, (3) proportion of non-incapacitating injury crashes, (4) proportion of incapacitating injury crashes and (5) proportion of fatal crashes. The dependent variable proportions and sample size for pedestrian and bicycle crashes are presented in Table 5-29. From the Table we can observe that fatal crash proportion is higher for pedestrian than bicycle involved crashes.

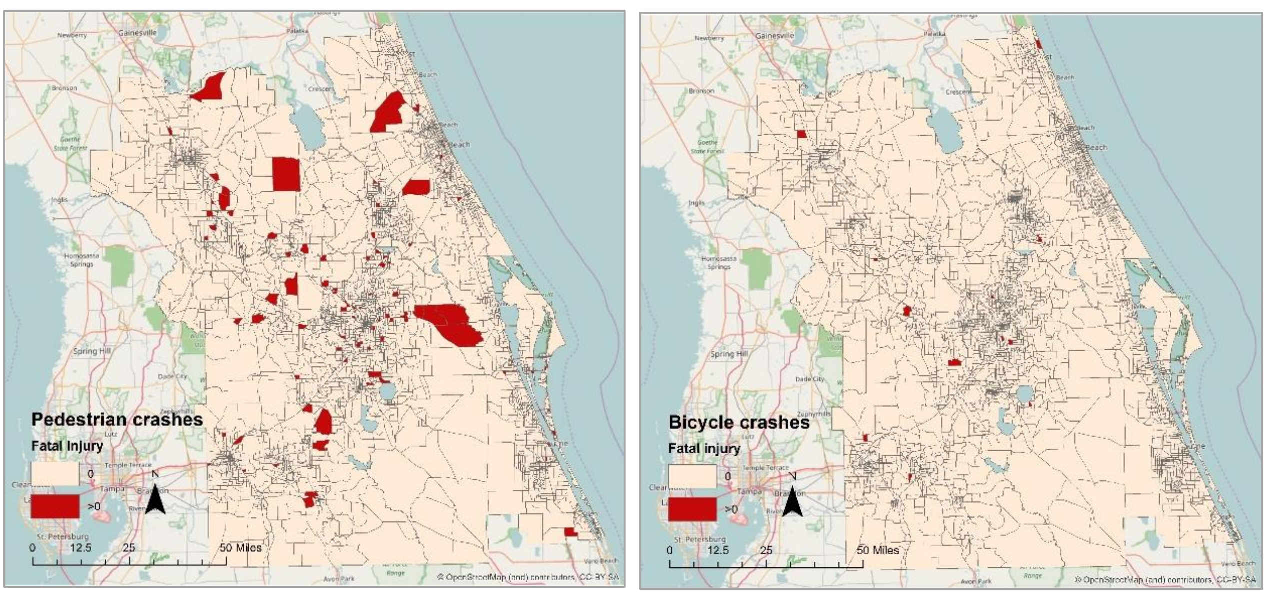


Figure 5-19: Zones with Fatal Pedestrian and Bicycle Crashes for the Year 2010

Table 5-30: Severity Proportions

Crash severity levels	Pedestrian	Bicycle
Sample	949	719
Proportion of property damage only crashes	0.113	0.115
Proportion of minor injury crashes	0.237	0.320
Proportion of non-incapacitating injury crashes	0.382	0.407
Proportion of incapacitating injury crashes	0.183	0.141
Proportion of fatal crashes	0.085	0.017

In addition to the crash database, the explanatory attributes considered in the empirical study are also aggregated at the TAZ level accordingly. To reflect the base year characteristics of the analysis zone, all attributes are generated for the year 2010. For the empirical analysis, the selected explanatory variables can be grouped into four broad categories: sociodemographic characteristics, roadway and traffic attributes, built environment characteristics and land use characteristics. Table 5-30 offers a summary of the sample characteristics of the exogenous variables and the definition of variables considered for final model estimation along with the zonal minimum, maximum and average.

Table 5-31: Summary Characteristics for Zonal-level Crash Severity Models

Variable name	Description	Pedestrian Zonal			Bike Zonal		
		Minimum	Maximum	Mean	Minimum	Maximum	Mean
Sociodemographic Characteristics							
Population density	Total number of population of TAZ/ Area of TAZ in acres	0.000	19.956	3.362	0.000	19.956	3.622
Proportion of people aged 22 to 29	Total number of population of TAZ who are 22 to 29 years old / Total number of population of TAZ	0.000	0.373	0.111	-	-	-
Roadway and Traffic Attributes							
Number of flashing beacon signs	Total number of flashing beacons of TAZ	-	-	-	0.000	1.000	0.006
Number of school signals	Total number of school signals of TAZ	-	-	-	0.000	1.000	0.003
Availability of bike lanes	Availability of bike lanes in TAZ	-	-	-	0.000	1.000	0.058
VMT	Vehicle miles traveled = Total road length in miles * Average annual daily traffic / 100000	0.000	17.052	0.430	-	-	-
Drive Demand	Total drive demand in a TAZ/10000	0.000	13.901	1.129	0.009	9.941	1.064
Drive demand per housing unit	Ln[(Total drive demand/total housing unit in a TAZ)+1]	0.000	13.610	3.089	0.000	11.730	3.070
Built Environment							
Number of commercial centers	Total number of commercial centers of TAZ	0.000	3.000	0.113	-	-	-
Number of hospitals	Total number of hospitals of TAZ	-	-	-	0.000	2.000	0.033
Number of parks and recreational centers	Total number of parks and recreational centers of TAZ	-	-	-	0.000	7.000	0.307
Land-use Characteristics							
Urban area	Ln (Urban area in a TAZ in acres)	-6.254	8.384	5.236	-4.661	8.384	5.328
Residential area	Ln (Residential area in a TAZ in acres)	-	-	-	-9.052	7.647	4.070
Exposure measures							
Total pedestrian trip demand per household	Total pedestrian daily trip demand in a TAZ/(Total number of households in a TAZ*100)	0.000	1.316	0.021	-	-	-
Total bicycle trip demand per household	Total bicycle daily trip demand in a TAZ/Total number of households in a TAZ	-	-	-	0.000	134.686	0.498

5.3.4 Estimation Results

In this research effort, we estimate two different OPFS models: one model for pedestrian crash severity proportions at the zonal level and another model for bicycle crash severity proportions at the zonal level. Table 5-31 presents the estimation results of the OPFS models. The pedestrian crash severity proportion results are presented in 2nd and 3rd columns of Table 5-31 and bicycle crash severity proportion model component 4th and 5th columns of Table 5-31. In OPFS models, the positive (negative) coefficient corresponds to increased (decreased) proportion for severe injury categories. The final specification of the model was based on removing the statistically insignificant variables in a systematic process based on statistical significance and intuitive coefficient effect. In estimating the models, several functional forms and variable specifications are explored. The functional form that provided the best result is used for the final model specifications. The effects of exogenous variables in model specifications for both pedestrian and bicycle crash severity proportion models are discussed in this section by variable groups.

Table 5-32: Estimation Results of Ordered Probit Fraction Split Models

Variable name	Pedestrian		Bike	
	Estimates	t-stat	Estimates	t-stat
Threshold 1	-1.694	-12.917	-1.578	-6.172
Threshold 2	-0.856	-6.659	-0.523	-2.072
Threshold 3	0.160	1.245	0.671	2.643
Threshold 4	0.930	7.048	1.828	6.735
Sociodemographic Characteristics				
Population Density	-0.022	-1.947	-0.035	-2.155
Proportion of people aged 22 to 29	-1.158	-1.649	---	---
Roadway and Traffic Attributes				
Number of flashing beacon sign	---	---	0.922	2.309
Number of school signal	---	---	0.354	2.471
Availability of bike lane	---	---	-0.285	-1.777
VMT	0.053	1.774	---	---
Drive demand	-0.021	-0.664	---	---
Drive demand per housing unit	---	---	-0.030	-0.661
Built Environment				
Number of commercial center	-0.145	-1.890	---	---
Number of hospital	---	---	-0.181	-1.698
Number of park and recreational center	---	---	0.136	2.715
Land-use Characteristics				
Urban area	-0.043	-2.164	-0.072	-1.954
Residential area	---	---	0.056	1.844
Exposure Measures				
Total pedestrian trip demand per household	-1.046	-2.702	---	---
Total bicycle trip demand per household	---	---	-0.004	-0.952
Log-likelihood Value	-1386.527		-937.993	

Sociodemographic Characteristics: With respect to sociodemographic characteristics, the estimates indicate that population density results in lower likelihood of severe crash proportions for both pedestrian and bicycle crashes. Proportion of 22-29 years old group of population has negative impact on proportion of pedestrian crash severity outcomes implying a reduced likelihood of more severe pedestrian crashes.

Roadway and Traffic Attributes: The result associated with zonal level proportion of collector road reflects higher probability of severe bicycle crash proportions. The OPFS model results for bicycle reveal higher proportion of severe crash outcomes for zones with higher number of flash beacon sign and higher number of school signal. With respect to traffic attributes, higher heavy vehicle traffic volume (Truck AADT) is positively associated with more severe crash proportions in pedestrian crash proportion model. As is expected, availability of bike lane is found to reduce the likelihood of less severe bicycle crash proportion. Unlike, crash frequency models, drive demand has negative impact on the likelihood of severe crash proportions for both models.

Built Environment: The crash proportion model for pedestrian involved crashes reveal that the pedestrian crash proportion of severe crashes is lower in TAZs with higher number of commercial center. Higher number of hospitals associated with lower likelihood of severe crash proportion in OLFS model for bicycle. At the same time, the OLFS model results reveal that higher number of park and recreational center increases the possibility of higher proportions of severe bicycle crash outcomes.

Land-use Characteristics: From both pedestrian and bicycle models, we find that the possibility of more severe crashes decreases with increasing share of urbanized area of a TAZ. Residential area is found to be a significant determinant of bicycle crash proportion by severity outcomes. The estimate for residential area has a positive coefficient suggesting that proportion of severe bicycle crashes increases with increasing zonal level residential area.

5.5 SUMMARY

The chapter summarized base year safety trends of the multi-modal mobility study for Central Florida. Base year safety analysis was focused on crash frequency and crash severity analysis of pedestrian and bicycle involved crashes. Specifically, we estimated crash count models for examining pedestrian and bicycle crash count events by using the Negative Binomial model, while the disaggregate level severity outcomes of pedestrian and bicycle crashes were examined using the ordered logit model. We also estimated zonal-level crash severity models for examining pedestrian and bicyclist crash injury severity by proportions by using ordered probit fractional split model. It is worthwhile to mention here that the disaggregate-level crash severity analysis was focused on examining crash events. These models cannot be directly employed to incorporate safety considerations in the transportation planning process. On the other hand, the outcomes of aggregate-level crash count models, specifically macro-level models, can be used to devise safety-conscious decision support tools to facilitate proactive approach in assessing medium- and long-term policy-based countermeasures. Moreover, the tool plays an important role in safety implications of land use planning initiatives and alternate network-planning initiatives. Therefore, for further analysis, we focus on aggregate-level crash count models and aggregate level crash count by severity models as these are more feasible for planning-level policy analysis and identifying planning-level policy measures.

CHAPTER VI: BASE YEAR PUBLIC TRANSIT RIDERSHIP ANALYSIS

6.1 INTRODUCTION

The objective of this chapter is to document and present the base year transit ridership analysis in evaluating the benefits of multi-modal investments on promoting travel mobility for Central Florida. The component of public transit ridership evaluation of the research effort is mainly focused on the coverage area of Lynx and SunRail network systems for the greater Orlando area. The chapter also presents and identifies the catchment area of SunRail stations for the potential customers. For developing different models and measures for the project, the research team has considered 2010 as the base year. However, the team has access to the bus ridership data from August-2013 to December-2016; whereas the SunRail ridership data is available from January-2015 to October-2015. Therefore, the transit ridership analysis is focused on these available ridership information rather than ridership data of the year 2010.

With respect to transit ridership analysis, in this research effort, we estimate and present four different sets of ridership models: <u>for Lynx network system</u> – (1) stop level average weekday boarding bus ridership analysis, and (2) stop level average weekday alighting bus ridership analysis; finally, <u>for SunRail network system</u> – (3) daily boarding rail ridership analysis, and (4) daily alighting rail ridership analysis. It is worthwhile to mention here that one of the major focus of the proposed bus ridership research effort is to evaluate the influence of recently inaugurated commuter rail system “SunRail” in Orlando on bus ridership while controlling for host of other exogenous variables. We have presented the data compilation procedures, model estimation procedures and outcome of these models. In terms of SunRail catchment area, we identify catchment area of rail stations for four different modes; specifically for walk, bike, bus transit and drive mode.

The remaining of the chapter is organized as follows: The next section provides an overview of the public transit systems. The subsequent section focuses on transit ridership analysis and catchment area identification of SunRail followed by the summary section.

6.2 AN OVERVIEW OF PUBLIC TRANSIT SYSTEM

The component of public transit ridership evaluation of the research effort is mainly focused on the coverage area of Lynx and SunRail network systems. Figure 6-20 represents the study area along with Lynx bus route, bus stops, SunRail line and SunRail station locations.

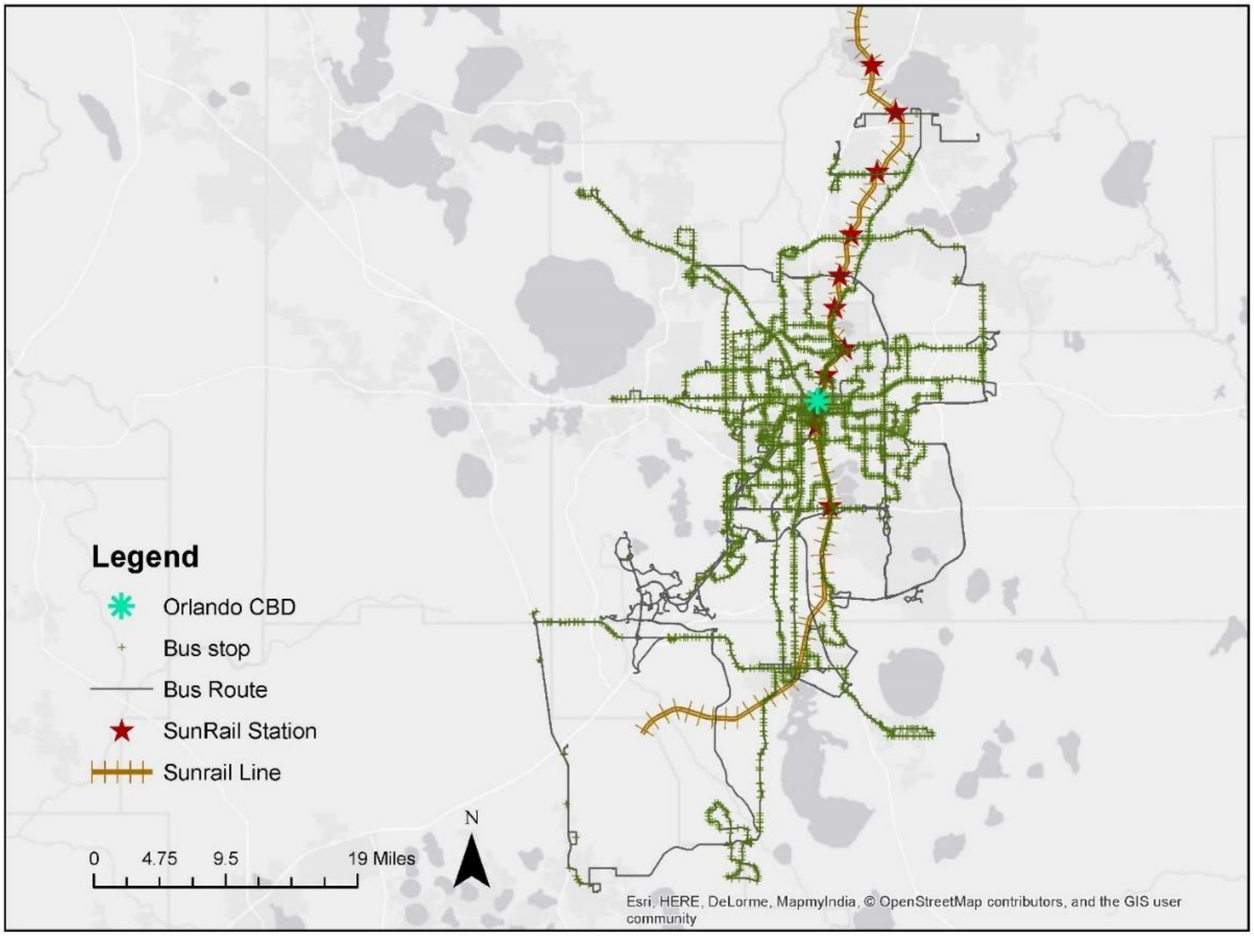


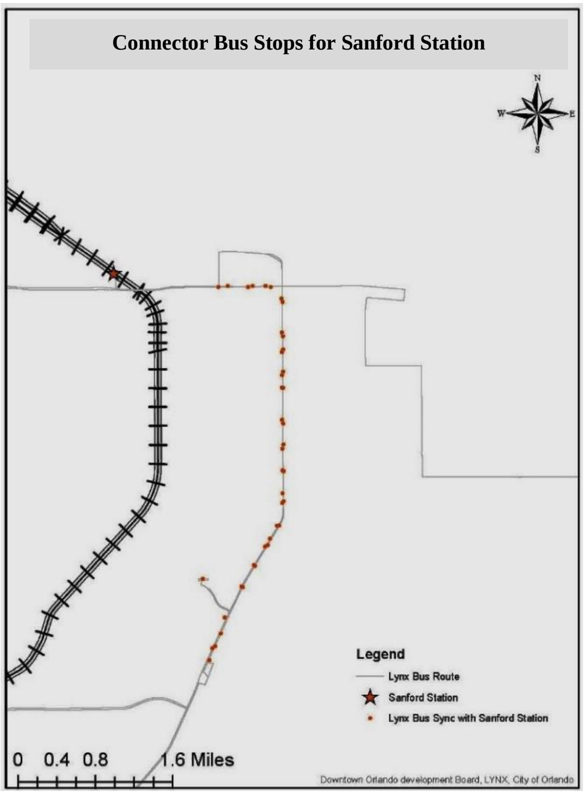
Figure 6-20: Public Transit System (LYNX and SUNRAIL) of Greater Orlando

6.3 RIDERSHIP ANALYSIS OF PUBLIC TRANSIT

The consequences of the increased dependence on automobile mode are traffic congestion, increased air pollution and greenhouse gas (GHG) emissions. Policy makers are considering several alternatives to counter the negative externalities of this personal vehicle dependence. The development of an efficient multi-modal public transportation system is often the most considered solution. Many urban regions, across different parts of North America, are considering investments in public transportation alternatives such as bus, light rail, commuter rail, and metro. The main public transit system serving the Orlando metropolitan region is the Lynx transit system and a most recent addition to the transit network is SunRail which is a commuter rail service. Policy makers and stakeholders are encouraging communities to take advantage of the momentum of these improvements in transportation sector in reducing reliance on private automobiles and to adopt more sustainable mode choice. A critical component of devising strategic policies to incur modal shift is to identify critical factors contributing to transit ridership. To that extent, in this research effort, we estimate four different sets of ridership models: for Lynx network system – (1) stop level average weekday boarding bus ridership analysis, and (2) stop level average weekday alighting bus ridership analysis; finally, for SunRail network system – (3) daily boarding rail ridership analysis, and (4) daily alighting rail ridership analysis. A specific emphasis of bus ridership analysis is to identify the effect of SunRail on bus ridership. Therefore, we also analyze and identify the bus routes and bus stops which are likely to be within influence area of rail stations. In the following sections we have presented the data compilation procedures, model estimation procedures and outcome of these ridership models followed by proximity analysis for Lynx bus and SunRail systems.

6.4 PROXIMITY ANALYSIS FOR LYNX AND SUNRAIL SYSTEMS

As the specific emphasis of the study effort is on SunRail impact, we generated a variable that identifies bus stops and bus routes that are affected by SunRail or in other words are within the influence area of SunRail. While there is likely to be a system level effect, it is more realistic to consider the impact of SunRail on stop level ridership based on connectivity as well as proximity from SunRail stations. For this purpose, we perform proximity analysis of Lynx and SunRail systems by using system schedule and ArcGIS tool. We identified specific bus routes that intersect or pass through the SunRail system and defined those as connector bus routes. Of the 77 bus routes operated by Lynx, we found that 60 routes are within the SunRail influence zone (i.e. pass through SunRail). These routes account for 3,321 out of the 3,745 stops considered in our analysis, which we defined as <u>connector bus stops</u>. The locations of these connector bus stops from different rail stations identified are shown in Figure 6-21. To allow connector stops closer to SunRail to have a stronger impact on ridership we computed distance to the nearest SunRail station from each connector bus stop that is affected by SunRail. This will allow us to test for impact of SunRail using distance decay functions.



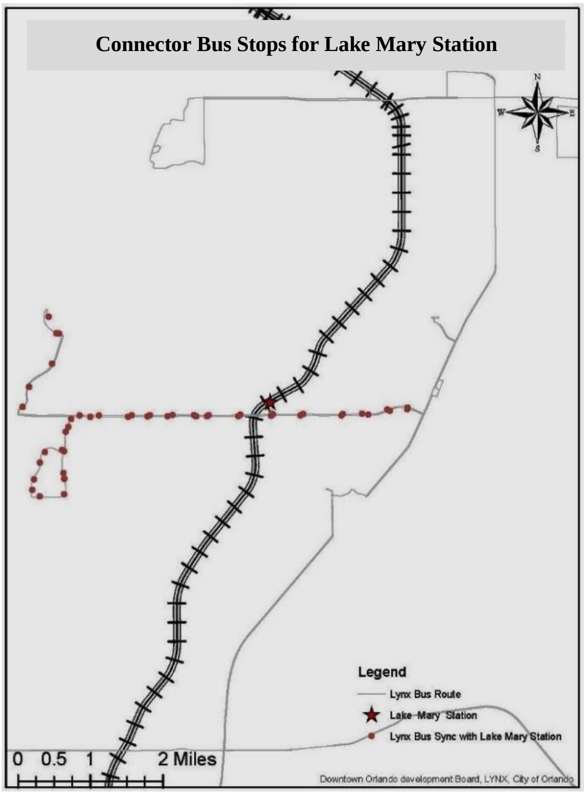


Figure 6-21: Location of Connector Lynx Bus Stops for Different SunRail Stations

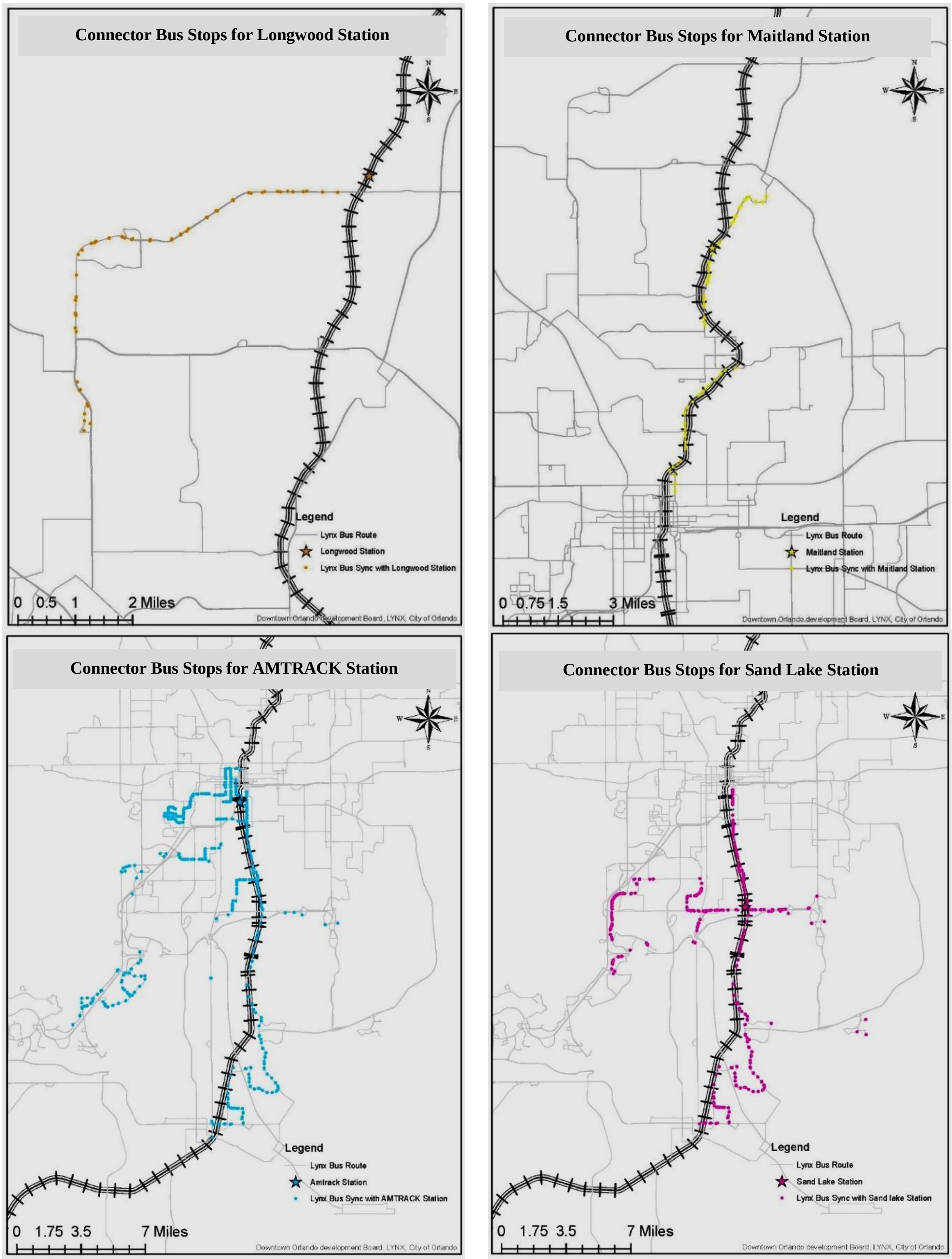


Figure 6-21 (Continued): Location of Connector Lynx Bus Stops for Different SunRail Stations

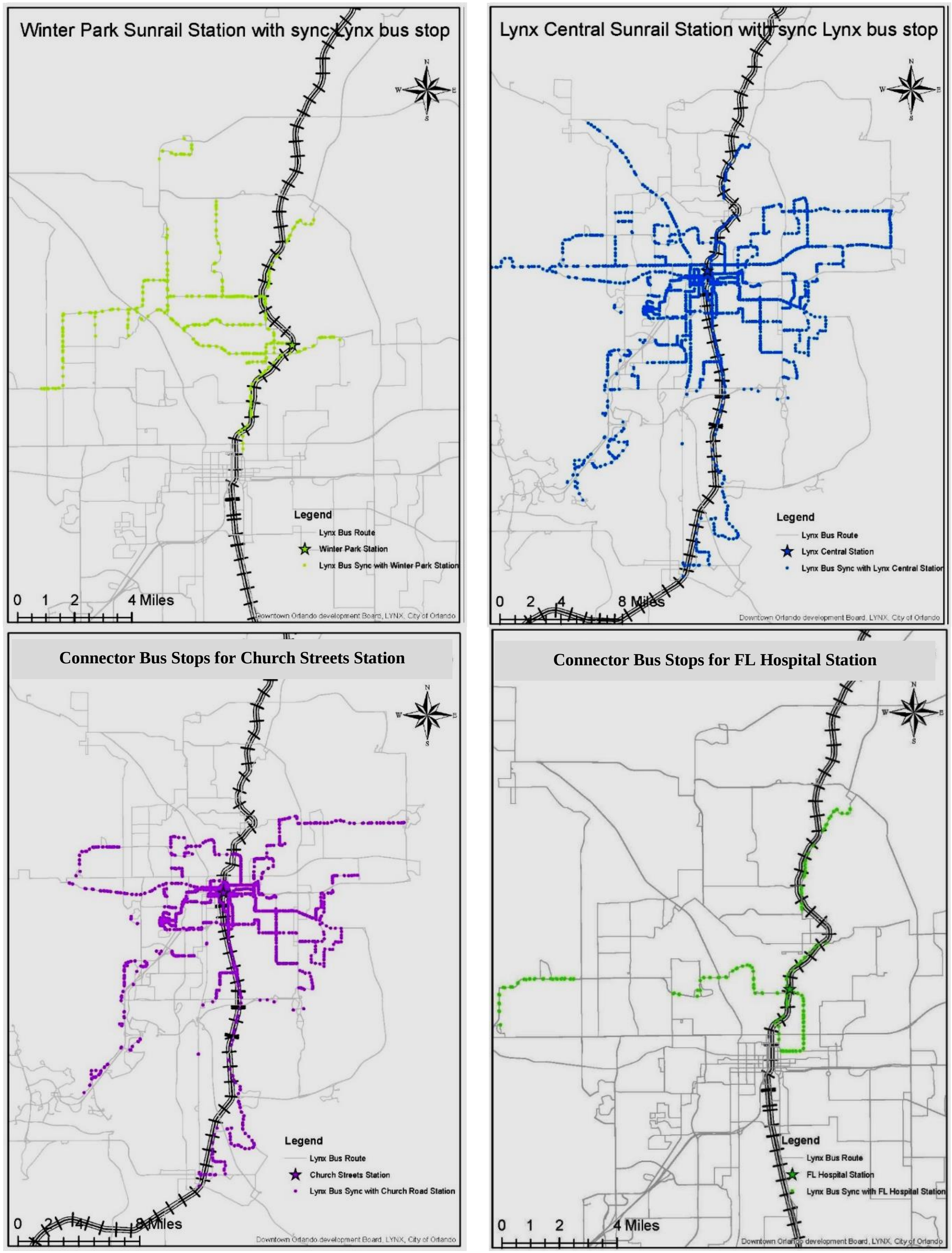


Figure 6-21 (Continued): Location of Connector Lynx Bus Stops for Different SunRail Stations

6.5 RIDERSHIP ANALYSIS FOR LYNX NETWORK SYSTEM

The main public transit system serving the Orlando metropolitan region is the Lynx transit system. The system has several services, including fixed route Bus, LYMMO, Xpress Bus, Vanpool, FastLink, Access Lynx, NeighborLink and Knight Lynx. Among these services, fixed route bus provide service seven days a week including holidays. The system has 77 daily routes. In 2015, more than 26 million ridership were reported for these fixed route bus services. In our current research effort, the bus ridership analysis is focused on only fixed route bus service systems. For simplicity, we will refer fixed route bus ridership as bus ridership in the following sections. The yearly bus ridership for five fiscal years is shown in Figure 6-22. From Figure 6-22, we can see that overall yearly ridership was increasing until year 2013, while total ridership has declined almost by 4% from 2014 to 2015 (Metroplan Orlando, 2016).

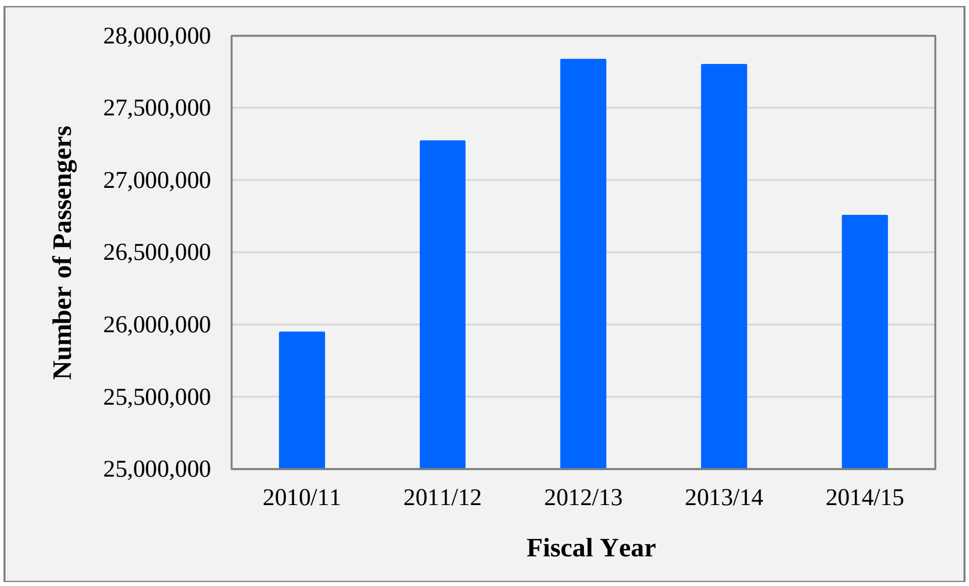


Figure 6-22: Total Bus Ridership Trend

This figure clearly highlights that it is imperative to understand the choice of such system in order to maintain and attract a significant ridership level. It is important to identify critical factors contributing to bus ridership to devise transit service deployment, enhancement and investment policies. To that extent, in this current study effort, we formulate and estimate bus ridership models. Specifically, we estimate two bus ridership model: (1) stop level average weekday boarding bus ridership model, and (2) stop level average weekday alighting bus ridership model. Based on the model results we identify important exogenous variables that influence bus boarding and alighting at stop level. The major focus of the proposed research effort is to identify critical factors contributing to bus ridership (boarding and alighting). In doing so, we also evaluate the influence of recently inaugurated commuter rail system "SunRail" in Orlando on bus ridership while controlling for host of other exogenous variables. We estimate these models by using Grouped Ordered Logit (GROL) models.

6.5.1 Model Framework

The focus of our study is to model stop level average weekday boarding and alighting of bus by employing GROL modeling framework. The econometric framework for the GROL model is presented in this section.

Let q (q = 1, 2,…, Q) be an index to represent observations, and j (j = 1, 2, 3,…, J) be an index to represent the number of boarding or alighting across different time period. Then, the equation system for modeling boarding/alighting may be written as follows:

$$B_q^* = \alpha' \boldsymbol{x}_q + \boldsymbol{\sigma}_j \boldsymbol{s}_{qj} + \varepsilon_q, B_q = j \ \ if \ \psi_{j-1} < B_q^* \leq \psi_j \tag{1}$$

In equation 1, B_q^* is the latent (continuous) propensity for boarding/alighting of observation q. This latent propensity B_q^* is mapped to the actual grouped ridership category j by the ψ thresholds, in the usual ordered-response modeling framework. In our case, we consider J = 13 and thus the ψ values are as follows: -∞, 5, 10, 20, 30, 40, 50, 60, 70, 80, 90, 100, 120, and +∞. x_q is a matrix of attributes that influence the boarding/alighting (including a constant); α is the corresponding vector of mean coefficients. Further $\boldsymbol{s}_{qj}$ is a vector of attributes specific to observation q and ridership alternative j and $\boldsymbol{\sigma}_j$ is the vector of corresponding bin-specific coefficients. ε_q is an idiosyncratic random error term assumed independently logistic distributed across choice occasions with variance ${\boldsymbol{\lambda}_q}^2$. In current study the variance vector is parameterized as follows:

$$\boldsymbol{\lambda}_q = exp(\boldsymbol{\theta} \boldsymbol{w}_q) \tag{2}$$

where, $\boldsymbol{w}_q$ is a set of exogenous variables (including a constant) associated with observation q and $\boldsymbol{\theta}$ is the corresponding vector of parameters to be estimated. The parameterization allows for the variance to be different across observations accommodating for heteroscedasticity. Thus, the probability expression for the ridership category can be written as:

$$P(B_q) = \Lambda \left[\frac{\psi_j - (\alpha' \boldsymbol{x}_q + \boldsymbol{\sigma}_j \boldsymbol{s}_{qj})}{\lambda_q} \right] - \Lambda \left[\frac{\psi_{j-1} - (\alpha' \boldsymbol{x}_q + \boldsymbol{\sigma}_j \boldsymbol{s}_{qj})}{\lambda_q} \right] \tag{3}$$

where Λ (.) is the cumulative standard logistic distribution. Finally, the log-likelihood function for the GROL model can be written as:

$$\mathrm{Ln(L)} = \sum_{t=1}^{T} \ln(P(B_q)) \tag{4}$$

The parameters are estimated using maximum likelihood approaches.

6.5.2 Data Description

Bus ridership is examined in order to identify the demand of bus transit at stop level across different time periods and to evaluate the influence of SunRail on bus ridership. For the purpose of our analysis, average daily weekday boarding and alighting ridership data was considered from 2013 to 2016 for following eleven (11) time periods: May through August 2013, September through December 2013, January through April 2014, May through August 2014, September through December 2014, January through April 2015, May through August 2015, September through December 2015, January through April 2016, May through August 2016, and September through December 2016. The ridership information was processed for all the 11 time periods and analyzed to ensure data availability and accuracy. The final sample consists of 37,884 records (3,444 stops × 11 quarters). The average daily stop level boarding (alighting) is around 18.84 (18.70) with a minimum of 0 (0) and maximum of 6,135 (5,943). The ridership data was augmented with stop level headway, route length as well as route to stop correspondence for Lynx across the 11-time periods. The station location coordinates were obtained from SunRail website.

From 3,444 stops, we randomly selected 2,800 number of stops for model estimation purposes and the rest 644 stops are considered for model validation purposes. Thus, our model estimation sample includes information from 2,800 stops for 11 time periods (2,800*11 = 30,8000 records). We consider thirteen categories for analysis ridership and these categories are: Bin 1 = 0~5; Bin 2 = >5~10; Bin 3 = >10~20, Bin 4 = >20~30, Bin 5 = >30~40, Bin 6 = >40~50, Bin 7 = >50~60, Bin 8 = >60~70, Bin 9 = >70~80, Bin 10 = >80~90, Bin 11 = >90~100, Bin 12 =>100~120 and Bin 13 = 120+ ridership. A summary of the records included in different bins for boarding and alighting is presented in Table 6-32.

Table 6-33: Summary Statistics of Lynx Bus Ridership for Different Bins

Categories	Bins	Boarding		Alighting	
		Frequency	Percentage	Frequency	Percentage
1	Bin 1 = 0~5	15544	50.468	16182	52.539
2	Bin 2 = 5~10	5306	17.227	5315	17.256
3	Bin 3 = >10~20	4433	14.393	4224	13.714
4	Bin 4 = >20~30	1906	6.188	1594	5.175
5	Bin 5 = >30~40	982	3.188	888	2.883
6	Bin 6 = >40~50	683	2.218	581	1.886
7	Bin 7 = >50~60	383	1.244	468	1.519
8	Bin 8 = >60~70	298	0.968	302	0.981
9	Bin 9 = >70~80	231	0.750	218	0.708
10	Bin 10 = >80~90	158	0.513	157	0.510
11	Bin 11 = >90~100	108	0.351	113	0.367
12	Bin 12 =>100~120	190	0.617	182	0.591
13	Bin 13 = 120+	578	1.877	576	1.870
Total		**30,800**	**100.000**	**30,800**	**100.000**

The number of bus stops and bus route length was calculated by using Lynx GIS shapefiles. For the analysis and creating exogenous variables, we have considered several buffer distances (800m, 600m, and 400m) for each bus stop. The exogenous attributes considered in our study can be divided into four broad categories: (1) Stop level attributes (headway, number of bus stops, bus route length and presence of shelter), (2) Transportation infrastructures (secondary highway length, local roadway length, rail road length, sidewalk length and bike route length), (3) Built environment and land use attributes (land use categories, land use mix and distance from Central Business District (CBD)), (4) Sociodemographic and socioeconomic variables (income, vehicle ownership, and age and gender distribution) and (5) SunRail and I-4 construction effects. Land use mix is defined as: $\left[\frac{-\sum_k(p_k(lnp_k))}{lnN}\right]$, where k is the category of land-use, p_k is the proportion of the developed land area devoted to a specific land-use k, N is the number of land-use categories in a buffer. In our study, six land use types were considered including residential, commercial, industrial, institutional, public land and recreational land use. The value of this index ranges from zero to one - zero (no mix) corresponds to a homogenous area characterized by single land use type and one to a perfectly heterogeneous mix).The descriptive statistics of exogenous variables are presented in Table 6-33.

The final specification of the model development was based on removing the statistically insignificant variables in a systematic process based on statistical confidence (95% confidence level). The specification process was also guided by prior research and parsimony considerations. In estimating the models, several functional forms and variable specifications are explored. The functional form that provided the best result is used for the final model specifications. In determining the appropriate buffer sizes, each variable for a buffer size was systematically introduced (starting from 800m to 400m buffer size) and the buffer variable that offered the best fit was considered in the final specification. We considered GROL model for boarding and alighting ridership separately. In Table 6-33, the variable definitions are presented based on these final functional forms of variables.

6.5.3 Estimation Results

In this research effort, we estimate two different GROL models: one model for stop level average weekday alighting ridership and another model for stop level average weekday boarding ridership. Table 6-34 presents the estimation results of the GROL models. The alighting ridership model results are presented in 2nd and 3rd columns of Table 6-34 and the boarding ridership model components are presented in 4th and 5th columns of Table 6-34. In GROL models, the positive (negative) coefficient corresponds to increased (decreased) ridership propensities. The effects of exogenous variables in model specifications for both alighting and boarding models are discussed in this section by variable groups.

Table 6-34: Summary Statistics for Lynx Ridership Analysis

Variable Name	Variable Description	Percentage	Minimum	Maximum	Mean
Stop level attributes					
Dummy for headway category 1	Headway 0~15 minutes	9.094%	-	-	-
Dummy for headway category 2	Headway 15~30 minutes	37.688%	-	-	-
Dummy for headway category 3	Headway >30 minutes	53.218%	-	-	-
Number of bus stop (800m buffer)	No of bus stop within 800m buffer of a stop/10	-	0.100	9.300	1.727
Number of bus stop (600m buffer)	No of bus stop within 600m buffer of a stop/10	-	0.100	6.300	1.142
Number of bus stop (400m buffer)	No of bus stop within 400m buffer of a stop/10	-	0.100	3.400	0.650
Bus route length in a 800m buffer	Bus route length in kilometers (Bus route length in 800 m buffer/10)	-	0.000	8.710	0.878
Bus route length in a 600m buffer	Bus route length in kilometers (Bus route length in 600 m buffer/10)	-	0.105	5.984	0.516
Bus route length in a 400m buffer	Bus route length in kilometers (Bus route length in 400 m buffer/10)	-	0.048	4.169	0.276
Presence of shelter in bus stop	(1 = Yes and 0 = No)	22.750%	-	-	-
Transportation infrastructures					
Side walk length in an 800m buffer	Side walk length in kilometers	-	0.000	20.234	2.884
Side walk length in an 600m buffer	Side walk length in kilometers	-	0.000	14.280	1.845
Side walk length in an 400m buffer	Side walk length in kilometers	-	0.000	7.557	0.985
Bike Lane Length (800m buffer)	Bike Lane length in km in 800m buffer within bus stop	-	0.000	9.100	0.458
Bike Lane Length (600m buffer)	Bike Lane length in km in 600m buffer within bus stop	-	0.000	5.198	0.297
Bike Lane Length (400m buffer)	Bike Lane length in km in 400m buffer within bus stop	-	0.000	3.224	0.166
Secondary highway length (800m buffer)	Secondary highway length in 800 m buffer / 10	-	0.000	4.278	0.964
Secondary highway length (600m buffer)	Secondary highway length in 600 m buffer / 10	-	0.000	2.910	0.622
Secondary highway length (400m buffer)	Secondary highway length in 400 m buffer / 10	-	0.000	1.709	0.333
Local road length in an 800m buffer	Local road length in 800 m buffer / 10	-	0.000	6.048	2.138
Local road length in an 600m buffer	Local road length in 600 m buffer / 10	-	0.000	3.611	1.304
Local road length in an 400m buffer	Local road length in 400 m buffer / 10	-	0.000	1.850	0.613
Rail road length in an 800m buffer	Rail road length in kilometers	-	0.000	6.312	0.301
Rail road length in an 600m buffer	Rail road length in kilometers	-	0.000	4.908	0.178
Rail road length in an 400m buffer	Rail road length in kilometers	-	0.000	2.336	0.087

Table 6-33 (Continued): Summary Statistics for Lynx Ridership Analysis

Variable Name	Variable Description	Percentage	Minimum	Maximum	Mean
Built environment and land use attributes					
Industrial area (800m buffer)	Proportion of the industrial area = Industrial/Total area	-	0.000	0.738	0.054
Industrial area (600m buffer)	Proportion of the industrial area = Industrial/Total area	-	0.000	0.657	0.054
Industrial area (400m buffer)	Proportion of the industrial area = Industrial/Total area	-	0.000	0.842	0.054
Institutional area (800m buffer)	Proportion of the Institutional area = Institutional /Total area	-	0.000	0.720	0.041
Institutional area (600m buffer)	Proportion of the Institutional area = Institutional /Total area	-	0.000	0.790	0.043
Institutional area (400m buffer)	Proportion of the Institutional area = Institutional /Total area	-	0.000	0.871	0.042
Residential area (800m buffer)	Proportion of the Residential area = Residential /Total area	-	0.000	0.992	0.443
Residential area (600m buffer)	Proportion of the Residential area = Residential /Total area	-	0.000	0.998	0.435
Residential area (400m buffer)	Proportion of the Residential area = Residential /Total area	-	0.000	0.992	0.438
Recreational area (800m buffer)	Proportion of the Recreational area = Recreational /Total area	-	0.000	0.557	0.012
Recreational area (600m buffer)	Proportion of the Recreational area = Recreational /Total area	-	0.000	0.604	0.010
Recreational area (400m buffer)	Proportion of the Recreational area = Recreational /Total area	-	0.000	0.641	0.010
Office area (800m buffer)	Proportion of the office area = Office/Total area	-	0.000	0.957	0.171
Office area (600m buffer)	Proportion of the office area = Office/Total area	-	0.000	0.983	0.190
Office area (400m buffer)	Proportion of the office area = Office/Total area	-	0.000	1.000	0.184
Land use mix (800 m buffer)	Land use mix is defined as: $\left[\frac{-\sum_k(p_k(lnp_k))}{lnN}\right]$, where k is the category of land-use, p_k is the proportion of the developed land area devoted to a specific land-use k, N is the number of land-use categories in a buffer.	-	0.000	0.926	0.304
Land use mix (600 m buffer)		-	0.000	0.947	0.510
Land use mix (400 m buffer)		-	0.000	0.939	0.462
Central business district (CBD) distance	(Central business area distance in km from bus stop)/10	-	0.003	5.058	1.183

Table 6-33 (Continued): Summary Statistics for Lynx Ridership Analysis

Variable Name	Variable Description	Percentage	Minimum	Maximum	Mean
Sociodemographic and Socioeconomic variables					
Zero vehicle in HH	Percentage of zero vehicle HH	6.087%	-	-	-
One vehicle in HH	Percentage of one vehicle HH	34.116%	-	-	-
Two or more vehicle in HH	Percentage of two or more vehicle HH	59.798%	-	-	-
Low income (<34k)	Percentage of Low income HH (<34k)	43.688%	-	-	-
Medium income (35k~99k)	Percentage of Medium income HH (35k~99k)	43.202%	-	-	-
High income (>100k)	Percentage of High income HH (>100k)	13.111%	-	-	-
Household Owner	Percentage of HH owner	49.942%	-	-	-
Household rent	Percentage of HH renter	50.058%	-	-	-
SunRail and I-4 construction effects					
Distance Decay Function for SunRail*SunRail operation period	Interaction term of distance decay function for SunRail (summation of inverse distance of SunRail stations from all bus stops which are within the influence area of SunRail stations) and SunRail operation period (May through August 2014, September through December 2014, January through April 2015)	-	0.000	31.703	0.234
Sops within I-4 construction zone Area 1 (5 mile buffer)	Stops within area 1 influence area of I-4 construction zone within 5 mile buffer area	8.200%	-	-	-

Table 6-35: Lynx Ridership Analysis Results

Variable Name	Alighting		Boarding	
	Estimates	t-stat	Estimates	t-stat
Constant	13.730	-0.5.767	-30.581	-9.89
Stop Level Attributes				
Headway (Base: Category 1) *Dummy for headway category 2*	-47.508	-36.217	-52.435	-36.521
Dummy for headway category 3	-75.633	-50.556	-81.743	-49.287
No of Bus stop in a *800 m buffer*	-4.378	-10.759	-4.347	-9.806
Presence of shelter in bus stop	19.491	24.595	33.580	36.807
Bus route Length in an 800 m buffer	-2.549	-5.761	-3.559	-7.568
Transportation Infrastructures				
Side walk length in an *400 m buffer*	2.515	7.278	2.299	6.116
Secondary road length in an *800 m buffer*	8.329	13.642	6.231	9.476
Local road length in an *800 m buffer*	4.913	10.268	4.599	8.511
Built environment and land use attributes				
Land use mix in a *600 m buffer*	5.013	2.278	11.298	4.523
Land use area type in an 800m buffer				
Institutional area	20.841	4.198	-	-
Residential area	-	-	21.956	9.627
Office area	38.824	14.971	44.218	12.830
Recreational area	-83.009	-9.877	-71.547	-7.771
Central business district (CBD) distance	-2.660	-5.166	-2.380	-4.190
Sociodemographic and socioeconomic variables				
Zero vehicle in HH	77.481	13.544	69.074	10.930
Household rent	30.402	17.118	34.790	17.785
SunRail and I-4 construction effects				
Distance Decay Function for SunRail*SunRail operation period	-5.140	-8.210	-5.029	-7.593
Sops within I-4 construction zone Area 1	6.811	5.835	8.602	6.752

<u>*Stop Level Attributes*</u>

As is expected, headway at the stop level has a significant influence on ridership. We observe that with increasing headway boarding and alighting are likely to reduce. The result highlights how transit frequency directly affects ridership. The results for number of Lynx bus stops indicates that the ridership is likely to reduce with increased number of bus stops within an 800 m buffer area of a stop. This is possibly a result of competition across the stops for the same ridership population. By prioritizing of which bus stop should stay (considering high ridership, locations, etc.), Transit center can improve the ridership at that location. The coefficient for presence of shelter at the bus stop has a positive impact on the ridership for both boarding and alighting. By having shelters in a bus stop, passengers can wait longer time and also it can protect passengers from adverse weather condition. Bus route length in the buffer has a negative impact on ridership for both alighting and boarding.

Transportation Infrastructures

Transportation infrastructure offered quite complex effects on total ridership. The variable indicating sidewalk length in a 400m buffer area of a stop is found to have a positive impact on both alighting and boarding. Along with the sidewalk, secondary highway and local road length in 800m buffer are also increasing the ridership.

Built environment and land use attributes

Built environment and land use attributes indicate significant influence on bus ridership at the stop level. The land use mix variable within 600 m buffer area of a stop increased the bus ridership for both alighting and boarding. While an increase in proportion of institutional area is positively associated with number of alighting, an increase in proportion of residential area contributes to higher likelihood of boarding. However, the proportion of office area significantly increase the bus ridership for both boarding and alighting. On the other hand, increased proportion of recreational area within an 800m buffer of a stop is likely to decrease bus ridership. The distance from the CBD variable highlights how ridership reduces as the distance from CBD increases.

Sociodemographic and Socioeconomic Variables

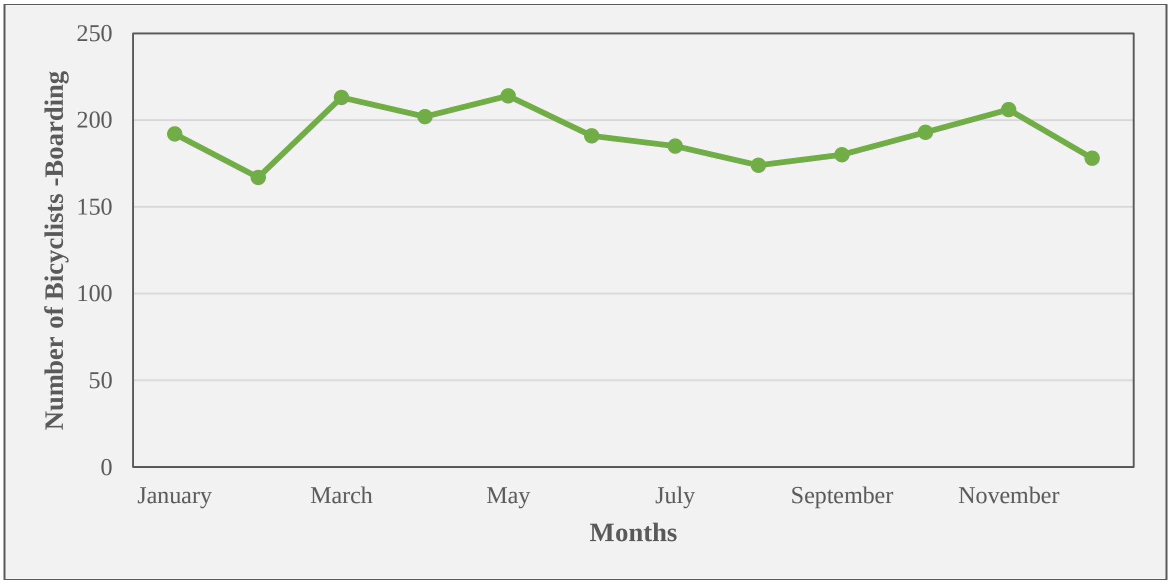
The sociodemographic and socioeconomic variables has significant effect on bus ridership. Zero vehicle ownership variable has positive impact on ridership components. The increased share of the household renters is likely to increase the bus ridership.

SunRail and I-4 Construction Effect

To identify the influence of SunRail system while controlling for all other attributes over lynx bus system, we have considered the distance decay function as (stops affected by SunRail/the distance from SunRail) and have significant impact on bus ridership. If the distance increase from SunRail then the ridership of Lynx bus is likely to decrease. The construction of I-4 for Area 1(Attraction area) also has significant effect on Lynx bus ridership. The bus stops within 5 miles buffer area of I-4 attraction zone specific to Area 1 has positive impact on ridership components.

6.6 RIDERSHIP ANALYSIS FOR SUNRAIL NETWORK SYSTEM

SunRail has potential to alter some travel patterns in the region, specifically it provides more viable transit options for Central Florida residents who live along the I-4 construction corridor. Moreover it has potential for improving overall liveability, property values, transit-oriented development and in turn reducing overall carbon footprint – which is the focus of building a smart city. For example, it is reported in a recent FDOT's report that SunRail has yielded some substantial positive property value impacts in the form of property tax increases (FDOT, 2017). A glimpse of SunRail system usage by bicyclist for the year 2015 is presented in Figure 6-23.



Source: Metroplan Orlando (2016)

Figure 6-23: Total Number of Bicycle Boarding in SUNRAIL

From Figure 6-23 it is evident that the system has potential in developing an integrated and more sustainable transport network. However, the success of any transport system in attracting travelers depends on its connectivity and accessibility including other built environment attributes. Therefore, it is imperative to identify critical factors contributing to SunRail ridership to promote a more sustainable and transit-oriented development. To that extent, in our current research effort, we formulate and estimate SunRail ridership models. Specifically, we estimate two ridership model: (1) daily boarding ridership model, and (2) daily alighting ridership model. Based on the model results we identify critical exogenous variables that influence rail boarding and alighting which is important to devise service deployment, enhancement and investment policies. We estimate these models by using linear regression models.

6.6.1 Model Framework

The focus of our study is to model average daily boarding and alighting of SunRail by employing linear regression (LR) modeling approach. The econometric framework for the LR model is presented in this section.

Let i $(i = 1,2,3, \ldots, N)$ be an index to represent weekdays, and r $(r = 0,1,2, \ldots, R)$ be an index to represent the number of boarding or alighting. Then, the equation system for modeling boarding/alighting may be written as follows:

$$y_i = \boldsymbol{x}_i \boldsymbol{\beta} + \varepsilon_i, \; for\; i = 1,2, \ldots \ldots \ldots, N \tag{5}$$

where, i $(i = 1,2, \ldots \ldots \ldots, N)$ represents the observations, $\boldsymbol{x_i}$ is a vector of exogenous variables, $\boldsymbol{\beta}$ is a vector of unknown parameters to be estimated (including a constant), ε_i is normal distributed error term. Least square estimation technique, often referred to as "ordinary least square" method, is used for estimating the regression model parameters as defined in equation 5.

6.6.2 Data Description

In our study, the rail ridership analysis is focused on the 12 active stations (Phase one). The main data source of SunRail daily ridership is the SunRail authority. For the purpose of our analysis, we have compiled stop level daily boarding and alighting ridership data for ten months from January 2015 to October 2015. The daily ridership data includes weekdays only as SunRail did not operate during weekends during the data collection period. This ridership data is processed and analyzed to ensure data availability and accuracy. A summary of the system level ridership (boarding and alighting) is provided in Table 6-35. The average daily boarding (alighting) across the 10-month periods range from 124.26 (134.09) to 451.17 (512.18). It is interesting to observe that the two end stations (Sand Lake and Debary Stations) have the highest difference in daily boarding and alighting values relative to other stations. The 10-month, 12 station data provided us 2,496 observations. Out of 2,496 observations, 2,124 observations were randomly selected for model estimation and remaining 372 observations were set aside for model validation.

6.6.3 Variable Considered

For the empirical analysis, the explanatory variables can be grouped into three broad categories: temporal and seasonal variables, transportation infrastructure, land use variables, sociodemographic variables, and weather variables. The data at the station level was generated by creating a buffer around the rail station using ArcGIS. However, the influence buffer size area may vary across different variables (see Chakour & Eluru, 2016). To accommodate for such an effect on transit ridership, we have computed attributes of different variables by using 1500m, 1250m, 1000m, 750m, and 500m buffer sizes around each station. Temporal and seasonal variables considered include day of week and month of the year. Transportation infrastructure variables considered include local roadway length, number of bus stops, and presence of free parking facilities at stations. Land use variables considered include number of commercial centers, number of educational centers, number of financial centers and land use mix. Sociodemographic variables considered include number of households with zero, one and two vehicle ownership level. Sociodemographic variables are computed within the influence area of Sunrail stations at census tract level. Finally, weather variables considered include temperature, average wind speed and rainfall.

Table 6-36: Summary Statistics for SunRail Average Daily Ridership (January 2015 to October 2015)

Station Name	Boarding		Alighting	
	Mean	Standard Deviation	Mean	Standard Deviation
Sand Lake Station (SLR)	451.168	82.127	512.178	111.112
Amtrak Station (ARTRAK)	124.260	20.507	134.091	16.969
Church Street Station (CSS)	393.135	79.184	400.962	96.775
Lynx Central Station (LCS)	403.769	35.282	377.813	34.610
Florida Hospital (FLHS)	201.976	26.562	224.168	29.862
Winter Park Station (WPS)	411.707	205.107	443.433	203.524
Maitland Station (MLS)	180.962	27.084	183.697	23.986
Altamonte Springs station (ATSS)	244.163	40.788	251.135	35.830
Longwood Station (LWS)	240.909	36.959	227.024	29.418
Lake Mary Station (LMS)	337.005	55.139	312.221	51.052
Sanford Station (SFS)	258.952	45.735	235.202	38.199
Debary Station (DBS)	445.178	90.608	391.260	93.938

Table 6-36 offers a summary of the sample characteristics of the exogenous factors used in the estimation data set. Table 6-36 represents the definition of variables considered for final model estimation along with the minimum, maximum and average values of the exogenous variables. The final specification of the model development was based on removing the statistically insignificant variables in a systematic process based on statistical confidence (95% confidence level). The specification process was also guided by prior research and parsimony considerations. In estimating the models, several functional forms and variable specifications are explored. The functional form that provided the best result is used for the final model specifications. For determining the appropriate buffer sizes, each variable for a buffer size was systematically introduced (starting from 1500m to 500m buffer size) and the buffer variable that offered the best fit was considered in the final specification.

Table 6-37: Descriptive Statistics of Exogenous Variables for SunRail Ridership

Variable Name	Variable Description	Minimum	Maximum	Mean
Temporal and Seasonal Variables				
Day of week				
Monday	Rail ridership on Monday	0.000	1.000	0.190
Friday	Rail ridership on Friday	0.000	1.000	0.206
Month of the Year 2015				
January	Rail ridership on January 2015	0.000	1.000	0.094
February	Rail ridership on February 2015	0.000	1.000	0.095
March	Rail ridership on March 2015	0.000	1.000	0.109
April	Rail ridership on April 2015	0.000	1.000	0.105
May	Rail ridership on May 2015	0.000	1.000	0.095
June	Rail ridership on June 2015	0.000	1.000	0.106
July	Rail ridership on July 2015	0.000	1.000	0.111
August	Rail ridership on August 2015	0.000	1.000	0.103
Transportation Infrastructures				
Local roadway length in a 1,500-m buffer	Local roadway length in kilometers	16.113	141.443	77.956
Number of bus stops in a 1,500-m buffer	Number of Lynx bus stop in 1,500-m buffer from SunRail station	0.000	205.000	55.667
Free Parking Facility	Free Parking Facility (Yes and No)	0.000	1.000	0.667
Land Use Patterns				
Number of Commercial centers in a 1,500-m buffer	Number of Commercial centers in a 1,500-m buffer	0.000	6.000	2.750
Number of Educational centers in a 1,500-m buffer	Number of Educational centers in a 1,500-m buffer	0.000	11.000	4.250
Number of Financial centers in a 1,500-m buffer	Number of Financial centers in a 1,500-m buffer	0.000	55.000	17.833
Land Use mix in a 1,500-m buffer	"Land-use mix = $\left[\frac{-\sum_k (p_k(lnp_k))}{lnN}\right]$", where $\boldsymbol{k}$ is the category of land-use, $\boldsymbol{p}$ is the proportion of the developed land area devoted to a specific land-use, $\boldsymbol{N}$ is the number of land-use categories	0.263	0.811	0.638
Sociodemographic Variables				
Vehicle Ownership – No vehicle	Vehicle Ownership – number of HH with No Vehicle in the influence area of station at census tract level	52.000	,4532.000	1,326.250
Vehicle Ownership – One vehicle	Vehicle Ownership – number of HH with One Vehicle in the influence area of station at census tract level	734.000	15,139.000	5,425.333
Vehicle Ownership – Two vehicles	Vehicle Ownership – Number of HH with Two Vehicles in the influence area of station at census tract level	2,000.000	9,189.000	4,898.667
Weather Variables				
Average Temperature in air	Average Temperature in air at 2 m height in degree Celsius	4.889	30.204	23.222
Average Wind speed in air	Average wind speed in air at 10 m height in miles per hour	2.892	12.040	5.566
Rainfall	Sum of rainfall at 2 m in inches	0.000	1.577	0.132

Temporal and Seasonal Variables

The day of the week variables offer interesting results. Specifically, the result indicates that boarding and alighting are likely to be lower on Mondays while on Fridays an opposite trend is observed. The higher ridership value on Friday is possibly associated with transit being adopted for cultural, sports and social activities (such as Orlando Lions football games or restaurants) in downtown Orlando with limited parking. To accommodate for seasonal variation in ridership we also consider the month variable. We considered the months of September and October as the base for the month variable. We find that, compared to the base months, the month of March is associated with highest positive impact on boarding and alighting. It is also observed that the association of various months with boarding and alighting are very similar.

Transportation Infrastructures

Several transportation infrastructure variables for various buffer sizes were considered in the model. Local highway length for a 1500m buffer area around rail stations presents a significant negative impact on boarding and alighting. On the other hand, number of bus stops within 1500m buffer variable highlights the symbiotic influence of bus transit on rail ridership. For both boarding and alighting, increase in number of bus stops is associated with higher ridership. The result while encouraging is also possibly indicative of presence of higher number of bus stops near the rail station. Finally, the availability of free parking space at SunRail stations also significantly affects both boarding and alighting ridership. The parking facilities have significantly higher impact on alighting relative to boarding.

Land Use Variables

Land use variables including presence of commercial centers, educational centers and financial centers within 1500 m distance from SunRail station have significant influence on ridership. The presence of higher commercial centers in 1500m buffer surrounding the station positively influences boarding and alighting. The number of commercial centers variable impact varies substantially across the stations as evidenced by the significant standard deviation parameters for both boarding and alighting models. The presence of financial centers affects boarding positively while having no impact on alighting. SunRail stations are located near downtown Orlando and provide access to commercial and financial hubs of Orlando city. In these locations, availability of parking spaces, cost of parking, and traffic congestion encourage the adoption of SunRail. On the other hand, the presence of education centers around rail stations reduces rail ridership. The result is quite intriguing.

Sociodemographic Variables

Several socioeconomic variables were tested in the boarding and alighting models. Of these variables only one variable offered a statistically significant impact. The number of households with access to no vehicles in the influence area around the station at a census tract level is negatively associated with boarding and alighting. While the result is counterintuitive on first glance, it is possible that the result is a surrogate for lower job participation in these neighborhoods. The result warrants more detailed analysis.

Table 6-38: SunRail Ridership Model Estimation Results

Variable Name	Boarding Ridership		Alighting Ridership	
	Coefficient	**t-stat**	**Coefficient**	**t-stat**
Constant	410.053	20.191	228.535	8.818
Temporal and Seasonal Variables				
Day of week (Base: Tuesday, Wednesday, Thursday)				
Monday	-21.058	-3.978	-22.072	-3.492
Friday	48.155	11.852	48.004	10.604
Season/Month of the Year (Base: September, October)				
January	51.085	5.908	61.701	6.111
February	48.283	4.248	53.774	4.305
March	69.643	10.948	74.101	9.798
April	40.127	5.655	44.357	5.125
May	23.001	2.670	24.675	2.660
June	43.559	4.368	41.215	4.078
July	48.178	6.392	46.287	5.135
August	26.462	3.803	28.013	3.246
Transportation Infrastructures				
Local roadway length in a				
1500 m buffer	-7.189	-38.125	-6.948	-36.956
Number of bus stop in a				
1500 m buffer	9.587	22.573	10.096	23.146
Free Parking Facility	18.315	2.210	91.194	10.437
Land Use Patterns				
Number of Commercial centers in a				
1500 m buffer	50.317	13.918	68.541	16.568
Standard Deviation	1.869	25.513	2.068	31.388
Number of Educational centers in a				
1500 m buffer	-46.088	-10.034	-38.291	-14.896
Number of Financial centers in a				
1500 m buffer	5.442	5.924	--	--
Land Use mix in a				
1500 m buffer	347.969	20.089	538.002	29.858
Sociodemographic Variables				
Vehicle Ownership - No vehicle	-0.307	-18.523	-0.326	-21.788
Weather Variables				
Average Temperature in air	1.753	2.813	1.844	2.257
Average Wind speed in air	-3.924	-3.603	-3.832	-3.036
Rainfall	-27.756	-4.028	-25.528	-2.962

Weather Variables

We also account for the impact of weather variables on ridership. While we cannot control weather patterns, these variables are included in the model to ensure that the impact of other attributes is accurately determined. The average temperature variable indicates that with higher temperature, boarding and alighting are likely to be higher. On the other hand, higher average wind speed is associated with lower boarding and alighting. The wind speed might be an indicator for possible wind gusts from hurricanes in the Orlando region. Finally, rain occurrence discourages rail usage as indicated by the negative coefficient in boarding and alighting components. The result is expected for any public transit alternative.

6.7 CATCHMENT AREA OF SUNRAIL STATIONS

One of the most effective approach for increasing public transit ridership is to improve multimodal accessibility to the public transit systems. However, accessibility to a public transit facility are mode specific. For instance, people will walk to a transit station if the station is within a reasonable walking distance from the trip origin. A transit bus rider can have an option to transfer to a commuter railway if there are supporting bus connections around the rail station. Therefore, it is important to identify mode specific catchment area for a specific transit facility in order to promote and target an integrated and multimodal transportation network. To that extent, in our current research effort, we have identified catchment area of SunRail stations for different modes; specifically for walk, bike, bus transit and drive mode. A catchment area can be defined based on different attributes; such as land use, built environment, roadway characteristics and mode specific characteristics. In our study, we have defined catchment area of SunRail stations based on mode specific characteristics including a reasonable travel distance and speed.

6.7.1 Catchment Area of SunRail Stations for Walk Mode

For defining catchment area of SunRail for walk mode, we assume that a person will usually walk up to 10 minutes with a speed of 3 mph to access a transit facility. Based on this assumption, the catchment area of rail station will be a half-mile buffer around the station for walk mode. It is worthwhile to mention here that the most commonly defined catchment area for walking in the US is considered to be a half mile circular buffer area surrounding the station as it is de facto standard for the planning of Transit Oriented Developments (TOD) in America (Guerra et al., 2012). Figure 6-24 shows the catchment area for walk mode. Transit authority may target to improve the walkable environment of the community with the catchment area shown in Figure 6-24 in order to provide a more walk supportive transit system.

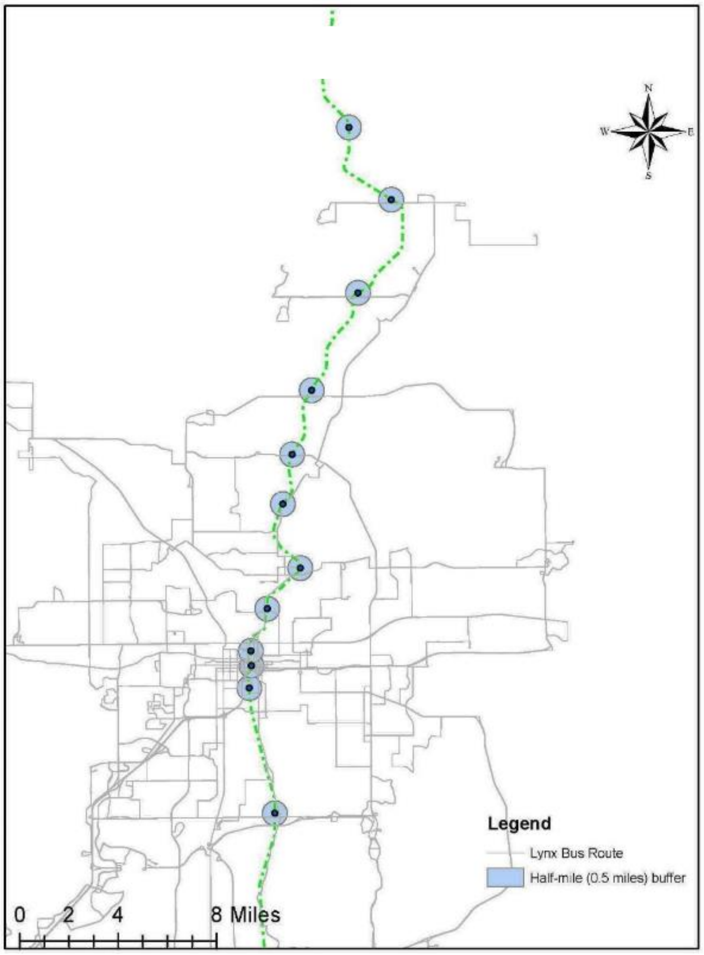


Figure 6-24: Catchment Area of SUNRAIL Stations for Walk Mode

6.7.2 Catchment Area of SunRail Stations for Bike Mode

Transit agencies are motivating bicyclist to use transit as a connector by implementing several station/stop level bike friendly facilities (such as bike lane, bike racks, bike parking and bike slot facilities) and in turn to increase transit ridership. In doing so, it is important to identify the target area to attract cyclist towards transit. In existing literature, there are evidence that cyclists travel a generalized distance of 2 to 3 miles in a relatively flat terrain to access transit (Adjei, 2010; Flamm and Rivasplata, 2014). It is also observed that cyclist ride with an average speed of 10 mph for about 18 minutes to access transit (Bergman et al., 2011). Based on these studies, we assume a 3 mile buffer area around SunRail station as catchment area for bike mode. Figure 6-25 shows the catchment area for bike mode. Transit authority may target to improve the bike infrastructures (such as bike lane) of the community with the catchment area shown in Figure 6-25 in order to provide a more bike supportive transit system.

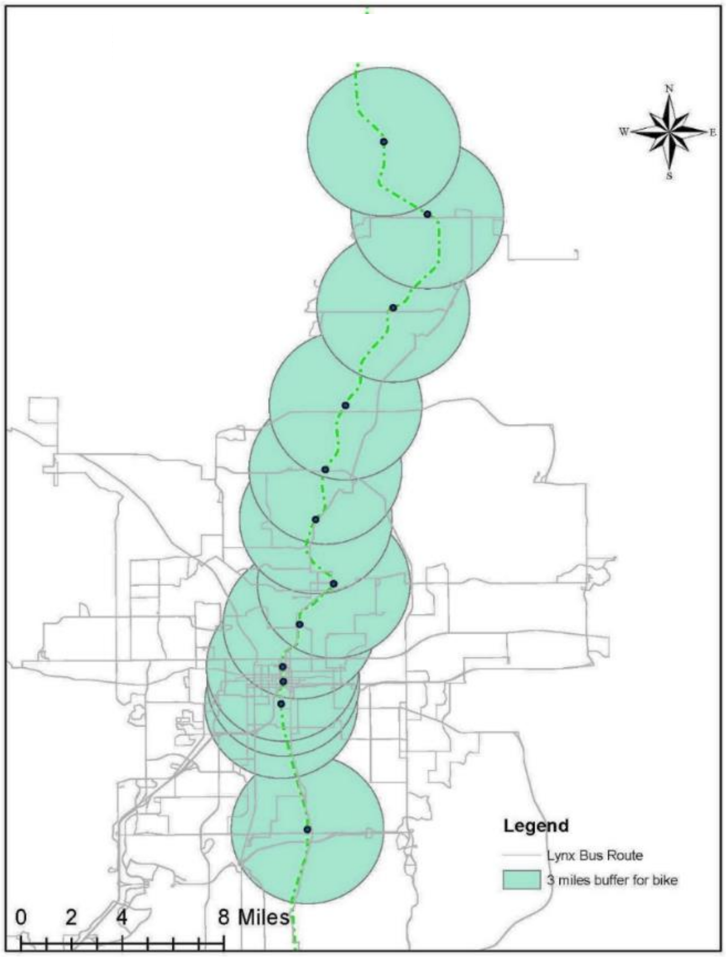


Figure 6-25: Catchment Area of SunRail Stations for Bike Mode

6.7.3 Catchment Area of SunRail Stations for Transit Mode

Coordinated operation among different transit systems are crucial to increasing overall transit ridership. In doing so, it is important to identify connections among different transit systems within influence area of other transit systems. To that extent, in our study we compute the catchment area of rail for Lynx fixed-route bus system. For defining catchment area for bus mode, we assume that average speed of bus transit operation is 20 mph; and people will generally ride bus up to 30 minutes to access rail and vice versa. Based on this assumption, we consider a 10 mile buffer area around rail station as catchment area for bus transit mode. Further within this buffer area, we identify the bus stops that provide supporting connections to different stations. The connector bus stops for identified connector bus routes (as presented in section 6.4) are considered for this purpose. Figure 6-26 shows the catchment area for bus transit mode along with the bus stops locations for connector bus routes. The bus stops within the buffer area are considered as supporting bus stops.

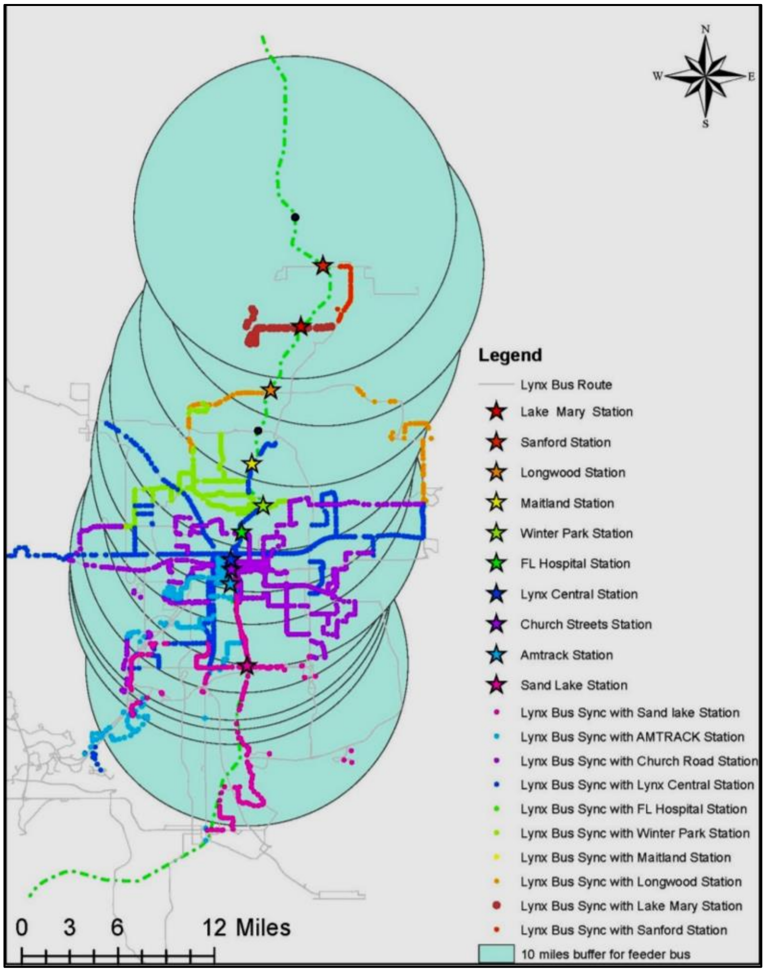


Figure 6-26: Catchment Area of SUNRAIL Stations for Transit Mode

Transit authority may consider following recommendations for the transit system within the catchment area shown in Figure 6-26 to provide a more coordinated transit system.

- Coordinated ticketing and connections.
- Walk/bike friendly space in between connecting stops to rail stations.
- Safe access to rail station from bus stops.
- Real time information of transit systems.

6.7.4 Catchment Area of SunRail Stations for Drive Mode

One of the major focuses of implementing, enhancing and investing in transit system is to divert people from private automobile based travel towards more sustainable travel options. To that extent, it is important to identify the target population to devise and implement target based policies in promoting greener transportation options. Park/Kiss and ride is the most common coordination system between transit and drive modes. Typically park/Kiss and ride mode requires the parking facilities, waiting areas/benches and/or restrooms in transit facilities. Among 12 SUNRAIL stations, 8 stations have free parking facilities and the rest of the stations have paid parking facilities. Moreover, these stations have facilities for waiting at station, restrooms and vending machines. Presence of these facilities at rail stations provide evidence that the commuter rail system has potential to attract more driving population to ride the rail. In our study, in defining the catchment area of rail stations for drive mode, we consider speed limits of local, secondary highway and major highway around rail stations. We assume that these roadway systems have speed limits of 30, 45 and 55 mph, respectively. In order to compute an average speed limit of drive mode to rail stations, we use the computed roadway lengths in 1500m buffer area for these road categories. By using the roadway length for different road groups we computed an average access speed limit for drive mode which is computed as 37 mph. Further, we assume that people are willing to drive up to 15 minutes from their trip origin to access SUNRAIL. Based on this assumption, we consider a 9 mile buffer area around rail station as catchment area for drive mode. Figure 6-27 shows the catchment area for drive mode. Transit authority may target to provide incentives, in terms of parking cost or parking facilities or transit ride cost, to the community within the catchment area shown in Figure 6-27 to provide a more drive supportive transit system.

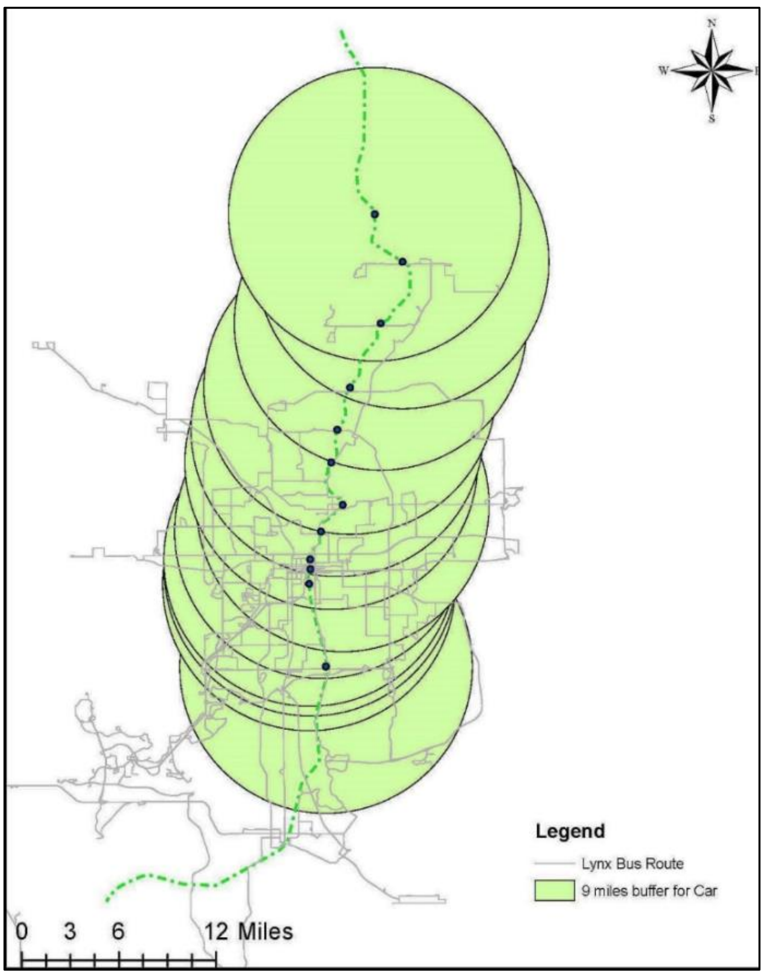


Figure 6-27: Catchment Area of SUNRAIL Stations for Drive Mode

6.8 SUMMARY

The chapter summarized transit ridership analysis results and catchment area identification methods for SunRail stations of the multi-modal mobility study for Central Florida. The component of public transit ridership evaluation of the research effort were mainly focused on the coverage area of Lynx and SunRail network systems for the Greater Orlando area. With respect to transit ridership analysis, in this research effort, we estimated and presented four different sets of ridership models: for Lynx network system – (1) stop level average weekday boarding bus ridership analysis, and (2) stop level average weekday alighting bus ridership analysis; finally, for SunRail network system – (3) daily boarding rail ridership analysis, and (4) daily alighting rail ridership analysis. Lynx ridership models were estimated by using grouped ordered logit model framework. SunRail ridership models were estimated by using linear regression based approach.

CHAPTER VII: VALIDATION OF THE ESTIMATED MODELS

7.1 INTRODUCTION

In evaluating the benefits of multi-modal investments on promoting travel mobility, the research team has developed different models for investigating mobility, safety and transit ridership trends for the Central Florida Region. With respect to mobility component, we estimated pedestrian generator, pedestrian attractor, bicycle generator and bicycle attractor model. We estimated four different zonal-level models – including two zonal level crash count models and two zonal-level crash count by severity levels – in evaluating the safety situation of pedestrian and bicyclists for Central Florida. Finally, two bus ridership and two SunRail ridership models were estimated with regards to transit ridership components. In an effort to assess the predictive performance of these estimated models for different components, several validation exercises are undertaken. The objective of this chapter is to document and present these validation results.

The remaining chapter is organized as follows: The next section provides discussion on the validation results of the mobility component. The subsequent section focuses validation exercise results from safety component followed by validation results of ridership component. The final section describes summary of the chapter.

7.2 MOBILITY COMPONENT

With respect to mobility component, we presented motorists demand component based on CFRPM 6.0 and hence the validation exercise is not evaluated for this road user group. On the other hand, for non-motorists road user group, we developed four non-motorists demand models: (1) Pedestrian generator model – based on zonal level pedestrian origin demand, (2) Pedestrian attractor model – based on zonal level pedestrian destination demand, (3) Bicycle generator model – based on zonal level bicycle origin demand, (4) Bicycle attractor model – based on zonal level bicycle destination demand. The estimation results of these models were presented and discussed in Chapter IV. In this section we present the validation exercise results for these estimated demand models for non-motorists road user group.

7.2.1 Validation Results of Mobility Component

In order to demonstrate the predictive performance of the estimated models, a validation experiment is also carried out. The most common approach of performing validation exercise for aggregate level model is to evaluate the in-sample predictive measures. To evaluate the in-sample goodness-of-fit measures, we computed the predicted count events for both zero and non-zero events and compared those with the observed values. These measures are presented in Table 7-38 below. From Table 7-38 we can see that the error between observed and predicted values are marginal and hence, we can argue that the predictive performance of the estimated models are reasonable for all four estimated demand models.

Table 7-39: Predictive Performance Evaluation

Models	Events	Observed	Predicted	Percentage Error
Pedestrian Generator Model	**Total Zones with zero trip count**	4,007.00	4,006.80	0.005
	Total number of zonal trips	1,260,090.60	1,255,479.90	0.366
	Average zonal trips	265.45	264.48	0.365
Pedestrian Attractor Model	**Total Zones with zero trip count**	4,010.00	4,010.49	-0.012
	Total number of zonal trips	1,242,270.50	1,236,690.70	0.449
	Average zonal trips	261.70	260.52	0.451
Bicycle Generator Model	**Total Zones with zero trip count**	4,574.00	4,573.82	0.004
	Total number of zonal trips	166,248.45	165,671.36	0.347
	Average zonal trips	35.02	34.90	0.343
Bicycle Attractor Model	**Total Zones with zero trip count**	4,581.00	4,581.18	-0.004
	Total number of zonal trips	165,845.77	171,959.97	-3.687
	Average zonal trips	34.94	36.22	-3.663

7.3 SAFETY COMPONENT

With respect to safety component, we estimated four different sets of aggregate-level models: (1) zonal-level crash count model for examining pedestrian–motor vehicle crash occurrences, (2) zonal-level crash count model for examining bicycle–motor vehicle crash occurrences (3) zonal-level crash severity model for examining pedestrian crash injury severity by proportions and (4) zonal-level crash severity model for examining bicycle crash injury severity by proportions. The estimation results of these models were presented and discussed in Chapter V. In this section we present the validation exercise results for these estimated demand models.

7.3.1 Validation Results of Crash Count Models

In order to demonstrate the predictive performance of the estimated crash count models, a validation experiment is also carried out. The most common approach to performing a validation exercise for an aggregate-level model is to evaluate the in-sample predictive measures. To evaluate the in-sample goodness-of-fit measures, we employ different fit measures that are widely used in statistical analysis. For crash frequency models, we compute mean prediction bias (MPB) and mean absolute deviation (MAD). These fit measures quantify the error associated with model predictions, and the model with lower fit measures provides better predictions of the observed data. These measures are computed as:

$$MPB = \frac{\sum_{i=1}^{n}(\hat{y}_i - y_i)}{n}$$

$$MAD = \frac{\sum_{i=1}^{n}\left|\hat{y}_i - y_i\right|}{n} \quad (1)$$

where, $\hat{y}_i$ and y_i are the predicted and observed values for event i (i be the index for event $(i = 1,2,3, \dots, N)$) and n is the number of events.

Table 7-39 presents the values for these measures for NB models for pedestrian and bicycle crash count models. Further, we also compared the predictive performance of NB models by comparing the observed and predictive counts across different count events, which are presented in Figure 7-28. From Table 7-39 and Figure 7-28, we can argue that the resulting fit measures for comparing the predictive performance clearly indicate that the models' predictive performances are overall reasonable with less error in predictions.

Table 7-40: Predictive Performance Evaluation

Models	Mean crash		MPB	MAD
	Observed	Predicted		
Pedestrian	0.31	0.33	-0.81	11.44
Bicycle	0.21	0.22	-0.28	6.41

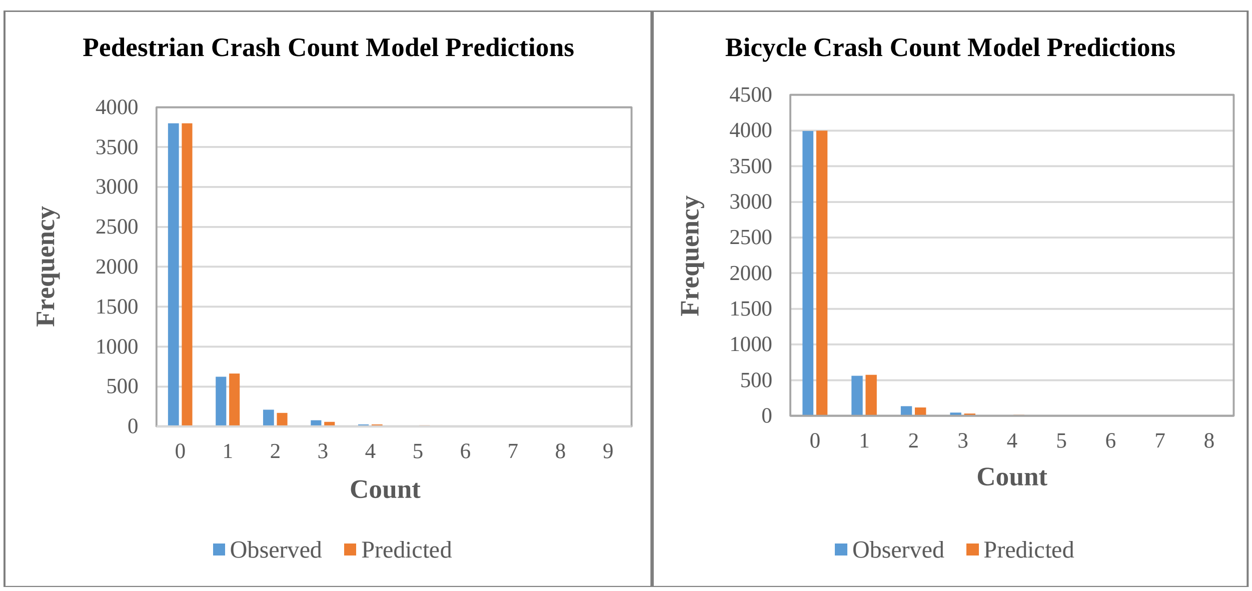


Figure 7-28: Crash Count Model Predictions

7.3.2 Validation Exercise of Crash Proportion Models

In order to demonstrate the predictive performance of the estimated crash proportion models, a validation experiment is also carried out. The most common approach to perform a validation exercise for an aggregate-level model is to evaluate the in-sample predictive measures. For crash proportion models, we compute mean absolute percentage error (MAPE) and root mean square error (RMSE). These fit measures quantify the error associated with model predictions, and the model with lower fit measures provides better predictions of the observed data. These measures are computed as:

$$MAPE = \sum_{i=1}^{n} \left| \frac{\hat{y}_i - y_i}{y_i} \right|$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (\hat{y}_i - y_i)^2}{n}} \qquad (2)$$

where, $\hat{y}_i$ and y_i are the predicted and observed values for event i (i be the index for event ($i = 1,2,3, \dots, N$)) and n is the number of events.

Table 7-40 presents the values for these measures for the OPFS models for the pedestrian and bicycle crash models. From Table 7-40, we can argue that the resulting fit measures for comparing the predictive performance clearly indicate that the models' predictive performances are overall reasonable with less error in predictions.

Table 7-41: Predictive Performance Evaluation

Models	Mean proportion			MAPE	RMSE
	Severity Levels	Observed	Predicted		
Pedestrian	Proportion of property damage only crashes	0.113	0.113	0.003	0.526
	Proportion of minor injury crashes	0.237	0.237		
	Proportion of non-incapacitating injury crashes	0.382	0.381		
	Proportion of incapacitating injury crashes	0.183	0.184		
	Proportion of fatal crashes	0.085	0.084		
Bicycle	Proportion of property damage only crashes	0.115	0.115	0.005	0.2912
	Proportion of minor injury crashes	0.320	0.320		
	Proportion of non-incapacitating injury crashes	0.407	0.407		
	Proportion of incapacitating injury crashes	0.141	0.141		
	Proportion of fatal crashes	0.017	0.017		

7.4 RIDERSHIP COMPONENT

With respect to ridership components, we evaluated ridership for two main public transit systems serving the Orlando metropolitan region: Lynx bus transit system and SunRail commuter rail system. Specifically, we estimated four different sets of ridership models: for Lynx network system – (1) stop level average weekday boarding bus ridership analysis, and (2) stop level average weekday alighting bus ridership analysis; finally, for SunRail network system – (3) daily boarding rail ridership analysis, and (4) daily alighting rail ridership analysis. The estimation results of these models were presented and discussed in Chapter VI. In this section we present the validation exercise results for these estimated models.

7.4.1 Validation Exercise of Lynx Ridership Models

Lynx bus ridership was examined in order to identify the demand of bus transit at stop level across different time periods and to evaluate the influence of SunRail on bus ridership. The validation sample of Lynx ridership includes information from 644 stops for 11 time periods (644*11 = 7,084 records). By using this hold-out sample, a validation experiment is carried out in order to ensure that the statistical results obtained from the estimated boarding and alighting models are not a manifestation of over fitting to data.

In order to explore the predictive performance of the estimated ordered group response models of riderships, we compute and compare the observed and predictive riderships across different ridership categories considered in our models estimation. We compute the predictive log-likelihood from our model and compared it with the log-likelihood at constant. Finally we compute MAPE and RMSE (presented in equation 2). Results of these fit measures are presented in Table 41. From Table 41 we can see that the predictive log-likelihoods for both boarding and alighting models are significantly better than the log-likelihoods at constant. Further from the computed RMSE and MAPE measure we can say that the validation exercise indicates satisfactory performance of the proposed model.

Table 7-42: Predictive Performance Evaluation

Fit measures	Boarding	Alighting
Log-likelihood at constant	-2,227.501	-2,282.542
Predictive log-likelihood	-2,094.691	-2,044.660
MAPE	0.685	0.434
RMSE	13.234	17.358

7.4.2 Validation Exercise of SunRail Ridership Models

SunRail ridership were examined in order to identify the daily demand of the commuter rail. A sample of 372 records was sampled out for the purpose of validation analysis. By using this hold-out sample, a validation experiment is carried out in order to ensure that the statistical results obtained from the estimated boarding and alighting models are not a manifestation of over fitting to data. For testing the predictive performance of the model, we compute two different fit measures: MAPE and MAD, along with the observed and predicted means. These fit measures quantify the error associated with model predictions and the model with lower fit measures provides better predictions of the observed data. Estimation results of these measures are presented in Table 42. From table we can argue that the predictive performance of the estimated models are good give the smaller range of the errors as we can see from different fit measures.

Table 7-43: Predictive Performance Evaluation for SUNRAIL Ridership

Models	Mean ridership		MAPE	MAD
	Observed	Predicted		
Boarding	309.422	316.530	0.241	67.136
Alighting	308.195	306.686	0.270	81.143

7.5 SUMMARY

The report summarized validation exercise results for mobility, safety and ridership components of the multi-modal mobility study for Central Florida. For validation exercise, we have estimated several measures which are commonly used in evaluating predictive performance of the discrete choice/outcome models. From the validation analysis results, we found that all of our estimated models, in terms of mobility, safety and ridership components, provided reasonably good predictions and hence we can argue that the estimated modes are valid for predicting different policy measures.

CHAPTER VIII: POLICY ANALYSIS

8.1 INTRODUCTION

The objective of this chapter is to present and document the policy scenario analysis based on non-motorists mobility, safety models and transit ridership analysis presented in Chapters IV, V and VI. In terms of non-motorists mobility, we developed and presented aggregate level demand models by considering non-motorists exposure as the dependent variable. Subsequently, we developed different models for investigating non-motorists safety both in terms of crash frequency and crash severity for the Central Florida Region. In terms of ridership analysis, the public transit component is mainly focused on the coverage area of Lynx and SunRail network systems for the greater Orlando region. In this chapter, we had presented and discussed the policy analysis by using the estimates from the developed models from different components. In this chapter, we also present a descriptive analysis on impact of I-4 expansion project to understand the impact of the expansion project on transit ridership.

The remaining document is organized as follows: The next section focuses on policy scenario analysis for mobility and safety components. The next section focuses on policy scenario analysis for Lynx system. The subsequent section focuses on policy scenario analysis for SunRail system followed by a descriptive analysis on impact of I-4 expansion project on transit ridership. Finally, we present the summary of the chapter.

8.2 MOBILITY AND SAFETY COMPONENTS

The parameter effects of exogenous variables in demand and safety models do not directly provide the magnitude of the effects on zonal-level non-motorist demand and crash risks (both in terms of frequency and proportions of severity) and therefore cannot be directly employed for policy scenario analysis. For policy scenario analysis, we compute aggregate-level "elasticity effects" of exogenous variables both in the demand models and safety models (crash frequency and crash severity by proportions) (see work by Eluru and Bhat, 2007 for a discussion on the methodology for computing elasticities). We investigate the effect as a percentage change in the expected total zonal demand, total zonal crash counts and total proportions by severity levels to the change in exogenous variables for the study region. In the current study context, we perform policy analysis for different scenarios as follows:

- Scenario 1: 10% reduction in drive demand for the walk activity zones.
- Scenario 2: 5% reduction in drive demand for the bike activity zones.
- Scenario 3: 10% reduction in drive demand and 10% reduction in traffic volume for the walk activity zones.
- Scenario 4: 5% reduction in drive demand and 5% reduction in traffic volume for the bike activity zones.
- Scenario 5: 50% reduction in drive demand with 2 miles buffer area of different central business district (CBD).

- Scenario 6: 15% reduction in drive demand with 4 miles buffer area of different central business district (CBD).
- Scenario 7: 5% reduction in drive demand with 6 miles buffer area of different central business district (CBD).
- Scenario 8: 50% increase in existing sidewalk length.
- Scenario 9: 15% reduction in zonal average maximum speed.
- Scenario 10: 25% reduction in zonal average maximum speed.
- Scenario 11: 15% reduction in zonal proportion of 3+lane road.
- Scenario 12: 25% reduction in zonal proportion of 3+lane road.

These scenarios are evaluated for all zones and for both the pedestrian and bicycle groups of road users separately. In identifying the walk activity zones, we consider those zones where walk activities were observed from NHTS dataset as walk activity zone. Moreover, the zones which are within the 2-mile buffer area of observed walk activity zones are also considered within the group of walk activity zones. In identifying the bike activity zones, we consider those zones where bike activities were observed from NHTS dataset as bike activity zone. Moreover, the zones which are within the 6-mile buffer area of observed bike activity zones are also considered within the group of bike activity zones. Moreover, we also evaluate Scenarios 5, 6 and 7 for the zones within 2 (for Scenario 5), 4 (for Scenario 6) and 6 (for Scenario 7) miles of buffer area for multiple CBDs in the Central Florida region, including Orlando, Sanford, Lakeland, Kissimmee, Deland, Ocala, Melbourne, Palm Bay, Leesburg, Daytona Beach and Port Orange. In evaluating each scenario, we perform policy scenario analysis for three different components:

1. Component 1: Policy analysis for non-motorist demand - Evaluate change in total demand due to the change considered in the scenario.
2. Component 2: Policy analysis for non-motorist crash frequency - Evaluate the change in total crash frequencies considering the change in the scenario and the change in demand from Component 1 accordingly.
3. Component 3: Policy analysis for non-motorist crash severity proportions - Evaluate the change in total crash proportions by severity considering the change in the scenario and the change in demand from Component 1 accordingly.

By performing policy scenario analysis for these three components, we ensure that the updated demand matrices for each scenario are produced and employed in developing exposure measures for non-motorized travel as well as vehicular volumes on roadways. With these new exposure measures, the safety models are re-run to generate estimates of scenario-based crash and severity rates and the change in safety situation. A comparison across scenarios would allow us to identify beneficial changes to the existing infrastructure for improving non-motorized road user safety. The spatial representation of the considered CBD locations is shown in Figure 8-29. In the following sections, we describe the results from these policy scenario matrices for all three components.

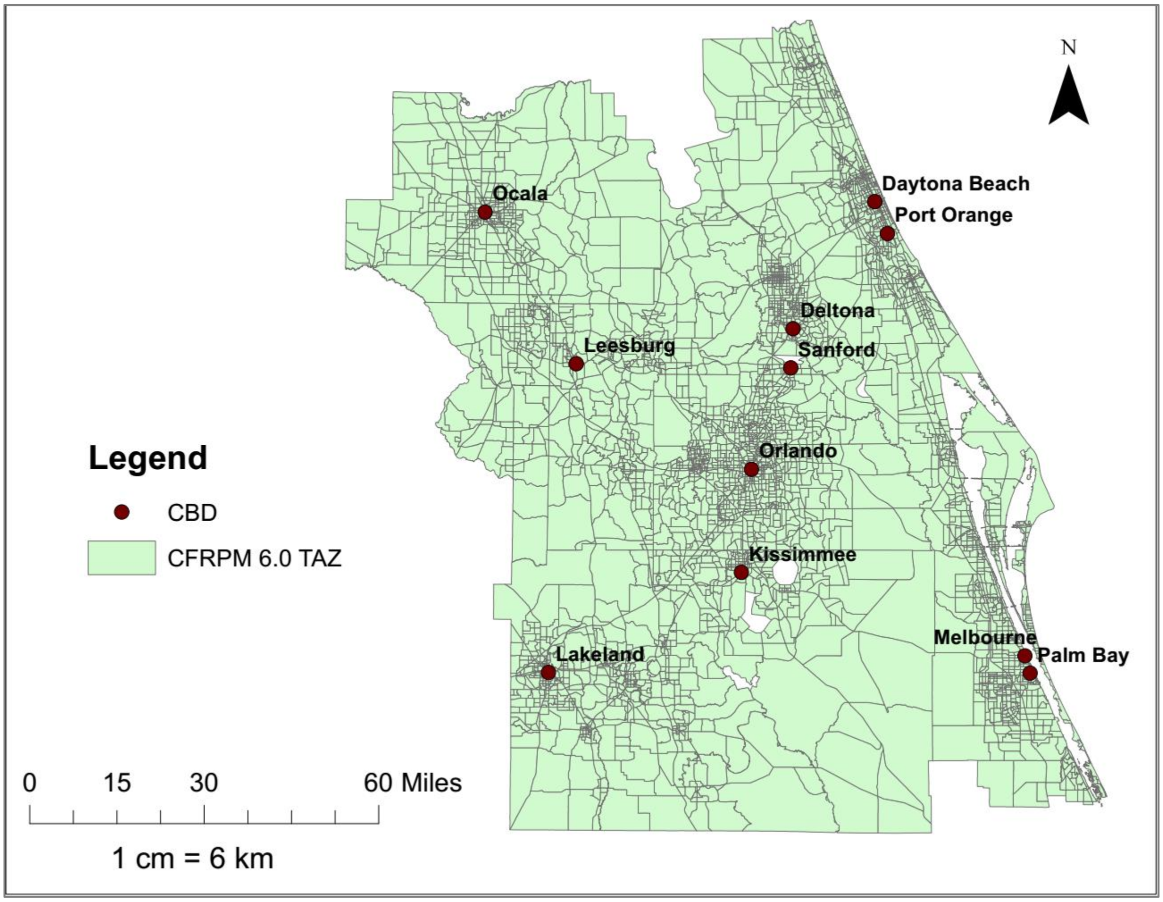


Figure 8-29: Considered Central Business District (CBD) Locations

8.2.1 Policy Analysis for Non-Motorist Demand

Policy scenario analysis for non-motorist travel demand is presented in this section. The change in total demand is evaluated across all scenarios for the pedestrian and bicycle groups of road users separately. The computed elasticities for total change in demand are presented in Table 8-433. The numbers in Table 8-43 may be interpreted as the percentage change in the expected total zonal demand per day due to the change in exogenous variable. The following observations can be made based on the elasticity effects presented in Table 8-43.

First, decreasing driver or vehicular traffic volume has positive impact on pedestrian demand, however, it is less likely to obtain higher bike volume by restricting or reducing vehicular demand. Second, increasing sidewalk facilities is likely to attract more non-motorists. Third, the reduction in speed has a greater impact on increasing pedestrian demand. However, for bicycles, the variable has no impact, as it was found insignificant in bicycle demand models. Fourth, a restriction in the number of traffic lanes is likely to have a similar impact; as we can see from Table 8-43, it increases non-motorist demand.

From the policy scenario analysis, it is quite clear that providing more walking- and bicycle-friendly facilities is likely to encourage more people to use non-motorized modes. Thus, we can argue that restricting lanes, reducing speed and reducing/restricting vehicular volume in a certain zone would increase non-motorist volume.

Table 8-44: Elasticity Effects for Non-Motorist Total Zonal Demand

Scenarios	Zones	Pedestrian	Bicycle
1	**All zones**	0.83	-3.847
	Walk activity zones	1.028	-10.586
2	**All zones**	0.711	-3.671
	Bike activity zones	-0.122	-2.588
3	**All zones**	0.219	-4.004
	Walk activity zones	0.417	-2.659
4	**All zones**	0.428	-3.751
	Bike activity zones	-0.436	-2.664
5	**All zones**	0.735	-3.674
	Zones within 2 miles buffer of CBD	-24.636	-60.154
6	**All zones**	0.697	-3.45
	Zones within 4 miles buffer of CBD	20.907	-26.395
7	**All zones**	0.661	-3.282
	Zones within 6 miles buffer of CBD	4.472	-12.314
8	**All zones**	-0.802	-4.081
9	**All zones**	-2.139	-3.506
10	**All zones**	-4.061	-3.506
11	**All zones**	0.037	-4.699
12	**All zones**	-0.36	-5.567

8.2.2 Policy Analysis for Non-Motorist Crash Frequency

Policy scenario analysis for non-motorist crash frequency is presented in this section. The change in total crash frequency is evaluated across all scenarios for the pedestrian and bicycle groups of road users separately. The computed elasticities for total change in crash frequency are presented in Table 8-44. To be sure, in evaluating the change in each scenario, the corresponding change in non-motorist demand (as presented in Section 8.2.1) is also incorporated for evaluating elasticity effects for non-motorist crash frequency. The numbers in Table 8-44 may be interpreted as the percentage change in the expected total zonal crashes per year due to the change in exogenous variable. The following observations can be made based on the elasticity effects presented in Table 8-44.

First, decreasing drive demand alone or along with traffic demand is likely to reduce pedestrian crashes, but is likely to increase bicycle crashes. Second, decreasing vehicular traffic volume near CBD locations is likely to reduce pedestrian crashes, with a greater impact within the vicinity of the CBD. However, bicycle crashes are likely to increase (other than for 2 miles radius). Third, the scenario of sidewalk length shows that providing walking facilities has the potential to improve pedestrian safety. On the other hand, bicycle crashes are likely to be high for increasing sidewalk length – perhaps indicating greater exposure. Fourth, reduction in speed and restrictions in traffic lanes decrease pedestrian crashes. On the other hand, restrictions in traffic lanes increase bicycle crashes by about 4%.

Table 8-45: Elasticity Effects for Non-Motorists Crash Frequency

Scenarios	Study region	Number of zones	Pedestrian	Bicycle
Scenario 1	**All zones**	4,747	-2.127	2.889
	Walk activity zones	4,168	-2.202	2.840
Scenario 2	**All zones**	4,747	-1.244	3.618
	Bike activity zones	4,091	-1.328	3.530
Scenario 3	**All zones**	4,747	-2.877	1.355
	Walk activity zones	4,168	-2.986	1.242
Scenario 4	**All zones**	4,747	-1.597	2.867
	Bike activity zones	4,091	-1.713	2.721
Scenario 5	**All zones**	4,747	-2.418	2.549
	Zones within 2 miles buffer of CBD	703	-12.443	-5.285
Scenario 6	**All zones**	4,747	-1.369	3.475
	Zones within 4 miles buffer of CBD	1,375	-3.634	1.735
Scenario 7	**All zones**	4,747	-0.894	3.897
	Zones within 6 miles buffer of CBD	1,985	-1.558	3.346
Scenario 8	**All zones**	4,747	0.558	4.301
Scenario 9	**All zones**	4,747	-0.477	0.000
Scenario 10	**All zones**	4,747	-0.486	0.000
Scenario 11	**All zones**	4,747	-0.469	4.301
Scenario 12	**All zones**	4,747	-0.473	4.323

8.2.3 Policy Analysis for Non-Motorist Crash Severity Proportions

Policy scenario analysis for non-motorist crash severity proportions is presented in this section. The change in total crash severity proportions is evaluated across all scenarios for the pedestrian and bicycle groups of road users separately. The computed elasticities for total change in crash frequency are presented in Table 8-45. To be sure, in evaluating the change in each scenario, the corresponding change in non-motorist demand (as presented in Section 8.2.1) is also incorporated for evaluating elasticity effects for non-motorist crash severity proportions.

Table 8-46: Elasticity Effects for Non-motorists Crash Severity Proportions

PEDESTRIAN

Scenarios	Study region	Number of zones	O*	C	B	A	K
Scenario 1	All zones	4,747	2.205	0.009	-0.271	-0.495	-0.689
	Walk activity Zones	4,168	2.303	0.007	-0.288	-0.529	-0.740
Scenario 2	All zones	4,747	2.431	0.096	-0.292	-0.611	-0.890
	Bike activity Zones	4,091	2.416	0.064	-0.289	-0.603	-0.890
Scenario 3	All zones	4,747	2.223	0.015	-0.273	-0.503	-0.701
	Walk activity Zones	4,168	2.322	0.012	-0.291	-0.537	-0.752
Scenario 4	All zones	4,747	2.440	0.099	-0.293	-0.614	-0.895
	Bike activity Zones	4,091	2.425	0.066	-0.290	-0.607	-0.896
Scenario 5	All zones	4,747	2.261	0.037	-0.275	-0.528	-0.752
	Zones with 2 miles buffer of CBD	703	7.228	-1.212	-0.928	-0.796	-0.827
Scenario 6	All zones	4,747	2.431	0.096	-0.292	-0.610	-0.891
	Zones with 4 miles buffer of CBD	1,375	4.379	-0.327	-0.520	-0.828	-1.226
Scenario 7	All zones	4,747	2.534	0.136	-0.301	-0.663	-0.983
	Zones with 6 miles buffer of CBD	1,985	3.481	-0.057	-0.412	-0.820	-1.269
Scenario 8	All zones	4,747	2.742	0.192	-0.327	-0.748	-1.118
Scenario 9	All zones	4,747	2.721	0.193	-0.324	-0.746	-1.113
Scenario 10	All zones	4,747	2.777	0.204	-0.332	-0.765	-1.141
Scenario 11	All zones	4,747	2.665	0.181	-0.316	-0.726	-1.085
Scenario 12	All zones	4,747	2.682	0.185	-0.319	-0.732	-1.092
BICYCLE							
Scenarios	Study region	Number of zones	O*	C	B	A	K
Scenario 1	All zones	4,747	-0.325	-0.162	0.075	0.343	0.606
	Walk activity Zones	4,168	-0.330	-0.165	0.077	0.358	0.653
Scenario 2	All zones	4,747	-0.074	-0.071	0.018	0.138	0.268
	Bike activity Zones	4,091	-0.078	-0.075	0.019	0.148	0.291
Scenario 3	All zones	4,747	-0.324	-0.162	0.075	0.343	0.606
	Walk activity Zones	4,168	-0.330	-0.165	0.077	0.358	0.653
Scenario 4	All zones	4,747	-0.074	-0.071	0.018	0.138	0.268
	Bike activity Zones	4,091	-0.078	-0.075	0.019	0.148	0.291
Scenario 5	All zones	4,747	-0.577	-0.234	0.138	0.507	0.798
	Zones with 2 miles buffer of CBD	703	-3.008	-1.061	0.782	2.737	4.778

Table 8-45 (Continued): Elasticity Effects for Non-motorists Crash Severity Proportions

BICYCLE

Scenarios	Study region	Number of zones	O*	C	B	A	K
Scenario 6	**All zones**	4,747	-0.149	-0.093	0.037	0.187	0.330
	Zones with 4 miles buffer of CBD	1,375	-0.711	-0.255	0.174	0.626	1.111
Scenario 7	**All zones**	4,747	0.016	-0.036	-0.002	0.057	0.120
	Zones with 6 miles buffer of CBD	1,985	-0.237	-0.082	0.059	0.204	0.365
Scenario 8	**All zones**	4,747	0.156	0.011	-0.034	-0.048	-0.047
Scenario 9	**All zones**	4,747	0.000	0.000	0.000	0.000	0.000
Scenario 10	**All zones**	4,747	0.000	0.000	0.000	0.000	0.000
Scenario 11	**All zones**	4,747	0.152	0.011	-0.033	-0.047	-0.046
Scenario 12	**All zones**	4,747	0.152	0.011	-0.033	-0.048	-0.048

**O=property damage only, C=minor injury, B=non-incapacitating injury, A=incapacitating injury, K=fatal*

The numbers in Table 8-45 may be interpreted as the percentage change in the expected total zonal crash severity proportion across different severity levels due to the change in exogenous variable. The following observations can be made based on the elasticity effects presented in Table 8-45. First, decreasing drive demand alone or along with traffic volume is likely to reduce pedestrian crash severity but is likely to increase bike severity. Second, decreasing vehicular traffic volume near CBD locations is likely to reduce pedestrian crash severity, with greater impact within the vicinity of the CBD. However, the impact on the bicycle mode severity out is higher. Third, the decrease in pedestrian fatal crash severity proportions is about 1% for increasing sidewalk length, reducing speed and restricting traffic lanes. The contributions of these measures on bicycle crash severity are less pronounced relative to pedestrian modes.

It is a well-known fact that non-motorist safety tends to decrease with increasing non-motorist exposure, and only after a certain level of exposure (when traffic becomes familiar with the higher number of non-motorists) does the safety tend to increase. From our policy analysis, we can see that non-motorist-friendly infrastructure has a mixed effect on non-motorist safety. Therefore, it is imperative that policy implications for improving non-motorist safety be identified by considering all known exogenous elements in identifying the appropriate tools. In general, restricting vehicular volume in a targeted zone would improve non-motorist safety.

8.3 RIDERSHIP COMPONENTS

With respect to transit ridership analysis, in our research effort, we estimated and presented four different sets of ridership models: for Lynx network system – (1) stop level average weekday boarding bus ridership analysis, and (2) stop level average weekday alighting bus ridership analysis; for SunRail network system – (3) daily boarding rail ridership analysis, and (4) daily alighting rail ridership analysis. It is worthwhile to mention here that, a specific emphasis of bus ridership analysis was to identify the effect of SunRail on bus ridership. Transit demand models were developed by considering attributes from temporal and seasonal variables, transportation infrastructures, land use variables, sociodemographic variables, and weather variables. In this section, we present the policy scenario analysis for the transit ridership component based on the estimated demand models for both Lynx and SunRail transit systems.

8.3.1 Policy Analysis for Lynx System

Policy scenario analysis for Lynx transit demand is presented in this section. In terms of bus ridership, we estimated two different GROL models: one model for stop level average weekday alighting ridership and another model for stop level average weekday boarding ridership. In order to highlight the effect of various attributes over time on boarding and alighting ridership, an elasticity analysis is also conducted (see Eluru and Bhat, 2007 for a discussion on the methodology for computing elasticities). We investigate the change in ridership, due to the change in selected independent variables. In our analysis, ridership is categorized into 13 bins: Bin 1 = ≤5; Bin 2 = 5-10; Bin 3 = 10-20, Bin 4 = 20-30, Bin 5 = 30-40, Bin 6 = 40-50, Bin 7 = 50-60, Bin 8 = 60-70, Bin 9 = 70-80, Bin 10 = 80-90, Bin 11 = 90-100, Bin 12 = 100-120 and Bin 13= >120. In our policy analysis, we compute the change in ridership (both boarding and alighting) for change in headway, sidewalk, bus route length, number of bus stops, land use mix, percentage of zero vehicle household (HH) and stops with shelter for the thirteen ridership categories. In the current study context, we perform policy analysis for different scenarios as follows:

- Scenario 1: 10% increase in sidewalk length in 400m buffer of stops.
- Scenario 2: 25% increase in sidewalk length in 400m buffer of stops.
- Scenario 3: 10% increase in bus route length within 800m buffer of stops.
- Scenario 4: 25% increase in bus route length within 800m buffer of stops.
- Scenario 5: Improving headway to 15-30 minutes for the stops with headway greater than 30 minutes.
- Scenario 6: Improving headway to less than 15 minutes for the stops with headway 15-30 minutes.
- Scenario 7: 10% increase in land-use mix in 600m buffer of stops.
- Scenario 8: 25% increase in land-use mix in 600m buffer of stops.
- Scenario 9: Providing shelter in 18% of the stops where at present there is no shelter.
- Scenario 10: 10% increase in percentage of household (HH) at a Census Tract level.
- Scenario 11: 25% increase in percentage of household (HH) at a Census Tract level.

The results for the elasticity analysis are presented in Table 8-40.

Table 8-47: Policy Analysis of Lynx

Scenarios	BOARDING												
	Bins (Percentage)												
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
Sidewalk													
1	-0.75	0.22	0.74	1.08	1.22	1.35	1.48	1.60	1.72	1.85	1.98	2.15	2.45
2	-0.30	0.09	0.30	0.43	0.49	0.54	0.59	0.64	0.68	0.73	0.78	0.85	0.97
Bus route length													
3	0.40	-0.11	-0.37	-0.57	-0.66	-0.75	-0.83	-0.91	-1.00	-1.08	-1.16	-1.26	-1.43
4	1.01	-0.27	-0.95	-1.43	-1.65	-1.86	-2.06	-2.27	-2.47	-2.66	-2.85	-3.10	-3.52
Headway													
5	-16.93	-13.42	6.59	30.06	42.67	54.94	66.16	75.84	83.74	89.90	94.50	98.87	103.60
6	-20.06	-39.22	2.84	47.27	69.82	91.12	110.10	126.07	138.84	148.57	155.71	162.30	169.04
Land-use mix													
7	-0.76	0.36	0.82	1.07	1.17	1.25	1.33	1.41	1.49	1.57	1.66	1.77	1.96
8	-1.91	0.89	2.03	2.69	2.93	3.15	3.35	3.55	3.75	3.97	4.19	4.48	4.98
Shelter													
9	-7.49	-1.56	5.52	11.37	14.24	17.21	20.27	23.38	26.41	29.26	31.81	34.80	39.18
Percentage of zero vehicle HH													
10	-0.55	0.18	0.56	0.79	0.89	0.98	1.06	1.16	1.25	1.36	1.46	1.62	1.89
11	-1.38	0.41	1.37	1.98	2.23	2.46	2.69	2.92	3.17	3.44	3.72	4.12	4.85

Table 8-46 (Continued): Policy Analysis of Lynx

Scenarios	ALIGHTING												
	Bins (Percentage)												
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
Sidewalk													
1	-0.36	0.07	0.32	0.48	0.56	0.63	0.70	0.77	0.84	0.92	0.99	1.08	1.22
2	-0.91	0.15	0.78	1.21	1.40	1.57	1.75	1.93	2.12	2.31	2.50	2.73	3.09
Bus route length													
3	0.32	-0.04	-0.25	-0.40	-0.48	-0.56	-0.65	-0.74	-0.83	-0.92	-1.00	-1.09	-1.24
4	0.79	-0.10	-0.62	-1.01	-1.21	-1.41	-1.63	-1.85	-2.07	-2.27	-2.47	-2.70	-3.05
Headway													
5	-16.34	-15.46	2.44	26.38	40.61	54.39	66.64	76.67	84.35	89.87	93.66	96.84	99.61
6	-18.41	-41.32	-2.75	41.36	65.52	88.03	107.40	122.84	134.36	142.46	147.89	152.28	155.79
Land-use mix													
7	-0.38	0.14	0.37	0.50	0.56	0.60	0.64	0.69	0.73	0.78	0.82	0.87	0.94
8	-0.95	0.34	0.92	1.26	1.39	1.51	1.62	1.73	1.84	1.95	2.05	2.18	2.36
Shelter													
9	-4.75	-0.99	2.93	6.21	7.94	9.80	11.80	13.93	16.09	18.15	20.04	22.30	25.64
Percentage of zero vehicle HH													
10	-0.69	0.12	0.60	0.93	1.07	1.20	1.33	1.46	1.60	1.74	1.89	2.07	2.37
11	-1.72	0.25	1.48	2.32	2.68	3.02	3.36	3.70	4.06	4.44	4.82	5.32	6.14

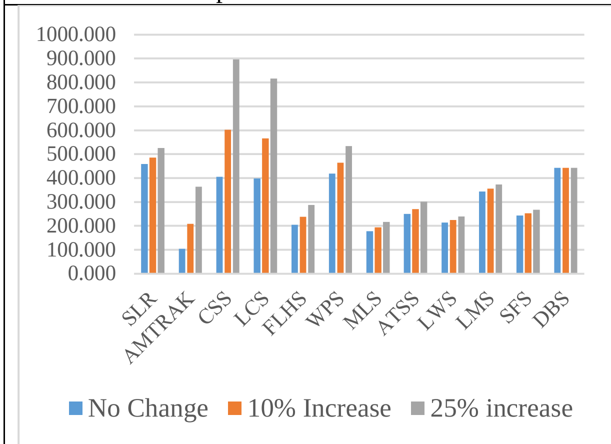
These results by ridership category can be translated into simple ridership numbers in a straightforward manner (if needed). Several observations can be made from the results presented in Table 8-46. First, headways and shelter are the most important variables in terms of high ridership categories. These results indicate that ridership is more sensitive to transit attributes and endorse the need to invest in improving transit infrastructure and service in order to encourage transit usage. Second, the effect of higher percentage of HH with zero personal vehicle further indicates that reduced accessibility to private automobile increases transit usage. Third, as is evident from Table 8-46, higher land-use mix also has a substantial contribution in increasing transit ridership providing credence to the rationale that dense urban environments contribute to a positive impact on ridership. Finally, more pedestrian friendly environment also have potential in increasing transit ridership. Based on our findings to increase the ridership, services related to public transit (improvement of headway and addition of shelters) should be considered.

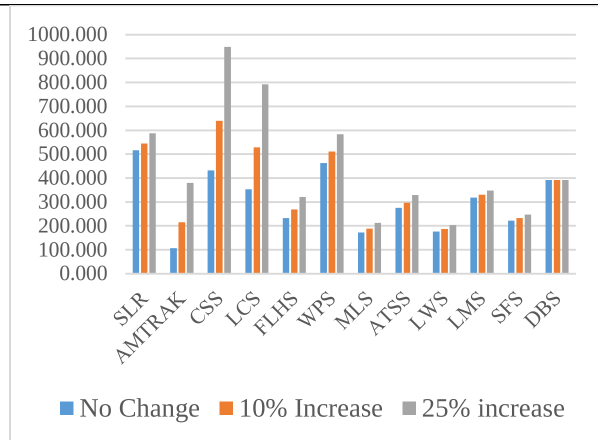
8.3.2 Policy Analysis for SunRail System

Policy scenario analysis for SunRail transit demand is presented in this section. In terms of rail ridership, we estimated two different linear regression models: one model for station level daily weekday boarding and one model for station level daily weekday alighting. Rail ridership was examined in order to identify the daily demand of the commuter rail. We compute aggregate level "elasticity effects" of exogenous variables. Specifically, we identified the average daily boarding and alighting ridership for changes for some selected exogenous variables. We consider the number of bus stops, land use mix and the number of commercial centers in 1500 m buffer around the SunRail stations for this purpose. In calculating the expected average predicted daily ridership, we increase the value of these variable by 10% and 25%. The computed ridership due to the change in these variables are shown in Figure 8-30 along with the observed daily ridership.

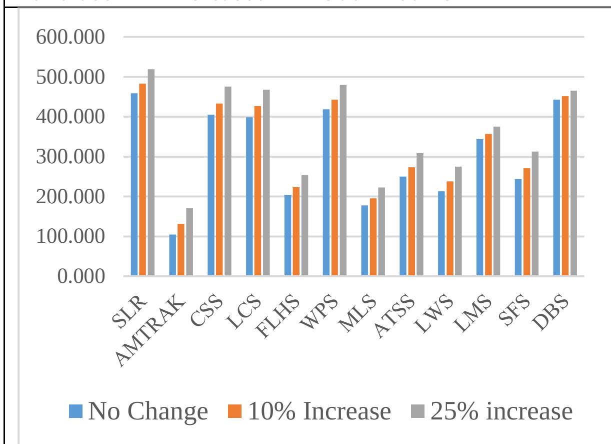
Several observations can be made from Figure 8-30. First, increased number of bus stops in 1500 m buffer have higher impact on increasing the ridership at almost every SunRail station. The highest impact is observed at AMTRAK, Church Street and Lynx Central stations. These results indicate that in the downtown area, the ridership is sensitive to bus stops around SunRail station; thus supporting investments on transit infrastructure for encouraging an integrated transit system. Second, the effect of land use mix indicates that improving the mix of land use patterns has positive impact on ridership. The land-use mix variable has almost similar impact across all stations. Finally, increasing the number of the commercial centers also considerably increases the ridership. However, there was no impact on ridership for SFS and DBS stations as expected because the original variables were 0 for these stations (an increase by percentage does not result in an increase). The elasticity analysis conducted provides an illustration on how the proposed model can be applied for policy evaluation for SunRail ridership.

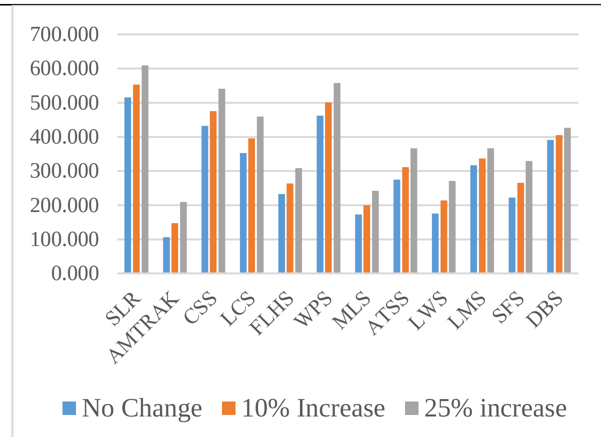
Boarding Ridership	Alighting Ridership
Number of bus stop increased in 1500 m buffer	



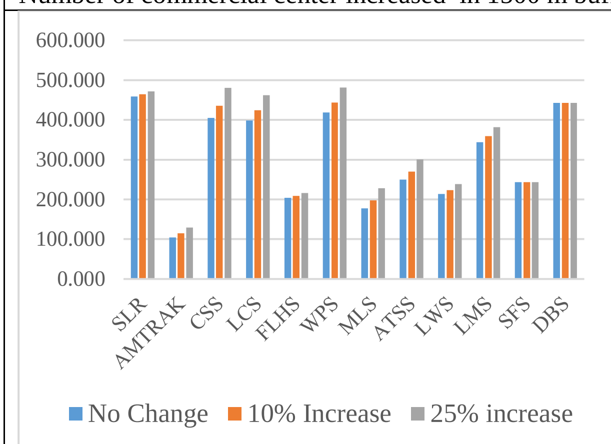


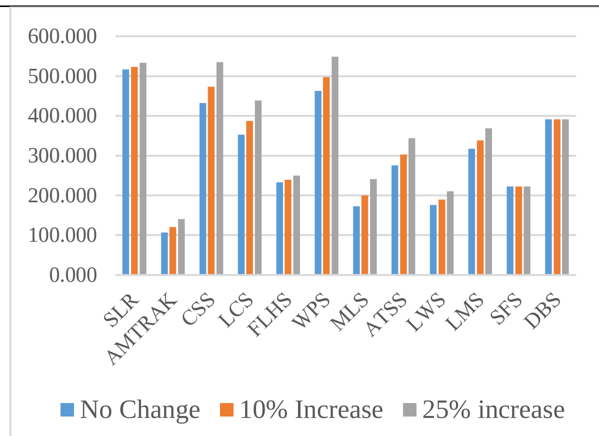
Land use mix increased in 1500 m buffer





Number of commercial center increased in 1500 m buffer





Note: SLR=Sand Lake Road, AMTRAK Station, CSS=Church Street Station, LCS=Lynx Central Station, FLHS=Florida Hospital Station, WPS=Winter Park Station, MLS=Maitland Station, ATSS=Altamonte Spring Station, LWS=Longwood Station, LMS=Lake Mary Station, SFS=Sanford Station and DBS= DeBary Station

Figure 8-30: Policy Analysis of SunRail

8.4 IMPACT OF I-4 CONSTRUCTION ON BUS RIDERSHIP

In order to understand the impact of I-4 construction on transit ridership, we also perform a descriptive analysis. The I-4 ultimate improvement project is focused on a 21 mile stretch of I-4 and the project began in March 2015.

The travellers using the corridor for their daily trips are likely to face congestion due to the on-going construction project. The authorities are encouraging travellers to use public transit to avoid construction related delay. In this research effort, we perform a descriptive analysis to understand the impact of the construction project on overall public transportation ridership. To understand the impact of I-4 expansion project, we assume that the buffer area within 1, 2 and 3 mile of the construction zone will be highly, moderately and marginally impacted respectively. The impact area of I-4 expansion along with SunRail line, SunRail stations and bus stops are presented in Figure 8-31.

In order to understand the impact of the expansion project on bus ridership, we consider ridership records from May 2013 to April 2015 as before construction period; while May 2015 to December 2016 as after construction period. We have compared the average daily ridership for before and after period for the different influence areas. These results are presented in Table 8-47. From Table 8-47, we can see that the average daily ridership of the stops within the influence areas (1, 2 and 3 miles buffer areas) have decreased after May 2015 relative to the before construction period. The percent reduction is lower within the 1 mile buffer area compared to 2 and 3 mile buffer areas. While it is expected that more people might choose transit as an alternate option to avoid construction related delay, it is also important to realize that the overall bus ridership has decreased after 2014 as presented in Figure 8-32. The reduction in bus ridership is probably reflective of improving economic conditions in the Central Florida region.

To consider this overall trend of ridership reduction, we have also computed the percentage change in ridership of stops outside the buffer area. From Table 8-47, it is evident that after May 2015, ridership has also decreased for stops outside I-4 expansion influence area. However, the reduction in ridership within the influence area of the construction zone is lower than the stops outside the influence area. Moreover, some of the change in bus ridership within the influence area might be attributed to the new transit infrastructure addition – SunRail. Therefore, we can argue that I-4 expansion project has an overall positive impact on Lynx ridership even though the bus ridership at a stop level has seen an overall reduction after 2014.

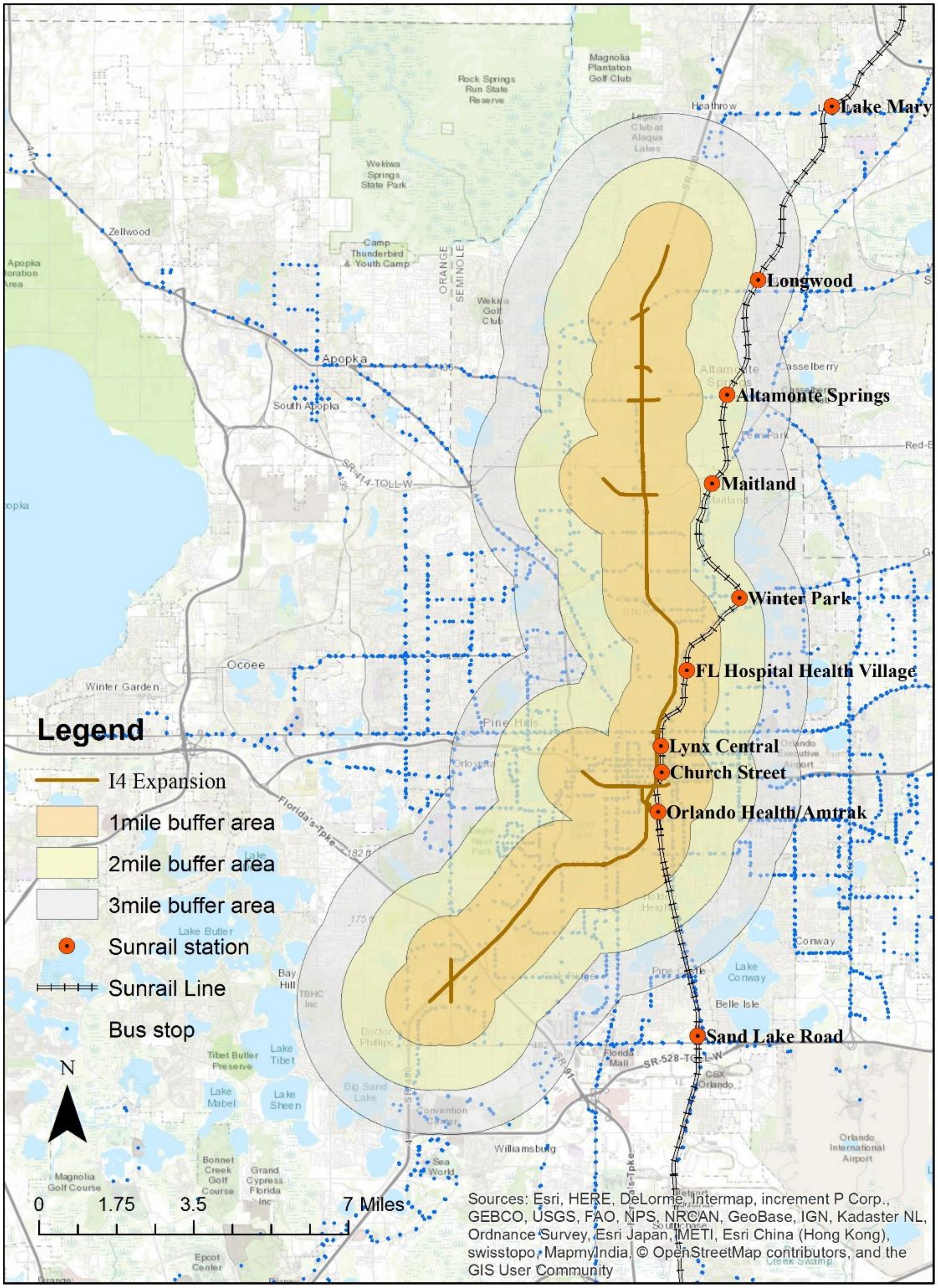


Figure 8-31: Impact Area of I-4 Expansion Project

Table 8-48: Expansion Project and Change in Ridership

Study period	Average daily		Change in average daily ridership (Percentage)	
	Boarding	Alighting	Boarding	Alighting
After (*May 2015 to December 2016)*	19.73	19.80	-4.07	-4.17
Before *(May 2013 to April 2015)*	20.56	20.67		
Influence area				
Inside 1mile buffer area				
After (*May 2015 to December 2016)*	34.52	33.95	-2.71	-2.62
Before *(May 2013 to April 2015)*	35.48	34.86		
Outside 1mile buffer area				
After (*May 2015 to December 2016)*	15.31	15.58	-4.96	-5.16
Before *(May 2013 to April 2015)*	16.11	16.43		
Inside 2mile buffer area				
After (*May 2015 to December 2016)*	27.50	27.18	-3.34	-2.89
Before *(May 2013 to April 2015)*	28.45	27.98		
Outside 2mile buffer area				
After (*May 2015 to December 2016)*	15.01	15.33	-4.86	-5.52
Before *(May 2013 to April 2015)*	15.78	16.23		
Inside 3mile buffer area				
After (*May 2015 to December 2016)*	25.42	25.27	-3.08	-3.03
Before *(May 2013 to April 2015)*	26.23	26.06		
Outside 3mile buffer area				
After (*May 2015 to December 2016)*	14.34	14.64	-5.68	-5.98
Before *(May 2013 to April 2015)*	15.21	15.57		

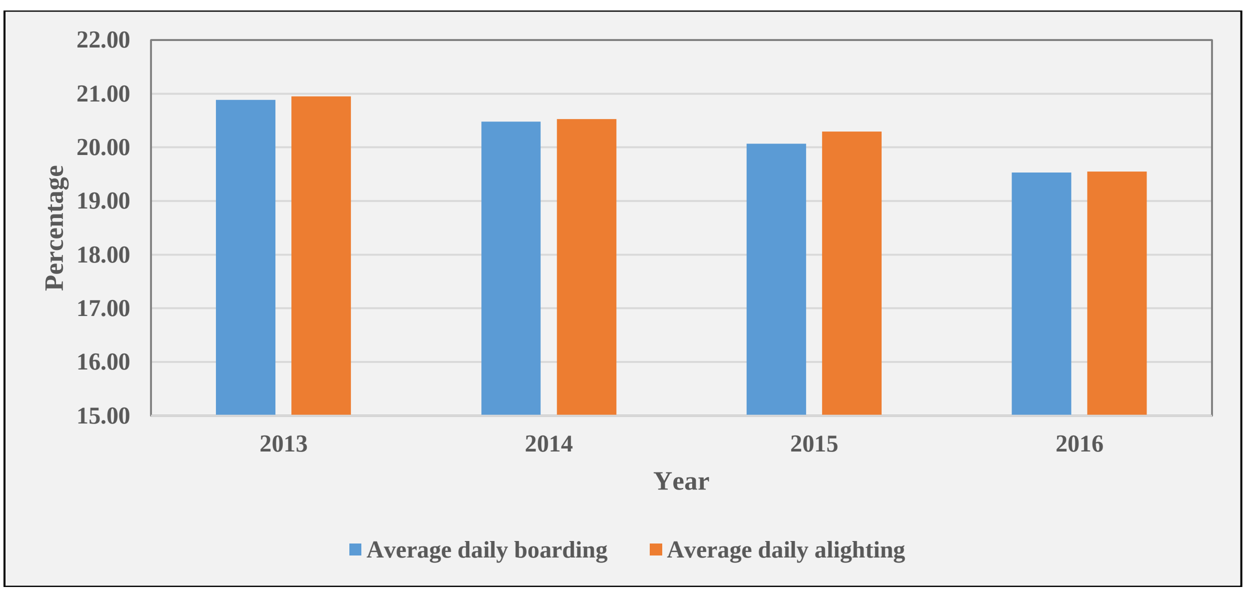


Figure 8-32: Average Daily LYNX Ridership

8.5 SUMMARY

The report summarized forecasting exercise results for non-motorists mobility and safety components along with forecasting exercise results for transit ridership components of the multi-modal mobility study for Central Florida. With respect to policy scenario analysis, we considered 12 hypothetical scenarios and evaluated the impact of change in variables on mobility and safety (both frequency and severity) components of non-motorized road user group. Further, we considered 11 and 6 hypothetical scenarios for Lynx and SunRail systems, respectively, and evaluated the impact of change in ridership for both systems separately. Based on our findings to increase the ridership, services related to public transit (improvement of headway and shelter) and dense community building should be considered.

CHAPTER IX: COST-BENEFIT ANALYSIS

9.1 INTRODUCTION

The objective of this chapter is to document and present the cost-benefit analysis (CBA) of the recently added SunRail transit system in Orlando. Transit systems are an integral part of the development of a community. But comprehensive benefits of these systems often are not estimated or remain unmeasured. Though the capital cost of developing a transit system is significantly higher, total benefits accrued from a transit system operation in the long run is likely to surpass the higher investment cost. CBA is considered to be one of the most appropriate tools in evaluating net benefits of a transportation system (Litman, 2001). With the focus of encouraging more people to use sustainable transportation alternatives, FDOT is constructing a new, 17.2-mile extension to the existing 31-mile SunRail commuter rail. A comprehensive CBA of the existing operational SunRail system would assist planners and policy makers to evaluate the "real" benefit of these investments and provide evidence to justify allocation of more funding for improving/building transit infrastructures. To that extent, in this research effort, we present and discuss CBA result for the existing 31-mile SunRail system.

The remaining chapter is organized as follows: The next section focuses on components of cost-benefit analysis for SunRail system. The subsequent section focuses on the result of cost-benefit analysis. Finally, we present the summary of the chapter.

9.2 COST-BENEFIT ANALYSIS FOR SUNRAIL

SunRail is in operation since May, 2014 in greater Orlando. The existing operational SunRail system comprises of 31-mile rail length along with 12 active stations - Sand Lake Station, Amtrak Station, Church Street Station, Lynx Central Station, Florida Hospital Station, Winter Park Station, Maitland Station, Altamonte Springs Station, Longwood Station, Lake Mary Station, Sanford Station and Debary Station. In this research effort, we focus on this existing SunRail system for the CBA. We projected cost and benefit for 30 years (from 2014 to 2044) considering 2014 as base year.

9.2.1 Factors Considered

The potential cost-benefit components of SunRail is identified based on literature review and the components identified in Task 1. With regards to cost component, the factors we consider included: (1) capital costs and (2) operation and maintenance costs. In terms of the benefit component, the factors we consider included: (1) personal automobile cost savings, (2) crash cost savings, (3) parking cost savings, (4) energy conservation savings, and (5) assessed property value increase. In the current study context, we assume that SunRail trips has an impact on personal automobile mode only. However, SunRail could have potential impact on individuals using other modes including bus, walk or bike. However, in computing benefits, we assume that SunRail trip would have negligible effect on other modes since we did not have information on actual modal shifts that may have induced by SunRail.

9.2.2 Demand Attributes

Transit demand attributes (such as ridership, passenger miles travelled, frequencies, headway etc.) determine the magnitude of benefits from any transit investments as these attributes represents the demand and efficiency of the system. Therefore, the first step of CBA is to identify these demand attributes. In this research effort, we compute the benefit factors as function of daily ridership, passenger miles travelled and train frequency. In this section, we describe the procedure for computing these attributes.

Daily Ridership

For the purpose of identifying average daily ridership of SunRail at a system-level, we have compiled stop level daily boarding and alighting ridership data for ten months from January 2015 to October 2015. The daily ridership data includes weekdays only as SunRail did not operate during weekends over the data collection period. The 10-month, 12 station data provided us 2,496 observations. A summary of the system level ridership (boarding and alighting) is provided in Table 9-48. From Table 9-48, we can see that the average daily system-level ridership is almost 3,700. Therefore, for the current study, we consider an average daily ridership of 3,700 at a system-level for computation of benefit factors.

Table 9-49: Summary Statistics for SunRail Average Daily Ridership (January 2015 to October 2015)

Station Name	Mean	
	Boarding	Alighting
Sand Lake Station	451.168	82.127
Amtrak Station	124.260	20.507
Church Street Station	393.135	79.184
Lynx Central Station	403.769	35.282
Florida Hospital	201.976	26.562
Winter Park Station	411.707	205.107
Maitland Station	180.962	27.084
Altamonte Springs station	244.163	40.788
Longwood Station	240.909	36.959
Lake Mary Station	337.005	55.139
Sanford Station	258.952	45.735
Debary Station	445.178	90.608
Total	**3,693.183 = 3,700**	**3,693.183 = 3,700**

Passenger Miles Travelled

For the purpose of identifying passenger miles travellers, we selected station level ridership for a random day. From the stop-level daily ridership information including boarding and alighting, we computed the train occupancy between stations. The occupancy and station to station distance was employed to generate person level mileage on the system. Table 9-49 represents the passenger miles travelled computation details. From Table 9-49, we can see that on an average a passenger travelled about 16.57 miles by using SunRail on a typical weekday. Therefore, we have considered 17 miles as average passenger miles travelled for computation of benefit factors.

Table 9-50: Passenger Miles Travelled Calculations for SunRail

SOUTHBOUND							
No.	**Stations**	**Distance from station to station (miles)**		**Number of passenger**			**Total passenger miles (Remained boarded*Distance from station to station)**
				Boarded	**Alighted**	**Remained boarded**	
1	**DeBary Station**	1-2	5	451	0	451	2,255.00
2	**Sanford Station**	2-3	4.5	253	15	689	3,100.50
3	**Lake Mary Station**	3-4	5.5	331	18	1,002	5,511.00
4	**Longwood Station**	4-5	3	207	39	1,170	3,510.00
5	**Altamonte Springs Station**	5-6	3	167	72	1,265	3,795.00
6	**Maitland Station**	6-7	3.5	129	42	1,352	4,732.00
7	**Winter Park Station**	7-8	2.5	152	266	1,238	3,095.00
8	**Florida Hospital Station**	8-9	2.3	70	157	1,151	2,647.30
9	**Lynx Central Station**	9-10	0.7	64	322	893	625.10
10	**Church Street Station**	10-11	1.2	46	299	640	768.00
11	**AMTRAK Station**	11-12	5.7	13	118	535	3,049.50
12	**Sand Lake Road Station**	---	---	0	535	---	---
Total Southbound				**1,883**	**1,883**		**33,088.40**
NORTHBOUND							
No.	**Stations**	**Distance from station to station (miles)**		**Number of passenger**			**Total passenger miles (Remained boarded*Distance from station to station)**
				Boarded	**Alighted**	**Remained boarded**	
1	**Sand Lake Station**	1-2	5.7	395	0	395	2,251.50
2	**Amtrak Station**	2-3	1.2	109	13	491	589.20
3	**Church Street Station**	3-4	0.7	326	41	776	543.20
4	**Lynx Central Station**	4-5	2.3	343	62	1,057	2,431.10
5	**Florida Hospital**	5-6	2.5	139	86	1,110	2,775.00

Table 9-49 (Continued): Passenger Miles Travelled Calculations for SunRail

NORTHBOUND								
No.	**Stations**	**Distance from station to station (miles)**		**Number of passenger**			**Total passenger miles (Remained boarded*Distance from station to station)**
				Boarded	**Alighted**	**Remained boarded**	
6	**Winter Park Station**	6-7	3.5	243	175	1,178	4,123.00
7	**Maitland Station**	7-8	3	48	153	1,073	3,219.00
8	**Altamonte Springs station**	8-9	3	92	177	988	2,964.00
9	**Longwood Station**	9-10	5.5	41	203	826	4,543.00
10	**Lake Mary Station**	10-11	4.5	17	314	529	2,380.50
11	**Sanford Station**	11-12	5	10	235	304	1,520.00
12	**Debary Station**	---	---	0	304	---	---
Total Northbound				**1,763**	**1,763**		**27,339.50**
Total Passenger miles travelled		**33,088.40 + 27,339.50 = 60,427.90**					
Average passenger miles travelled		**60,427.90/(1,883+1,763) = 16.57**					

Train frequency

We identify train frequency based on SunRail train frequency operation. The frequency of SunRail is 18 in each direction, therefore, we consider train frequency as 36 per day (representing both direction run) for computation of benefit factors.

9.3 COST FACTORS

In our current study, we consider two cost factors: (1) capital costs, and (2) operation and maintenance costs. Capital costs include costs for planning, design and constructing the infrastructure for SunRail operation along with costs for buying the trains. Operation and maintenance costs include compensation cost of train operators, operation and maintenance personnel, electricity bills, buying replacement parts, supplies from vendors and other regular operation cost. For the current research purposes, we consider SunRail capital costs as $615 million (FDOT, 2016; 2017b). In terms of operation and maintenance costs, we consider it as $34.4 million for the base year (sourced from Taylor and Paramore, 2016, 2017). For 30 year cost projection, we assume an increase rate of 2.8% per year in computing operation and maintenance cost.

9.4 BENEFIT FACTORS

9.4.1 Personal Automobile Cost Savings

Personal automobile cost (PAC) savings refers to the cost saving to riders due to the shift from personal automobile to transit mode. There are marginal costs associated with driving a personal vehicle in terms of fuel usage, depreciation, insurance, maintenance, parking cost and vehicle ownership cost. By shifting from driving to transit, travellers are likely to reduce their annual transportation costs related to owning and operating a personal vehicle. In fact, Litman (2004) computed the savings to be $1,300 per household in cities with established rail transit system. Thus, there is likely to be cost savings for train riders from reduced personal automobile usage. For our current research purpose, we assume PAC savings to be $0.65 per vehicle-mile (AAA, 2013). The value is identified by assuming that a vehicle is driven approximately 15,000 miles per year and the cost includes operating (gas, maintenance, and tires) and ownership (insurance, depreciation, license, registration, taxes, and finance charge) components of driving personal automobile. Further, in identifying PAC savings per person, we assume that the average occupancy of a vehicle is 1.67 (, NHTS, 2017). According to NHTS 2009, average vehicle occupancy rate for commuter trips were 1.13 while in Florida, the rate is greater than 2. As a result, for our analysis, we used 1.67 as the vehicle occupancy factor. Thus, the PAC cost savings is computed for a person as $\frac{\$0.65}{1.67\ person-mile}$. Table 9-50 provides our estimates of per year PAC savings of SunRail.

Table 9-51: Personal Automobile Cost Savings

Cost category	Unit cost ($/rider-miles)	Average train-miles travelled (miles/rider-day)	Personal automobile cost savings ($/rider-day)
Personal automobile cost savings	$\frac{0.65}{1.67}$	17	$\frac{0.65}{1.67} * 17$
$\textbf{Total personal automobile savings} \left(\frac{\$}{\textbf{year}}\right) = \frac{\mathbf{0.65}}{\mathbf{1.67}} * \mathbf{17} * \mathbf{3700} * (\mathbf{5} * \mathbf{52}) = \$\mathbf{6,365,329.34}$			

Note: $(5 * 52)$ *represents 5 days of the week and 52 weeks operation period of SunRail per year*

9.4.2 Crash Cost Savings

In general, public transportation has better safety record per unit of travel relative to passenger vehicle. As documented by Litman (2014), crash rate of commuter rail from road traffic crashes is 0.43 per billion passenger miles, while the crash rate for passenger vehicle is 7.28. The value clearly signify the benefit of transit mode in terms of road safety. In our current research effort, we compute the crash cost savings of SunRail by subtracting SunRail crash cost from the automobile crash cost for trips to reflect the net benefit of replacing automobile trips with transit mode. For computing crash cost savings, we assume crash cost of automobile as $0.10 per vehicle mile and crash cost of SunRail as ($0.258 (external risk)+0.05*occupant(internal risk)) per vehicle mile. Table 9-51 provides our estimates of per year crash cost savings of SunRail (following Litman, 2011).

Table 9-52: Crash Cost Savings

Cost category	Unit cost ($/rider-miles)	Average train-miles travelled (miles/rider-day)	Automobile crash cost ($/rider-day)
Automobile crash cost	$\frac{0.10}{1.67}$	17	$\frac{0.10}{1.67} * 17$
$\textbf{Total automobile crash cost} \left(\frac{\$}{\textbf{year}}\right) = \frac{\mathbf{0.10}}{\mathbf{1.67}} * \mathbf{17} * \mathbf{3700} * \mathbf{5} * \mathbf{52} = \$\mathbf{954,910.18}$			
Cost category	**Train-miles (per day)**	**External cost ($/day)**	**Internal cost ($/day)**
SunRail crash cost	$31 * 36$	$0.258 * 31 * 36$	$0.05 * 17 * 3700$
$\textbf{Total SunRail crash cost} \left(\frac{\$}{\textbf{year}}\right) = (\mathbf{0.258} * \mathbf{31} * \mathbf{36} * \mathbf{20} + \mathbf{0.05} * \mathbf{17} * \mathbf{3700}) * \mathbf{5} * \mathbf{52} = \$\mathbf{866,452.72}$			
$\textbf{Total crash cost savings} \left(\frac{\$}{\textbf{year}}\right) = \$\mathbf{979,281.44} - \$\mathbf{866,452.72} = \$\mathbf{8,8457.46}$			

9.4.3 Emission Cost Savings

One of the major benefits of transit over automobile is emission reduction benefits (Gallivan et al., 2015). Automobile and bus are likely to emit carbon monoxide, nitrogen dioxide, car dioxide and hydrocarbon in air. On the other hand, light rail is likely to produce 99% less hydrocarbons and carbon monoxide emissions per mile relative to that of automobile (Garrett, 2004). In our current study, we use air pollution cost as $0.08 per vehicle mile (Blonn et al., 2006), reflecting the fact that SunRail is located in urban area and the rail system also generates some air emissions. Thus, we compute emission cost savings as "change in automobile miles travelled*emission cost per automobile mile travelled". Table 9-52 provides our estimates of per year emission cost saving of SunRail.

Table 9-53: Emission Cost Savings

Cost category	Unit cost ($/rider-miles)	Average train-miles travelled (miles/rider-day)	Emission cost savings ($/rider-day)
Emission cost savings	$\frac{0.08}{1.67^{¥}}$	17	$\frac{0.08}{1.67} * 17$
$$\textbf{Total emission cost savings} \left(\frac{\$}{\textbf{year}}\right) = \frac{\mathbf{0.08}}{\mathbf{1.67}} * \mathbf{17} * \mathbf{3700} * \mathbf{5} * \mathbf{52} = \$\mathbf{763,928.14}$$			

¥ average vehicle occupancy is considered as 1.67

9.4.4 Parking Cost Savings

Parking personal automobiles are often associated with cost of parking spaces and time spent to find the space. Unlike automobile mode, transit mode does not have parking cost associated with it (except park and ride option). In our current study, we compute parking cost savings for trip to reflect the net benefit of replacing automobile trips with transit mode. For computing cost savings, we assume parking cost of automobile as $0.36 per vehicle mile (following Litman, 2018). Table 9-53 provides estimates of per year parking cost savings of SunRail.

Table 9-54: Parking Cost Savings

Cost category	Unit cost ($/rider-miles)	Average train-miles travelled (miles/rider-day)	Parking cost savings ($/rider-day)
Parking cost savings	$\frac{0.36}{1.67^{¥}}$	17	$\frac{0.36}{1.67} * 17$
$$\textbf{Total parking cost savings} \left(\frac{\$}{\textbf{year}}\right) = \frac{\mathbf{0.36}}{\mathbf{1.67}} * \mathbf{17} * \mathbf{3700} * \mathbf{5} * \mathbf{52} = \$\mathbf{3,467,376.65}$$			

¥ average vehicle occupancy is considered as 1.67

9.4.5 Energy Conservation Savings

Transit mode can provide significant energy efficiency. Shapiro et al. (2002) found that an average automobile consumes about double the energy per passenger-mile travel relative to transit mode. In our current research effort, we use energy conservation savings as $0.03 per vehicle miles (following Litman, 2018). Table 9-54 provides estimates of per year energy conservation cost savings of SunRail.

Table 9-55: Energy Conservation Savings

Cost category	Unit cost ($/rider-miles)	Average train-miles travelled (miles/rider-month)	Energy conservation savings ($/rider-month)
Energy conservation savings	$\frac{0.03}{1.67^{¥}}$	17	$\frac{0.03}{1.67} * 17$
$\textbf{Total energey conservatio savings} \left(\frac{\$}{\textbf{year}}\right) = \frac{\mathbf{0.03}}{\mathbf{1.67}} * \mathbf{17} * \mathbf{3700} * \mathbf{5} * \mathbf{52} = \$\mathbf{286,473.05}$			

¥ average vehicle occupancy is considered as 1.67

9.4.6 Assessed Property Value Increase

Development of transit infrastructure increases overall accessibility which in turn is likely to increase land values around transit stops/stations. Moreover, higher accessibility attributable to transit development is likely to attract more economic development, higher active transportation friendly environment, more activities, higher density and mixed-use community development. Clearly, there are positive impacts of transit development on land use value. In our current study, we also consider the change in land use values surrounding the SunRail stations as one of the elements in benefit computation. In calculating the land use values, we consider assessed property value or just value as a surrogate measure of direct land use value. Just value (land just value, building value and special feature value) of a property includes: present cash value; use; location; quantity or size; cost; replacement value of improvements; condition; income from property; and net proceeds if the property is sold. The net proceeds equal the value of the property minus 15% of the true market value. This accounts for the cost of selling the property. In the following sections, we refer to the assessed property value as property value for simplicity.

To capture the change in property value, we collected and compiled parcel level data from Department of Revenue (DOR) for 2011 to 2016. The data has tax information of each parcel along with parcel boundaries from the Florida Department of Revenue's tax database. Each parcel polygon (Parcel ID) has information on property/feature value, land value, land area in square feet, owner name, owner address, physical address, physical zip code, building details and land use type. From the land use categories of parcel data, we have considered six major land use categories for identifying the impact of SunRail on property value change. The considered land use categories are: (1) Single family residential, (2) Multiple family residential, (3) Institutional, (4) Industrial, (5) Recreational and (6) Retail/Office area. For our current research, we assume that one-mile buffer area around each SunRail station is the influence area of SunRail for property value impact computation. We labeled the parcels within the SunRail influence area as “Case Parcels”. For these case parcels, we computed property value by six land use types identified. To be sure, we have computed property value for case parcels from six years from 2011 to 2016. 2011 to 2013 period is considered to understand the change in property value before SunRail operation period, while 2014 to 2016 period shows the change in property value reflecting after SunRail operation period. Figure 9-33 and Figure 9-34 represent the spatial distribution of land use categories and property values for 2011 (before) and 2016 (after) within the SunRail influence area. From spatial representations, we can see that even though there are not much visible changes in land use categories from 2011 to 2016, the property values, on the contrary, have changed significantly after SunRail has become operational.

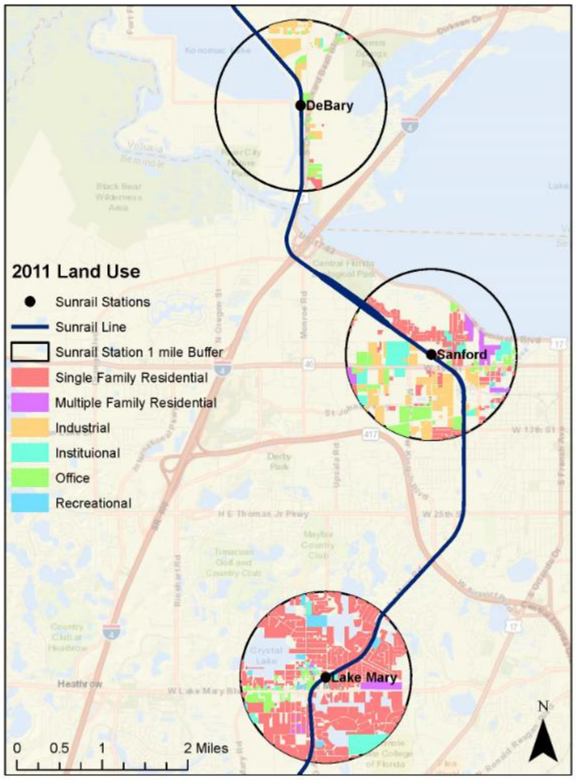
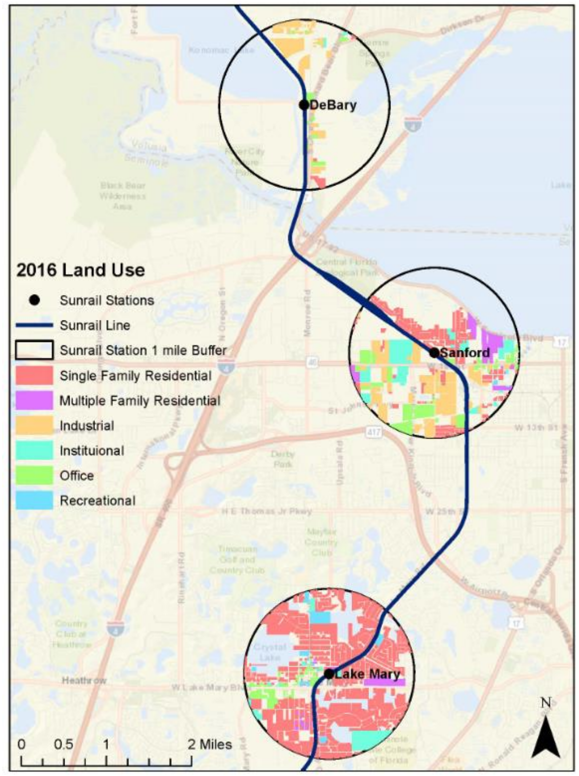
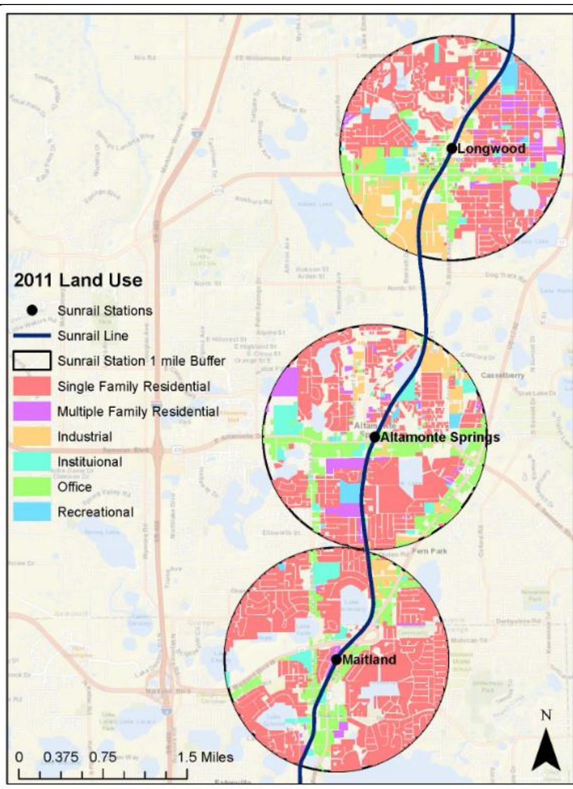
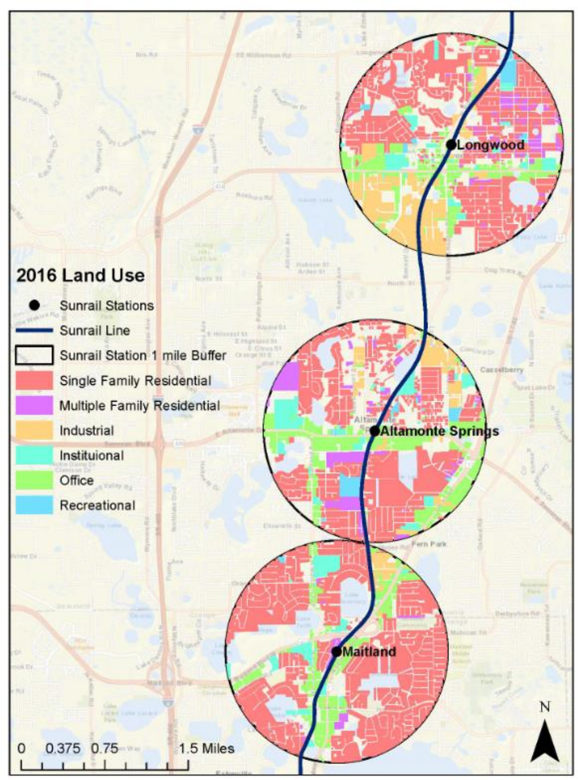
Year 2011	Year 2016
	
	

Figure 9-33: Land Use Types within SunRail Influence Area for 2011 and 2016

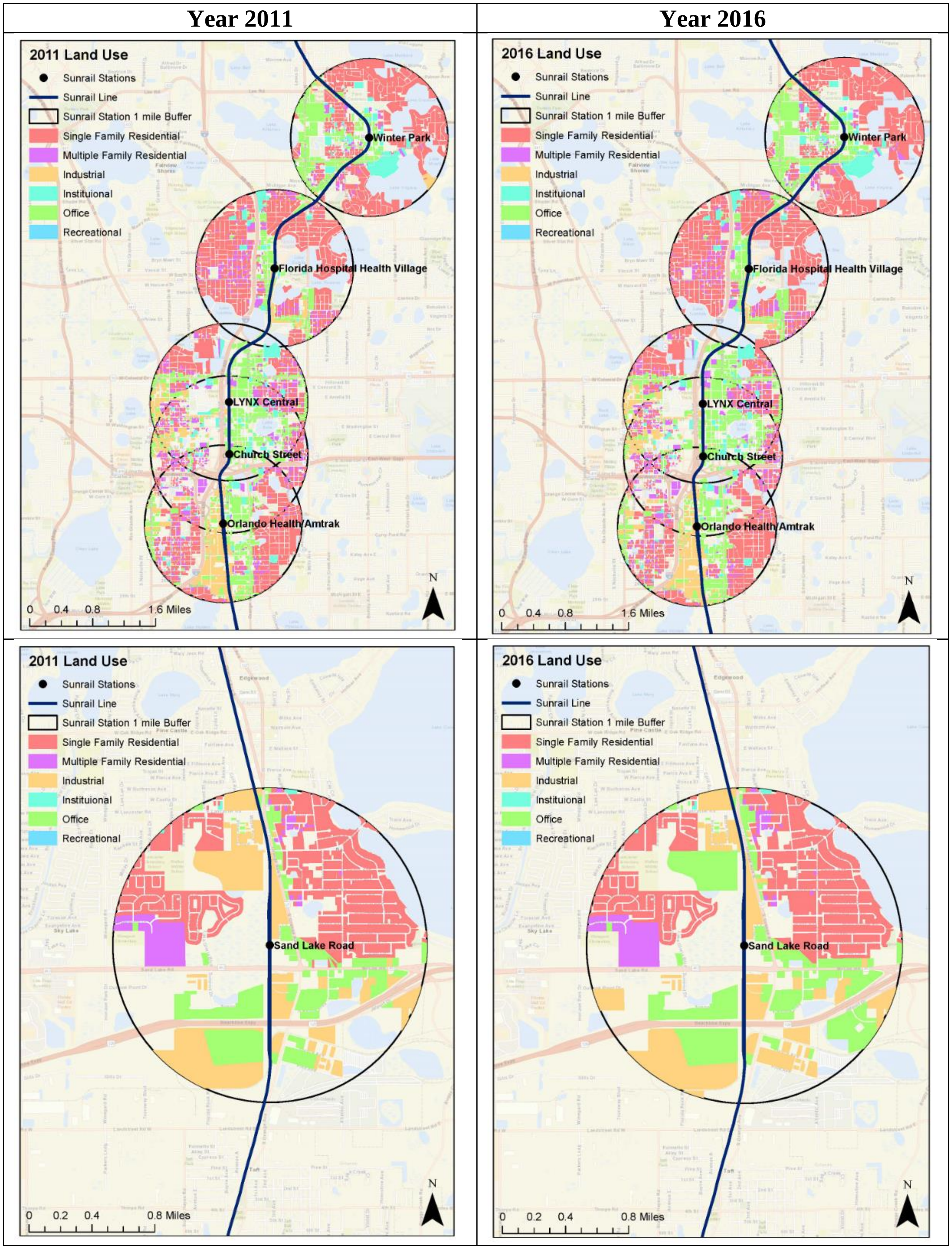


Figure 9-33 (Continued): Land Use Types within SunRail Influence Area for 2011 and 2016

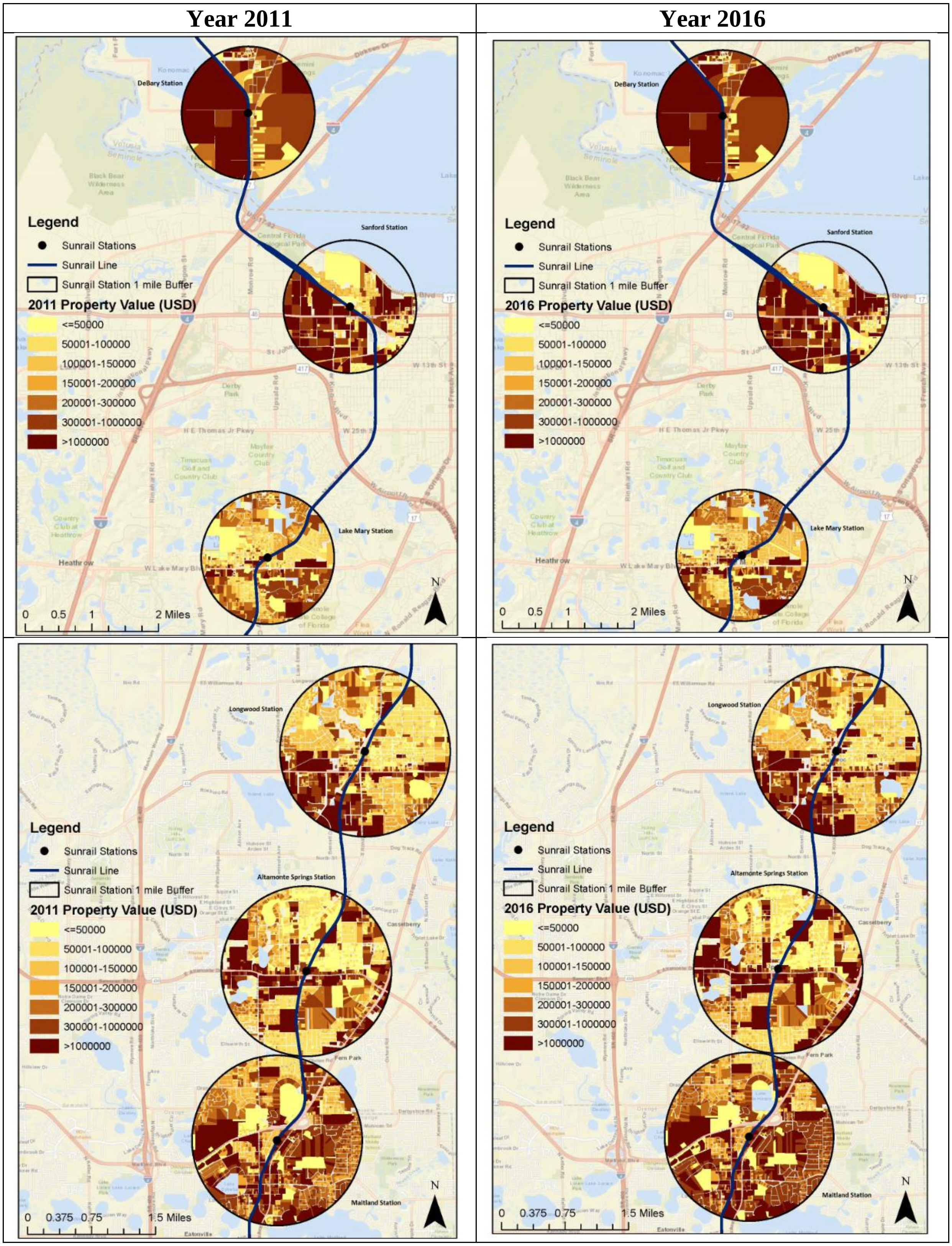


Figure 9-34: Property Values within SunRail Influence Area for 2011 and 2016

Year 2011	Year 2016

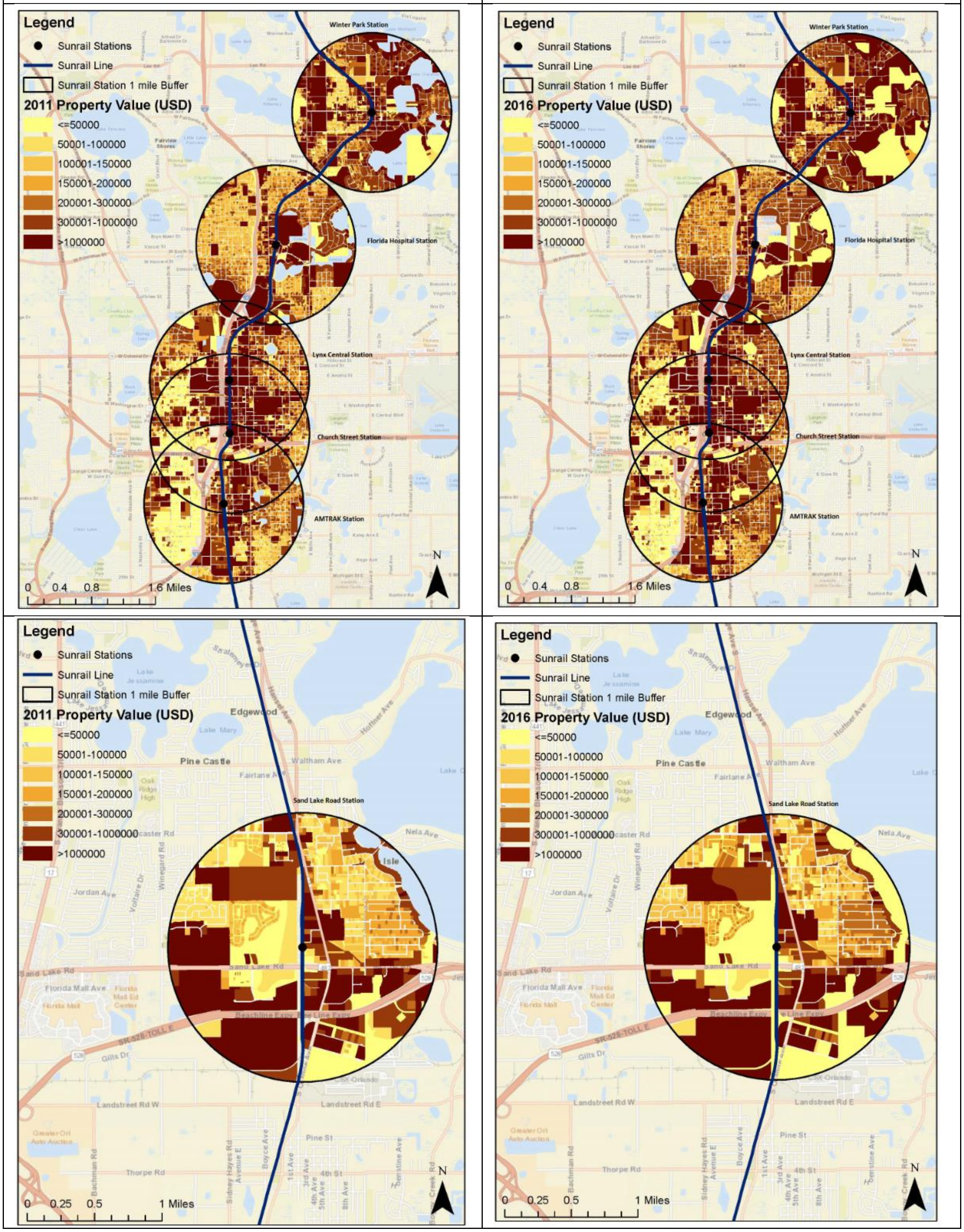
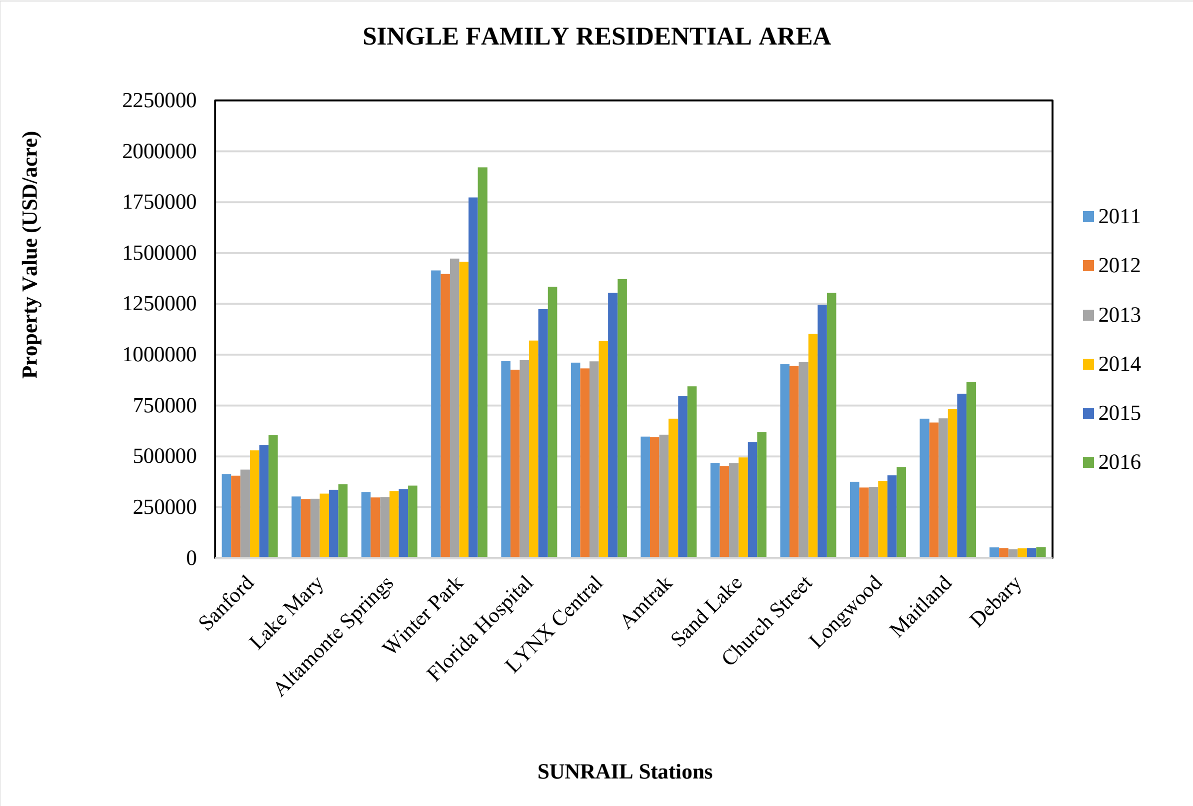


Figure 9-34 (Continued): Property Values within SunRail Influence Area for 2011 and 2016

For CBA, we are interested in the overall system-level impact of SunRail on property value. However, for future investment and improvement proposals, it is also important for us to understand the station-level impacts. Therefore, in this study effort, we also compute the property values of the influence area across different stations. However, as is evident from Figure 9-33 and 9-34, certain portion of the influence areas for some stations are not exclusive. For some stations, buffer areas within 1-mile radius overlap with each other. We allocate the parcels within the overlapping area to a particular station by using nearest distance or proximity to or from station (Hess and Almeida, 2007). For example, Lynx Central station and Church Street station are the closest stations in the downtown area. For taking care of the overlapping problem, we draw a straight line from the parcel to each station by using ArcGIS tool and then we assign the parcel to the nearest station in computing station-level property values. Figure 9-35 represents the property value per acre of different land use categories across twelve stations.

From Figure 9-35, we can observe that, compared to other stations, the property value is very high around Church Street station for multi-family residential, retail/office and institutional area categories while in case of single family residential and industrial area, Winter park station is found to be the expensive one. As expected, property value per unit area by land use category had increased over the years for almost every station. One interesting trend that can be observed from Figure 9-35 is that across all the land use categories, property price declined a little bit from 2011 to 2012 for all land use types except for multifamily residential. On the other hand, there is a huge increase in property price from 2014 to 2015 (after SunRail period) for industrial, single family residential, multi-family residential and office area around the Winter Park, Lynx Central, Florida Hospital and Church street station. On the other hand, for recreational areas, property price did not change much over the years for almost all stations except for Maitland station which shows a 25% increase in this category. For multifamily residential area, the property price has almost doubled from 2014 to 2016 for the Lynx Central, Florida Hospital and Winter Park stations.

In the current research effort, our main objective is to identify the effect of SunRail on property value. However, based on the property value change within the vicinity of station areas, it is not accurate to attribute all of these changes to the introduction of SunRail. It is possible that the Greater Orlando region experienced a boom in property price. To address this, we identify parcels outside the influence area to estimate changes in property values. In other words, we need to identify some controls in order to compute the SunRail specific effect of property value. In our study, we identify “Control Parcels” from the area which are outside 2-mile buffer boundary of SunRail stations but from within 8-mile buffer area. We randomly selected control parcels based on their land use category and the property value. If the parcel values of control parcels are within 25% range of case parcels, we selected those as control parcels and we repeated this procedure for all land use categories.



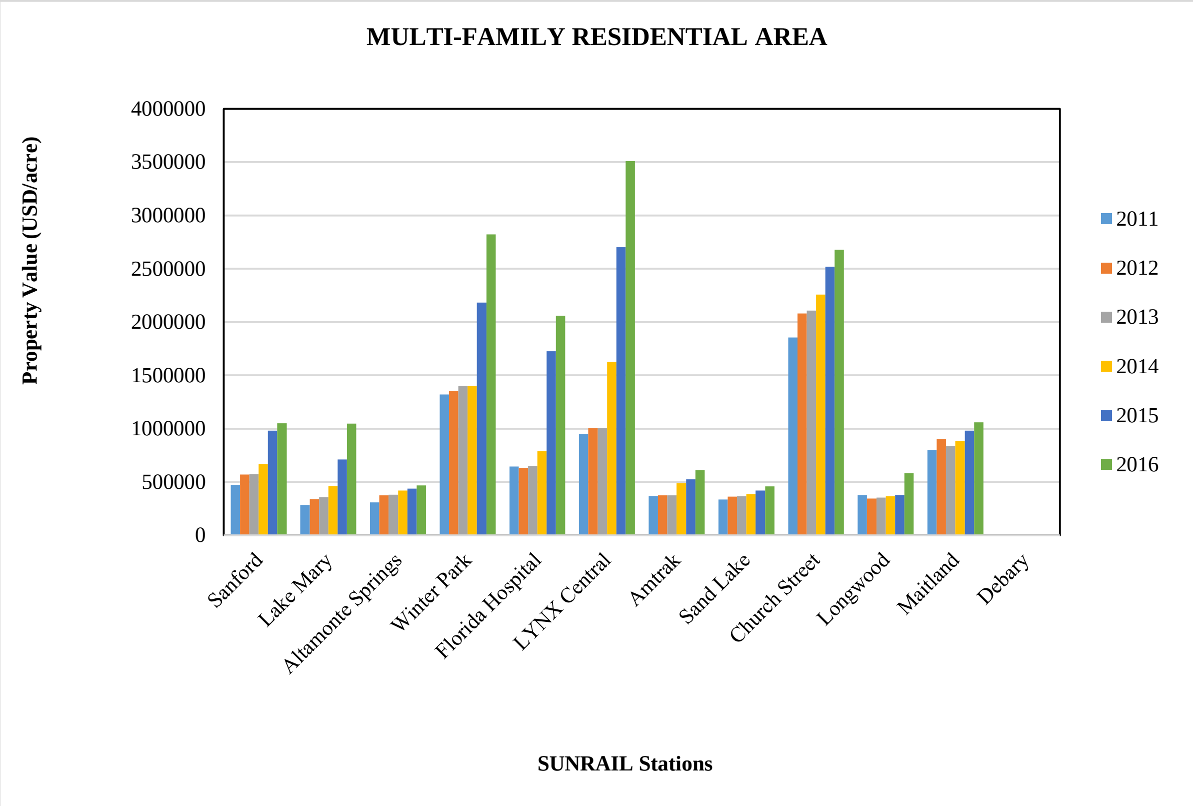
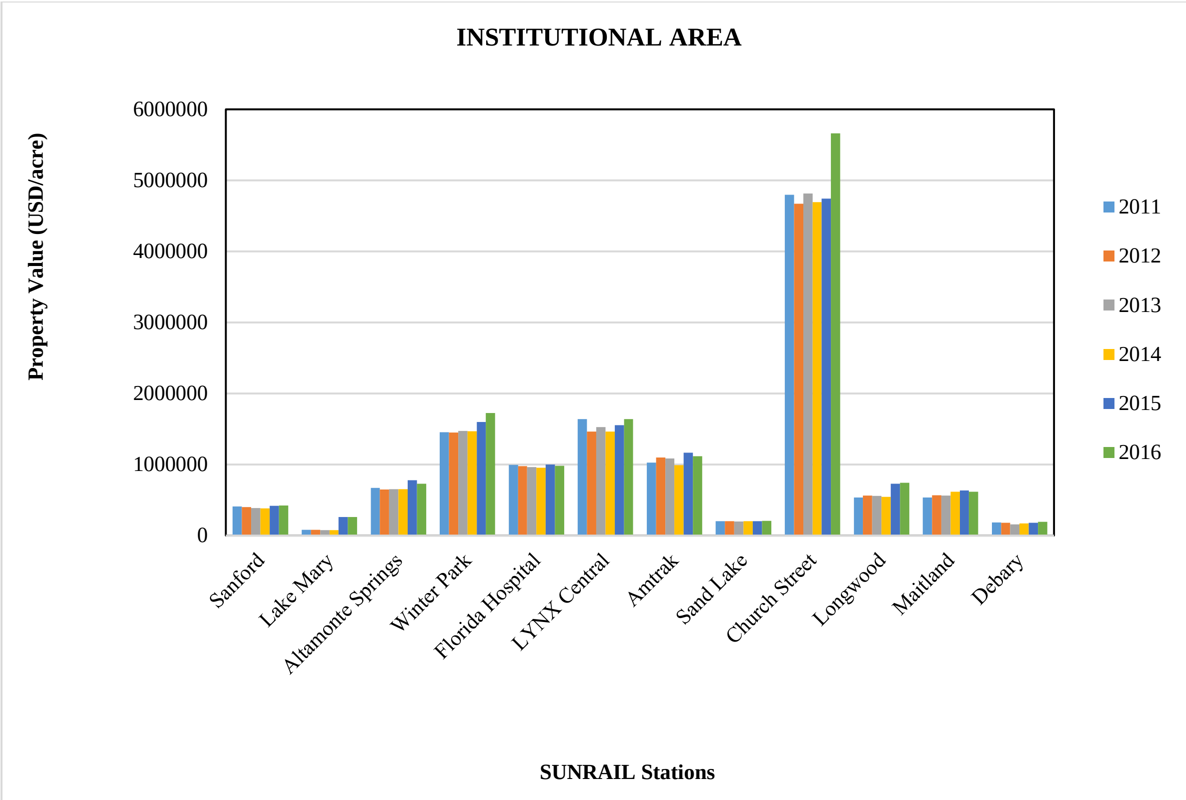


Figure 9-35: Station-level Property Value per Acre for Different Land Use Types



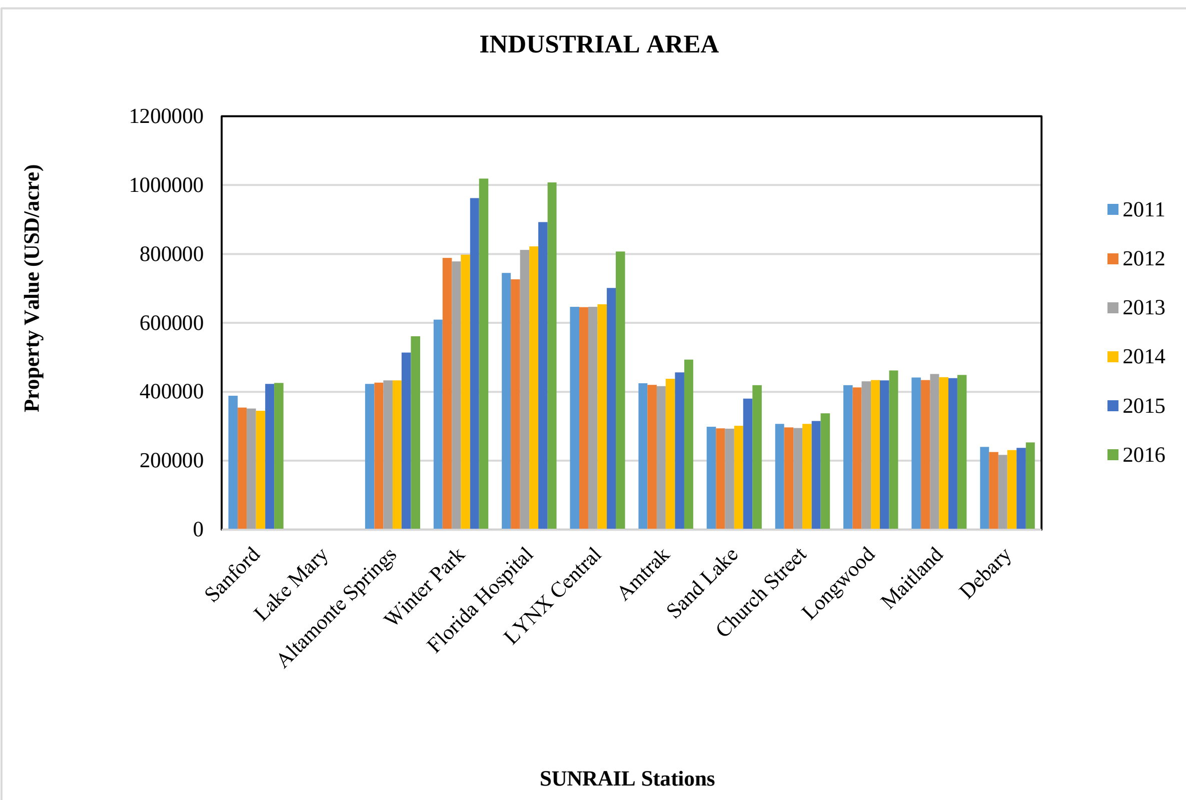
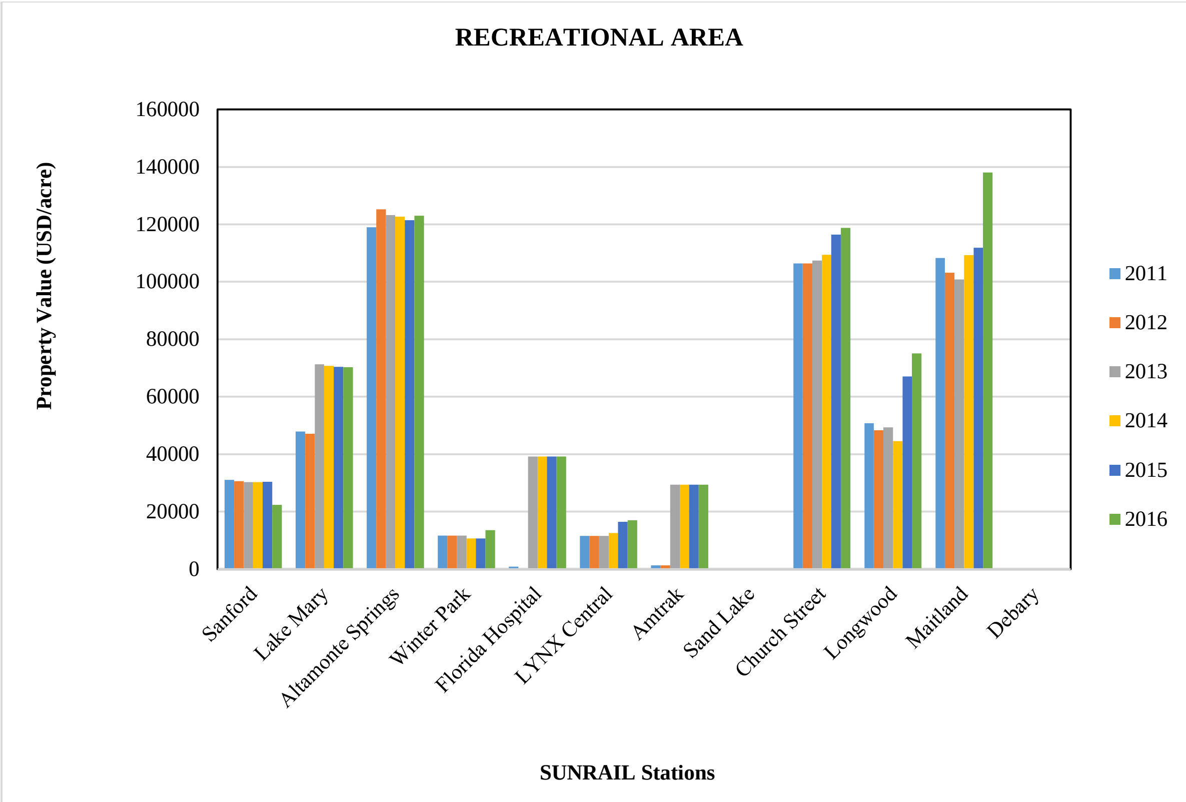


Figure 9-35 (Continued): Station-level Property Value per Acre for Different Land use Types



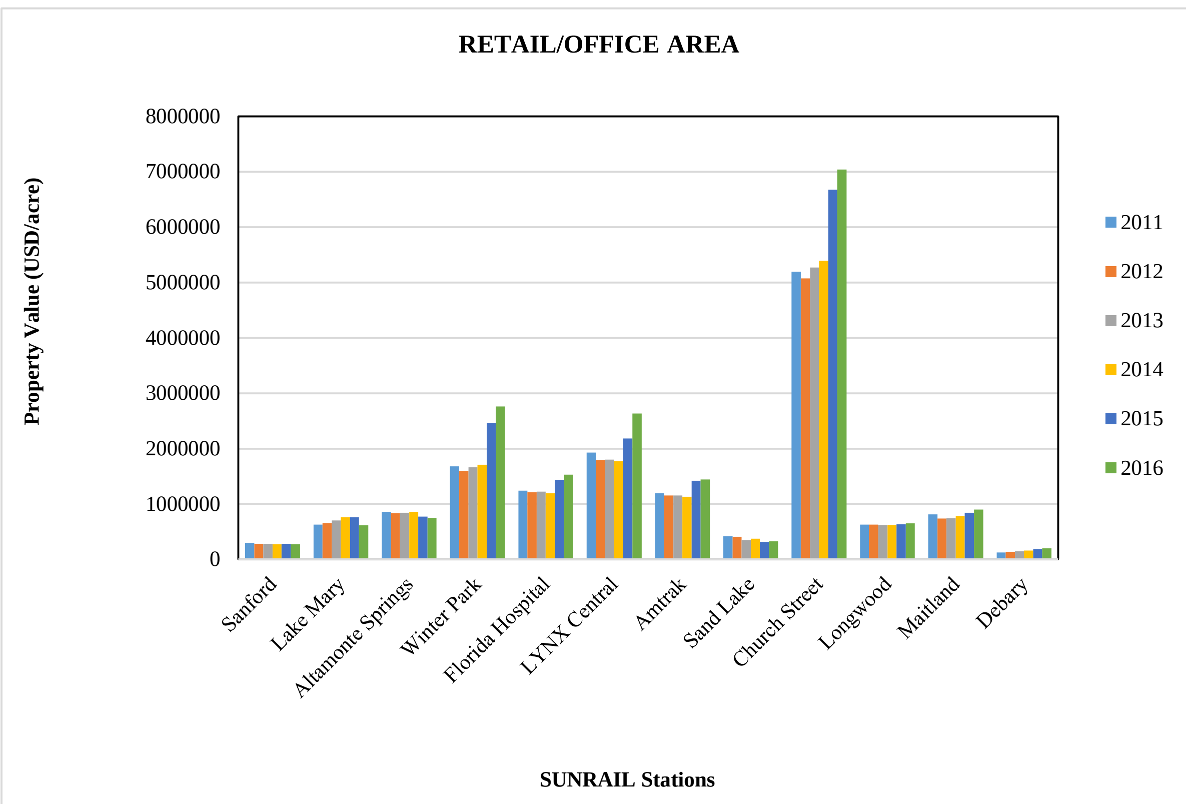


Figure 9-35 (Continued): Station-level Property Value per Acre for Different Land use Types

It is also important for us to recognize that the parcels within downtown area have different impact than those outside the downtown area since downtown area was already mostly developed before SunRail introduction. To reflect this, we have identified control parcels for downtown and outside downtown area separately. We have considered three stations as downtown stations (Lynx Central, Church Street, and AMTRAK station) and the rest 9 stations as outside downtown stations (DeBary station, Sanford Station, Lake Mary, Longwood Station, Altamonte Station, Maitland station, Winter Park station, Florida Hospital and Sand Lake road). By following this procedure, we finally consider as many control parcels as we have as case parcels. Finally, we compute the assessed base year property value increase of areas within the vicinity of SunRail stations as:

$$BYPVI = 0.85 * BP * [P_A^{cases} - P_B^{cases} - P^{control}] \quad (1)$$

Where,
$BYPVI =$ Base year Property value increase for SunRail influence area
$BP =$ Base year Property value for case parcels
P_A^{cases}= Annual percentage change in property value for case parcels from 2014-2016
P_B^{cases} = Annual percentage change in property value for case parcels from 2011-2013
$P^{control}$ = Annual percentage change in property value of control parcels

The factor 0.85 is employed to allow for a safety margin on the impact of SunRail. In addition to accounting for growth in the control parcels we attribute only 85% of the increase in property values to SunRail. This can be viewed as a conservative estimate of SunRail associated property increase. For the base year, the computed property value increase across different land use types are presented in Table 9-55.

Table 9-56: Computed Property Value Increase for Base Year

Land use types	Property value increase	
	Downtown	Outside downtown
Single family residential	$800,244,624.92	$4,250,778,859.61
Multiple family residential	$464,788,552.54	$424,960,294.01
Industrial	$136,904,784.32	$392,667,602.42
Institutional	$307,379,096.55	$441,908,986.35
Recreational	$29,485.69	$9,515,762.34
Retail/Office	$2,123,586,528.71	$1,686,474,314.84

9.5 RESULT OF COST-BENEFIT ANALYSIS

In performing the CBA, we assume that the useful life of the existing SunRail project will be 30 years with the beginning year as 2014. Therefore, we projected the costs and benefit values for 30 years, from 2014 to 2044, and computed the net benefit and benefit-cost ratio. In the current study context, we perform CBA for different scenarios as presented in Table 9-56. In evaluating net benefits of SunRail, we perform scenario analysis by assuming change in annual ridership and change in annual property value increase. Specifically, with respect to ridership change, we consider three scenarios:

> *Scenario 1:* No change in SunRail ridership over 30 years (Monthly ridership is 3800).
> *Scenario 2:* SunRail ridership increases by 2% each year over 30 years (Monthly ridership is 3800 for the base year 2014).
> *Scenario 3:* SunRail ridership increases by 10% each year over 30 years (Monthly ridership is 3800 for the base year 2014).

In terms of property value, we have considered seven different property value increase conditions for each ridership scenario. The scenarios consider projected growth rate as a function of previous year growth rate. We evaluate the impact of property price increase under various reducing growth rate scenarios with and without a threshold level. The rationale for these scenarios is to evaluate how the property value impacts change under various growth rate scenarios.

Overall, the total numbers of scenarios considered are twenty one (3*7). We consider change in ridership to reflect the possible ridership addition from Phase II and Phase III operations of SunRail in the future. To be sure, in computing the benefit components for scenario 2 and 3, we have updated the values of all the benefit components considered for cost-benefit analysis, since those factors are assumed to be a function of ridership. The computed net benefits and benefit-cost ratio for all the considered scenarios described are presented in Table 9-57. Positive net benefit and benefit-cost ration greater than 1 reflect the overall surplus over investment and operation costs of SunRail operation.

Table 9-57: Scenarios of Cost-Benefit Analysis

Scenarios	Description
Scenario 1: No change in SunRail ridership over 30 years (Monthly ridership is 3800)	
Scenario 1.1	➢ $Property\ value\ growth\ rate\ (PVGR) = \left(\frac{PVGR computed\ in\ Section\ 4.3}{3}\right)^{for\ first\ 15\ years} \sim \left(\frac{PVGR computed\ in\ Section\ 4.3}{6}\right)^{for\ last\ 15\ years}$ ➢ Everything else remain same
Scenario 1.2	➢ $Property\ value\ growth\ rate\ (PVGR)\ for\ year\ \tau = \left(\frac{PVGR\ for\ the\ year\ \tau-1}{2}\right)$ ➢ Everything else remain same
Scenario 1.3	➢ $Property\ value\ growth\ rate\ (PVGR)\ for\ year\ \tau = Maximum\left(\frac{PVGR\ for\ the\ year\ \tau-1}{2},\ 3.00\%\right)$ ➢ Everything else remain same
Scenario 1.4	➢ $Property\ value\ growth\ rate\ (PVGR)\ for\ year\ \tau = Maximum\left(\frac{PVGR\ for\ the\ year\ \tau-1}{2},\ 2.00\%\right)$ ➢ Everything else remain same
Scenario 1.5	➢ $Property\ value\ growth\ rate\ (PVGR)\ for\ year\ \tau = \left(\frac{PVGR\ for\ the\ year\ \tau-1}{5}\right)$ ➢ Everything else remain same
Scenario 1.6	➢ $Property\ value\ growth\ rate\ (PVGR)\ for\ year\ \tau = Maximum\left(\frac{PVGR\ for\ the\ year\ \tau-1}{5},\ 3.00\%\right)$ ➢ Everything else remain same
Scenario 1.7	➢ $Property\ value\ growth\ rate\ (PVGR)\ for\ year\ \tau = Maximum\left(\frac{PVGR\ for\ the\ year\ \tau-1}{5},\ 2.00\%\right)$ ➢ Everything else remain same
Scenario 2: SunRail ridership increases by 2% each year over 30 years (Monthly ridership is 3800 for the base year 2014)	
Scenario 2.1	➢ $Property\ value\ growth\ rate\ (PVGR) = \left(\frac{PVGR computed\ in\ Section\ 4.3}{3}\right)^{for\ first\ 15\ years} \sim \left(\frac{PVGR computed\ in\ Section\ 4.3}{6}\right)^{for\ last\ 15\ years}$ ➢ Adjusted benefit components due to the change in ridership
Scenario 2.2	➢ $Property\ value\ growth\ rate\ (PVGR)\ for\ year\ \tau = \left(\frac{PVGR\ for\ the\ year\ \tau-1}{2}\right)$ ➢ Adjusted benefit components due to the change in ridership
Scenario 2.3	➢ $Property\ value\ growth\ rate\ (PVGR)\ for\ year\ \tau = Maximum\left(\frac{PVGR\ for\ the\ year\ \tau-1}{2},\ 3.00\%\right)$ ➢ Adjusted benefit components due to the change in ridership
Scenario 2.4	➢ $Property\ value\ growth\ rate\ (PVGR)\ for\ year\ \tau = Maximum\left(\frac{PVGR\ for\ the\ year\ \tau-1}{2},\ 2.00\%\right)$ ➢ Adjusted benefit components due to the change in ridership
Scenario 2.5	➢ $Property\ value\ growth\ rate\ (PVGR)\ for\ year\ \tau = \left(\frac{PVGR\ for\ the\ year\ \tau-1}{5}\right)$ ➢ Adjusted benefit components due to the change in ridership

Table 9-56 (Continued): Scenarios of Cost-Benefit Analysis

Scenarios	Description
Scenario 2.6	➢ $Property\ value\ growth\ rate\ (PVGR)\ for\ year\ \tau = Maximum\left(\frac{PVGR\ for\ the\ year\ \tau-1}{5},\ 3.00\%\right)$ ➢ Adjusted benefit components due to the change in ridership
Scenario 2.7	➢ $Property\ value\ growth\ rate\ (PVGR)\ for\ year\ \tau = Maximum\left(\frac{PVGR\ for\ the\ year\ \tau-1}{5},\ 2.00\%\right)$ ➢ Adjusted benefit components due to the change in ridership
Scenario 3: SunRail ridership increases by 10% each year over 30 years (Monthly ridership is 3800 for the base year 2014)	
Scenario 3.1	➢ $Property\ value\ growth\ rate\ (PVGR) = \left(\frac{PVGRcomputed\ in\ Section\ 4.3}{3}\right)^{for\ first\ 15\ years} \sim \left(\frac{PVGRcomputed\ in\ Section\ 4.3}{6}\right)^{for\ last\ 15\ years}$ ➢ Adjusted benefit components due to the change in ridership
Scenario 3.2	➢ $Property\ value\ growth\ rate\ (PVGR)\ for\ year\ \tau = \left(\frac{PVGR\ for\ the\ year\ \tau-1}{2}\right)$ ➢ Adjusted benefit components due to the change in ridership
Scenario 3.3	➢ $Property\ value\ growth\ rate\ (PVGR)\ for\ year\ \tau = Maximum\left(\frac{PVGR\ for\ the\ year\ \tau-1}{2},\ 3.00\%\right)$ ➢ Adjusted benefit components due to the change in ridership
Scenario 3.4	➢ $Property\ value\ growth\ rate\ (PVGR)\ for\ year\ \tau = Maximum\left(\frac{PVGR\ for\ the\ year\ \tau-1}{2},\ 2.00\%\right)$ ➢ Adjusted benefit components due to the change in ridership
Scenario 3.5	➢ $Property\ value\ growth\ rate\ (PVGR)\ for\ year\ \tau = \left(\frac{PVGR\ for\ the\ year\ \tau-1}{5}\right)$ ➢ Adjusted benefit components due to the change in ridership
Scenario 3.6	➢ $Property\ value\ growth\ rate\ (PVGR)\ for\ year\ \tau = Maximum\left(\frac{PVGR\ for\ the\ year\ \tau-1}{5},\ 3.00\%\right)$ ➢ Adjusted benefit components due to the change in ridership
Scenario 3.7	➢ $Property\ value\ growth\ rate\ (PVGR)\ for\ year\ \tau = Maximum\left(\frac{PVGR\ for\ the\ year\ \tau-1}{5},\ 2.00\%\right)$ ➢ Adjusted benefit components due to the change in ridership

Table 9-58: Cost-Benefits Analysis of SunRail over 30 Years

Scenarios	Property Value increase	Other benefits	Total benefits (Property value increase + Other benefits)	Total Costs	Net benefit (Total benefits - Total costs)	Benefit-Cost ratio (Total benefits/Total Costs)
Scenario 1: No change in SunRail ridership over 30 years (Monthly ridership is 3800)						
Scenario 1.1	$4,851,851,234.56	$323,503,544.15	$5,175,354,778.71	$1,674,985,000.00	$3,500,369,778.71	3.09
Scenario 1.2	$566,800,853.30	$323,503,544.15	$890,304,397.44	$1,674,985,000.00	$(784,680,602.56)	0.53
Scenario 1.3	$9,791,139,652.85	$323,503,544.15	$10,114,643,197.00	$1,674,985,000.00	$8,439,658,197.00	6.04
Scenario 1.4	$5,802,933,688.77	$323,503,544.15	$6,126,437,232.92	$1,674,985,000.00	$4,451,452,232.92	3.66
Scenario 1.5	$238,176,844.62	$323,503,544.15	$561,680,388.77	$1,674,985,000.00	$(1,113,304,611.23)	0.34
Scenario 1.6	$9,733,889,988.41	$323,503,544.15	$10,057,393,532.56	$1,674,985,000.00	$8,382,408,532.56	6.00
Scenario 1.7	$5,656,322,022.42	$323,503,544.15	$5,979,825,566.57	$1,674,985,000.00	$4,304,840,566.57	3.57
Scenario 2: SunRail ridership increases by 2% each year over 30 years (Monthly ridership is 3700 for the base year 2015)						
Scenario 2.1	$4,851,851,234.56	$438,194,196.42	$5,290,045,430.98	$1,674,985,000.00	$3,615,060,430.98	3.16
Scenario 2.2	$566,800,853.30	$438,194,196.42	$1,004,995,049.72	$1,674,985,000.00	$(669,989,950.28)	0.60
Scenario 2.3	$9,791,139,652.85	$438,194,196.42	$10,229,333,849.27	$1,674,985,000.00	$8,554,348,849.27	6.11
Scenario 2.4	$5,802,933,688.77	$438,194,196.42	$6,241,127,885.20	$1,674,985,000.00	$4,566,142,885.20	3.73
Scenario 2.5	$238,176,844.62	$438,194,196.42	$676,371,041.05	$1,674,985,000.00	$(998,613,958.95)	0.40
Scenario 2.6	$9,733,889,988.41	$438,194,196.42	$10,172,084,184.83	$1,674,985,000.00	$8,497,099,184.83	6.07
Scenario 2.7	$5,656,322,022.42	$438,194,196.42	$6,094,516,218.84	$1,674,985,000.00	$4,419,531,218.84	3.64
Scenario 3: SunRail ridership increases by 10% each year over 30 years (Monthly ridership is 3700 for the base year 2015)						
Scenario 3.1	$4,851,851,234.56	$1,783,400,526.10	$6,635,251,760.66	$1,674,985,000.00	$4,960,266,760.66	3.96
Scenario 3.2	$566,800,853.30	$1,783,400,526.10	$2,350,201,379.40	$1,674,985,000.00	$675,216,379.40	1.40
Scenario 3.3	$9,791,139,652.85	$1,783,400,526.10	$11,574,540,178.95	$1,674,985,000.00	$9,899,555,178.95	6.91
Scenario 3.4	$5,802,933,688.77	$1,783,400,526.10	$7,586,334,214.88	$1,674,985,000.00	$5,911,349,214.88	4.53
Scenario 3.5	$238,176,844.62	$1,783,400,526.10	$2,021,577,370.73	$1,674,985,000.00	$346,592,370.73	1.21
Scenario 3.6	$9,733,889,988.41	$1,783,400,526.10	$11,517,290,514.51	$1,674,985,000.00	$9,842,305,514.51	6.88
Scenario 3.7	$5,656,322,022.42	$1,783,400,526.10	$7,439,722,548.52	$1,674,985,000.00	$5,764,737,548.52	4.44

From Table 9-57, we can observe that increased ridership is the most important factor in achieving an overall net benefit over long term for SunRail. The result has significant implication in terms of SunRail extension. With Phase II addition, it has the potential to increase ridership. It is also interesting to observe that property value increase plays an important role in accruing overall positive net benefit with a benefit-cost ratio over 1. The result is perhaps indicating benefits of transit oriented development for a personal automobile governed areas like Central Florida. Based on this result, we can argue that the SunRail commuter system has potential in promoting overall transit oriented development community concept in encouraging sustainable transportation alternatives.

9.6 SUMMARY

The chapter summarized cost-benefit analysis for the existing operation SunRail system (Phase I). With regards to cost component, the factors we considered included: (1) capital costs and (2) operation and maintenance costs. In terms of the benefit component, the factors we considered included: (1) personal automobile cost savings, (2) crash cost savings, (3) parking cost savings, (4) energy conservation savings, and (5) assessed property value increase. For cost-benefit analysis, we considered total 21 hypothetical scenarios reflecting the change in ridership and property value increase rate over thirty years. Based on this result, we can conclude that the SunRail commuter system has potential in promoting overall transit oriented development community concept in encouraging sustainable transportation alternatives.

In promoting sustainable urban transportation, policy makers are more focused on encouraging travellers to walk, bike or take transit among Floridians like many other auto oriented states and cities in the US. In Orlando, other than SunRail, another such initiative is Juice Bike share system of Downtown Orlando. It might also be interesting and worth investigating the cost-benefit analysis for Juice bike share system. The cost-benefit analysis for Juice bike share system would allow the policy makers to take such other initiative in consideration. The research team did not have any detailed data and information available on the bike share investment project and hence the cost-benefit analysis was not evaluated. However, the same framework, as presented in this technical report for SunRail, is applicable for performing cost-benefit analysis of Juice bike share system, which might be considered as a future research avenue.

CHAPTER X: CONCLUSION

This research effort was focused on employing the existing regional model framework of Central Florida to study multi-modal mobility for the Central Florida region (District 5). The analysis was conducted for the area defined for Central Florida Regional Planning Model Version 6.0. The overall research was geared towards enhancing the urban transportation infrastructure to increase non-auto mobility. This report developed and demonstrated frameworks for understanding transit and non-motorized demand and evaluating policies to alleviate auto related travel burden while enhancing non-auto mobility. The analysis provided findings from four major components, including (1) mobility component – demand analysis for non-motorists road user groups, (2) safety component – zonal level crash frequency and severity analysis for non-motorists road user groups, (3) ridership analysis – transit demand analysis for Lynx and SunRail systems and (4) cost-benefit analysis – cost-benefit analysis for SunRail commuter rail system. For all of these components, the estimated models were validated to ensure model prediction performance accuracy prior to deploying them for forecasting.

10.1 MOBILITY COMPONENT

In order to assess the benefit of investments in non-motorized infrastructures, it is important to evaluate and document demand of non-motorized road users. The aggregate level demand models examine critical factors contributing to non-motorists' generators and attractors at a zonal level. Outcome of these studies can be used to devise medium or long-term area-wide planning and investment policies in order to encourage and promote non-motorized activities. To that extent, in our current study, we investigated non-motorists' demand at a zonal level by using aggregate trip information based on origin and destination locations of trips. Specifically, we developed four non-motorists demand models: (1) Pedestrian generator model – based on zonal level pedestrian origin demand, (2) Pedestrian attractor model – based on zonal level pedestrian destination demand, (3) Bicycle generator model – based on zonal level bicycle origin demand, (4) Bicycle attractor model – based on zonal level bicycle destination demand. These models were estimated for the study area defined by CFRPM 6.0 area by using trip records from 2009 National Household Travel Survey (NHTS) database. The models were estimated by using Hurdle Negative-Binomial framework. Outcome of these models were used to generate zonal-level trip exposure matrices (zonal-level origin-destination and total trip tables) with the number of daily trip origins and daily trip destinations at the zonal level for both the pedestrian and bicycle modes.

For policy scenario analysis, we computed aggregate-level "elasticity effects" of exogenous variables. Specifically, we investigated the percentage change in the expected total zonal demand in response to change in exogenous variables for the study region. We performed policy analysis for twelve scenarios by considering change in drive demand, sidewalk length, speed limit and roadway geometry. From the policy analysis, it is evident that providing more walking- and bicycle-friendly facilities is likely to encourage more people to use non-motorized modes. Thus, we argued that restricting lanes, reducing speed and reducing/restricting vehicular volume in certain areas would increase non-motorist volume demand.

10.2 SAFETY COMPONENT

The safety risk posed to active transportation in terms of road traffic crashes is a global health concern. Any effort to reduce the social burden of these crashes and enhance non-motorists safety would necessitate the examination of factors that contribute significantly to crash likelihood and/or injury severity in the event of a crash and the implementation of policies that enhance safety for pedestrians and bicyclists. An important tool for identifying and evaluating road safety policies is forecasting and policy evaluation which are predominantly devised through evidence-based and data-driven safety analysis. To that extent, in this research effort, we estimated both crash frequency and crash severity models in understanding non-motorists safety factors. In terms of crash frequency, we estimated two models: (1) zonal-level crash count model for examining pedestrian–motor vehicle crash occurrences, and (2) zonal-level crash count model for examining bicycle–motor vehicle crash occurrences. With regards to crash severity, we estimated four different sets of models: (1) disaggregate-level crash severity model for examining pedestrian crash injury severity outcomes, (2) disaggregate-level crash severity model for examining bicycle crash injury severity outcomes, (3) zonal-level crash severity model for examining pedestrian crash injury severity by proportions and (4) zonal-level crash severity model for examining bicycle crash injury severity by proportions. These models were estimated for the study area defined by CFRPM by using crash records of the base year 2010. Crash frequency, crash severity and crash proportion models were estimated by using negative binomial, ordered logit and ordered probit fractional split frameworks, respectively. While the disaggregate-level crash severity models provide us important insights on crash mechanism and severity factors, these models cannot be directly employed to incorporate safety considerations in the transportation planning process. Therefore, for policy analysis of the safety component, we focused on aggregate-level crash count models and aggregate level crash count by severity models as these are more feasible for planning-level policy analysis and identifying planning-level policy measures.

For policy scenario analysis, we computed aggregate-level “elasticity effects” of exogenous variables for both crash frequency and crash proportion models. Specifically, we investigated the effect as a percentage change in the expected total zonal crash counts and total proportions by severity levels to the change in exogenous variables for the study region. We performed policy analysis for twelve scenarios by considering change in drive demand, sidewalk length, speed limit and roadway geometry. From our policy analysis, we found that non-motorist-friendly infrastructure has a mixed effect on non-motorist safety. Therefore, it is imperative that policy implications for improving non-motorist safety be identified by considering all known exogenous elements in identifying the appropriate tools. In general, restricting vehicular volume in a targeted zone would improve overall non-motorist safety.

10.3 RIDERSHIP COMPONENT

The over-reliance on private automobile in the US over the last few decades has resulted in various negative externalities including traffic congestion and crashes, and air pollution associated environmental and health concerns. There is renewed enthusiasm among policy makers and transportation professionals to invest in transit alternatives. In our research effort, we investigated transit demand for the coverage area of Lynx and SunRail network systems of

Greater Orlando Region. With respect to transit ridership analysis, we estimated and presented four different sets of ridership models: for Lynx network system – (1) stop level average weekday boarding bus ridership analysis, and (2) stop level average weekday alighting bus ridership analysis; for SunRail network system – (3) daily boarding rail ridership analysis, and (4) daily alighting rail ridership analysis. It is worthwhile to mention here that one of the major focus of the proposed bus ridership research effort was to evaluate the influence of recently inaugurated commuter rail system "SunRail" in Orlando on bus ridership while controlling for host of other exogenous variables. Lynx bus ridership models were estimated by using Grouped Ordered Logit model framework, while SunRail ridership models were estimated by using linear regression based approach.

For policy scenario analysis of Lynx system, we computed aggregate-level "elasticity effects" of exogenous variables for both boarding and alighting models. In our policy analysis, we computed the change in ridership (boarding and alighting) for changes in headway, sidewalk length, bus route length, number of bus stops, land use mix, percentage of zero vehicle household (HH) and stops with shelter for the thirteen ridership categories. Based on our findings, to increase the ridership, services related to public transit (improvement of headway and addition of shelters) should be considered.

For policy scenario analysis of SunRail system, we computed aggregate level elasticity effects of exogenous variables. Specifically, we identified the average daily boarding and alighting ridership for changes in some selected exogenous variables. We considered the number of bus stops, land use mix and the number of commercial centers in 1500 m buffer around the SunRail stations for this purpose. In calculating the expected average predicted daily ridership, we increased the value of these variable by 10% and 25%. These policy analysis indicated that in the downtown area, the ridership is sensitive to bus stops around SunRail station; thus supporting investments on transit infrastructure for encouraging an integrated transit system. The elasticity analysis conducted provided an illustration on how the proposed model can be applied for policy evaluation for SunRail ridership.

10.4 COST-BENEFIT ANALYSIS COMPONENT

Cost-benefit analysis is considered to be an effective tool in evaluating net benefits of a transportation system. A comprehensive cost-benefit analysis of the existing operational SunRail system would assist planners and policy makers to evaluate the "real" benefit of these investments and provide evidence to justify allocation of more funding for improving/building transit infrastructure. To that extent, in this research effort, we presented and discussed cost-benefit analysis result for the existing 31-mile SunRail system. We projected cost and benefit for 30 years (from 2014 to 2044) considering 2014 as base year. With regards to cost component, the factors we considered included: (1) capital costs and (2) operation and maintenance costs. In terms of the benefit component, the factors we considered included: (1) personal automobile cost savings, (2) crash cost savings, (3) parking cost savings, (4) energy conservation savings, and (5) assessed property value increase. In evaluating net benefits of SunRail, we performed scenario analysis by assuming change in annual ridership and change in annual property value increase. A total of twenty one scenarios were considered. Based on the cost-benefit analysis results, we argued that the SunRail commuter system has the potential for promoting transit oriented development communities and for encouraging sustainable transportation alternatives.

10.5 SUMMARY

The current research proposed and developed a practical approach to incorporate non-auto travel within the existing statewide travel demand modeling framework. The approach proposed and demonstrated policy makers a blueprint to begin incorporating non-auto mode choice alternatives within the traditional travel demand framework across various urban regions in Florida. While several data resources were compiled and employed in the various models developed, the availability of additional data sources such as non-motorized demand at a finer spatial resolution (if available) can be employed to further enhance the proposed framework. Future research efforts should explore the burgeoning availability of data in facilitating the incorporation of non-auto travel within the travel demand modeling approach.

REFERENCES

AAA (2013). *Your Driving Costs: How Much Are You Really Paying to Drive?* American Automobile Association. Retrieved from http://www.rideshareonline.com/Image/Your-Driving-Costs-2013.pdf.

Adjei, E. (2010). *Multi-modal urban transport: integrating non-motorized and bus transport*. Master's Thesis, International Institute for Geo-Information Science and Earth Observation Enschede, the Netherlands.

Ang-Olson, J., & Mahendra, A. (2011). Cost/benefit Analysis of Converting a Lane for Bus Rapid Transit: Phase II Evaluation and Methodology (Vol. 352). *Transportation Research Board*.

ARC, (2011), The Travel Forecasting Model Set For the Atlanta Region 2010 Documentation, ARC Model Documentation, Atlanta Regional Commission (ARC).

Bergman, Å., Gliebe, J., & Strathman, J. (2011). Modeling access mode choice for inter-suburban commuter rail. *Journal of Public Transportation*, *14*(4), 2.

Blonn, J., Carlson, D., Mueller, P., & Scott, I. (2006). Transport 2020 Bus Rapid Transit: A Cost Benefit Analysis. *Prepared for Susan Devos, Chai, Madison Area Bus Advocates, Madison, Wisconsin*.

Cameron, A. C., & Trivedi, P. K. (1998). *Regression Analysis of Count Data*. New York: Cambridge University Press.

CFRPM v5.6, (2012), *CFRPM v5.6: Transit Model Updates*, AECOM.

Chakour, V., & Eluru, N. (2016). Examining the influence of stop level infrastructure and built environment on bus ridership in Montreal. *Journal of Transport Geography*, *51*, 205-217.

Eluru, N., & Bhat, C. R. (2007). A joint econometric analysis of seat belt use and crash-related injury severity. *Accident Analysis & Prevention*, *39*(5), 1037-1049.

FDOT. (2017). Assessing the Property Impacts of SunRail Stations. BDV30 TWO 943-20, December 2013, final report. Retrieved From http://www.fdot.gov/transit/Pages/BDV30-943-20FinalReport.pdf.

Flamm, B., & Rivasplata, C. (2014). Public transit catchment areas: The curious case of cycle-transit users. *Transportation Research Record: Journal of the Transportation Research Board*, (2419), 101-108.

Fleming,G. (2010). *CFRPM v5.0: Model Calibration and Validation Results (*Florida Department of Transportation District V). Retrieved From http://www.lakesumtermpo.com/pdfs/2035/documentation/CFRPM_5_Model_Calibration_and_Validation_Results.pdf.

Gallivan, F., Rose, E., Ewing, R., Hamidi, S., & Brown, T. (2015). *Quantifying Transit's Impact on GHG Emissions and Energy Use—The Land Use Component* (No. Project H-46).

Garrett, T. A. (2004). Light rail transit in America: policy issues and prospects for economic development. *Unpublished Manuscript, Federal Reserve Bank of St. Louis, Research Department*.

Godavarthy, R., Mattson, J., & Ndembe, E. (2014). Cost-Benefit Analysis of Rural and Small Urban Transit. *University of South Florida, Tampa: National Center for Transit Research*.

Gordon, P., & Kolesar, P. E. (2011). A Note on Rail Transit Cost-Benefit Analysis: Do Nonuser Benefits Make A Difference?. *Public Works Management & Policy*, *16*(2), 100-110.

Gotschi, T. (2011). Costs and benefits of bicycling investments in Portland, Oregon. *Journal of Physical Activity and Health*, *8*(s1), S49-S58.

Greene, D., & Schafer, A. (2003). Reducing Greenhouse Gas Emissions From US Transportation, report prepared for the Pew Center on Global Climate Change. *Arlington, Virginia*.

Guerra, E., Cervero, R., & Tischler, D. (2012). Half-mile circle: does it best represent transit station catchments?. *Transportation Research Record: Journal of the Transportation Research Board*, (2276), 101-109.

Heilbron, D. C. (1994). Zero- altered and other regression models for count data with added zeros. *Biometrical Journal*, *36*(5), 531-547.

Hess, D. B., & Almeida, T. M. (2007). Impact of proximity to light rail rapid transit on station-area property values in Buffalo, New York. *Urban studies*, *44*(5-6), 1041-1068.

Jang, T. Y. (2005). Count data models for trip generation. *Journal of Transportation Engineering*, *131*(6), 444-450.

Korve, M. J., & Niemeier, D. A. (2002). Benefit-cost analysis of added bicycle phase at existing signalized intersection. *Journal of transportation engineering*, *128*(1), 40-48.

Krizec, K. J. (2007). Estimating the economic benefits of bicycling and bicycle facilities: An interpretive review and proposed methods. In *Essays on transport economics* (pp. 219-248). Physica-Verlag HD.

Litman, T. A. (2001). *What's it Worth?: Life Cycle and Benefit-cost Analysis for Evaluating Economic Value*. Victoria Transport Policy Institute.

Litman, T. (2004), *Evaluating active transport benefits and costs: Best Practices Guidebook*., Victoria Transport Policy Institute.

Litman, T. (2011). Evaluating Public Transit Benefits and Costs: Best Practices Guidebook. *Victoria Transport Policy Institute*. Retrieved from http://www.ee.ic.ac.uk/timothy.barr10/yr2proj/wordpress/wp-content/uploads/2012/02/evaluating-public-transport-system1.pdf.

Litman T. (2013). *Evaluating active transport benefits and costs: Best Practices Guidebook.* Victoria Transport Policy Institute. Retrieved from https://www.researchgate.net/profile/Todd_Litman/publication/254609012_Evaluating_public_transit_benefits_and_costs_Best_Practices_Guidebook/links/55477fcb0cf26a7bf4d90a72/Evaluating-public-transit-benefits-and-costs-Best-Practices-Guidebook.pdf.

Litman, T. (2014). A new transit safety narrative. *Journal of Public Transportation*, *17*(4),

Litman, T. (2018). *Evaluating Public Transit Benefits and Costs: Guide to Valuing Walking and Cycling Improvements and Encouragement Programs.* Victoria Transport Policy Institute. Retrieved From http://www.vtpi.org/tranben.pdf.

Lord, D., & Mannering, F. (2010). The statistical analysis of crash-frequency data: a review and assessment of methodological alternatives. *Transportation Research Part A: Policy and Practice*, *44*(5), 291-305.

Metroplan Orlando. (2016). *Tracking the Trends: A Report on Transportation System Indicators for the Orlando Metropolitan Area*. Retrieved From https://metroplanorlando.org/wp-content/uploads/TrackingTheTrends_June2016.pdf.

NERPM-AB v.1.0, (2015), *Technical report #4: Calibration and Validation report*, *Northeast regional Planning model: activity Based* (North Florida Transportation Planning Organization). Retrieved From http://northfloridatpo.com/images/uploads/docs/Tech_Memo_4_-_Validation_Report.pdf.

NHTS (2017). National Household Travel Survey. Retrieved from https://nhts.ornl.gov/.

NJRTME, (2008). *North Jersey Regional Transportation Model-Enhanced*. North Jersey Transportation Planning Authority (NJTPA). Retrieved From https://www.njtpa.org/data-maps/modeling/travel-demand-modeling/njtpa_session_3.aspx.

Pucher, J., & Renne, J. L. (2003). Socioeconomics of urban travel: evidence from the 2001 NHTS. *Transportation Quarterly*, *57*(3), 49-77.

Sælensminde, K. (2004). Cost–benefit analyses of walking and cycling track networks taking into account insecurity, health effects and external costs of motorized traffic. *Transportation Research Part A: Policy and Practice*, *38*(8), 593-606.

SANDAG, (2011), *2050 Regional Travel Demand Model Documentation*. San Diego Association of Government (SANDAG).

Santos, A., McGuckin, N., Nakamoto, H. Y., Gray, D., & Liss, S. (2011). *Summary of travel trends: 2009 national household travel survey* (No. FHWA-PL-ll-022).

Savolainen, P. T., Mannering, F. L., Lord, D., & Quddus, M. A. (2011). The statistical analysis of highway crash-injury severities: a review and assessment of methodological alternatives. *Accident Analysis & Prevention*, *43*(5), 1666-1676.

Schrank, D., & Lomax, T. (2005). *The 2005 Urban Mobility Report* (Texas Transportation Institute). The Texas A & M University System.

Shapiro, R. J., Hassett, K. A., & Arnold, F. S. (2002). Conserving energy and preserving the environment: The role of public transportation. *American Public Transportation Association*, *9*, 1-39.

Sze, N. N., & Wong, S. C. (2007). Diagnostic analysis of the logistic model for pedestrian injury severity in traffic crashes. *Accident Analysis & Prevention*, *39*(6), 1267-1278.

Tay, R., Choi, J., Kattan, L., & Khan, A. (2011). A multinomial logit model of pedestrian–vehicle crash severity. *International journal of sustainable transportation*, *5*(4), 233-249.

Taylor, J., & Paramore, J. (2016). *We've Been Working On The Railroad* (Florida Department of Transportation, Title VI). Central Florida Expressway Authority. Accessed from https://www.cfxway.com/wp-content/uploads/2016/06/SunRail-Presentation.pdf.

Taylor, J., & Paramore, J. (2017). *We've Been Working On The Railroad* (Florida Department of Transportation, Title VI). Central Florida Expressway Authority. Accessed from http://corporate.sunrail.com/wp-content/uploads/2017/08/SUN_CFCRC_Aug2017Final.pdf.

TBRPM v7.0, (2010), *Technical Report 2 - Tampa Bay Regional Planning Model (TBRPM) Version 7.0, Procedural Guide* (Florida Department of Transportation District VII).

Weisbrod, G. E., Vickerman, R. W., Gillen, D. W., Ogard, E., Simmonds, D., Johnson, D. H., ... & Stein, N. (2014). *Assessing productivity impacts of transportation investments*. Transportation Research Board.

Yasmin, S., Pinjari, A. R., & Eluru, N. (2013). Examining the continuum of injury severity: Pooling the GES and FARS datasets. *Procedia-Social and Behavioral Sciences, 104*, 1020-1029.

Yasmin, S., Eluru, N., & Ukkusuri, S. V. (2014). Alternative ordered response frameworks for examining pedestrian injury severity in New York City. *Journal of Transportation Safety & Security*, *6*(4), 275-300.

Yasmin, S., Eluru, N., Lee, J., & Abdel-Aty, M. (2016). Ordered fractional split approach for aggregate injury severity modeling. *Transportation Research Record: Journal of the Transportation Research Board*, (2583), 119-126.