Using Truck Fleet Data in Combination with Other Data Sources for Freight Modeling and Planning

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Final Report

Prepared for:

Florida Department of Transportation
Mr. Frank Tabatabaee, Project Manager

Prepared by:

University of South Florida
Dr. Abdul R. Pinjari
Mr. Akbar Bakhshi Zanjani
Mr. Aayush Thakur
Ms. Anissa Nur Irmania
Mr. Mohammadreza Kamali

American Transportation Research Institute
Mr. Jeffrey Short
Mr. Dave Pierce
Ms. Lisa Park

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METRIC CONVERSION

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

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16. Abstract

This project investigated the use of large streams of truck GPS data available from the American Transportation Research Institute (ATRI) for the following statewide freight modeling and planning applications in Florida:

(1) Average truck speed data were developed for each (and every) mile of Florida's Strategic Intermodal System (SIS) highway network for different time periods in the day.

(2) Algorithms were developed to convert raw truck GPS data into a database of truck trips. The algorithms were applied to convert four months of raw data, comprising 145 million GPS records, into more than 1.2 million truck trips traveling within, into, and out of Florida.

(3) The truck trip database developed from ATRI's truck GPS data was used to analyze truck travel characteristics, including trip duration, trip length, trip speed, and time-of-day profiles, for different regions in the state. Further, distributions of origin-destination (OD) truck travel times were derived for more than 1,200 OD pairs in the Florida Statewide Model (FLSWM).

(4) ATRI's truck GPS data were evaluated for their coverage of truck traffic flows in Florida. At an aggregate level, the data were found to capture 10 percent of heavy truck volumes observed in Florida.

(5) The data were used to develop OD tables of statewide freight truck flows within, into, and out of Florida. To do so, the truck trip database developed from ATRI's truck GPS data was combined with observed truck traffic volumes at different locations in Florida and other states using OD matrix estimation procedures. The OD tables were developed for the spatial resolution of traffic analysis zones used in FLSWM.

(6) Preliminary explorations were conducted with ATRI's truck GPS data for analyzing truck travel routes between different locations and for analyzing truck flows out of seaports.

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EXECUTIVE SUMMARY

An accelerated growth in the volume of freight shipped on American highways has led to a significant increase in truck traffic, influencing traffic operations, safety, and the state of repair of highway infrastructure. Traffic congestion, in turn, has impeded the speed and reliability of freight movement on the highway system. As freight movement continues to grow within and between urban areas, appropriate planning and decision making processes are necessary to mitigate the above-mentioned impacts. However, a main challenge in establishing these processes is the lack of adequate data on freight movements such as detailed origin-destination (OD) data, truck travel times, freight tonnage distribution by OD pairs, transported commodity by OD pairs, and details about truck trip stops and paths. As traditional data sources on freight movement are either inadequate or no longer available, new sources of data must be investigated.

A recently-available source of data on nationwide freight flows is based on a joint venture by the American Transportation Research Institute (ATRI) and the Federal Highway Administration (FHWA) to develop and test a national system for monitoring freight performance measures (FPM) on key corridors in the nation. These data are obtained from trucking companies that use GPS-based technologies to remotely monitor their trucks. ATRI's truck Geographical Position System (GPS) database contains GPS traces of a large number of trucks as they traveled through the national highway system. This provides unprecedented amounts of data on freight truck movements throughout the nation (and Florida). Such truck GPS data potentially can be used to support planning, operation, and management processes associated with freight movements. Further, the data can be put to better use when used in conjunction with other freight data obtained from other sources.

The overarching goal of this project is to investigate the use of ATRI's truck GPS data for statewide freight performance measurement, statewide freight truck flow analysis, and other freight planning and modeling applications in the state. The specific objectives are to:

1) Derive freight performance measures for Florida's Strategic Intermodal System (SIS) highways,
2) Develop algorithms to convert large streams of ATRI's truck GPS data into a more useable truck trip format,
3) Analyze truck trip characteristics in Florida using ATRI's truck GPS data,
4) Assess ATRI's truck GPS data in terms of its coverage of truck traffic flows in Florida,
5) Develop OD tables of statewide freight truck flows within, into, and out of Florida for different geographic resolutions, including the Florida Statewide Model (FLSWM) traffic analysis zones (TAZs), and
6) Explore the use of ATRI's GPS data for other applications of interest to Florida, including the analysis of truck flows out of two seaports, the re-routing patterns of trucks after a major highway incident, and the routing patterns of trucks traveling between Jacksonville and Ocala.

Project Outcomes and Findings

The outcomes and findings from the project are discussed next.

Freight Performance Measures on Florida's SIS Highway Network

The project resulted in the development of average truck speed data for each (and every) mile of the Strategic Intermodal System (SIS) highway network for different time periods in the day—AM peak, PM peak, mid-day, and off-peak—using three months of ATRI's truck GPS data in the year 2010. In doing so, it was found that the existing shape files of the SIS network available from FDOT either were not accurate enough or they lacked the details (for example, separate links by direction for divided highways) to derive performance measures using geospatial data. Therefore, a highly accurate network was developed to represent highways on the SIS network.

The SIS highway network shape file and the data on average truck speeds by time-of-day were submitted in a GIS shape file that can be used in an ArcGIS environment to identify the major freight bottlenecks on Florida's SIS highway network. In addition to the development of average speed measures, the project developed example applications of ATRI's truck GPS data for measuring truck speed reliability and analyzing highway freight bottlenecks.

Algorithms to Convert ATRI's Raw GPS Data Streams into a Database of Truck Trips

The raw GPS data streams from ATRI need to be converted into a truck trip format to realize the full potential of the data for freight planning applications. The project resulted in algorithms to convert the raw GPS data into a database of truck trips. The results from the algorithms were subjected to different validations to confirm that the algorithms can be used to extract accurate trip information from raw GPS data provided by ATRI.

These algorithms were then applied to four months of raw GPS data from ATRI, comprising a total of 145 million raw GPS data records, to develop a large database of truck trips traveling within, into, and out of the state. The resulting database comprised more than 1.2 million truck trips traveling within, into, and out of the state. This database of truck trips can be used for a variety of purposes, including the development of truck travel characteristics and OD truck flow patterns for different geographical regions in Florida. The database can be used to calibrate and validate the next-generation statewide freight travel demand model being developed by FDOT. In future work, this database potentially can be used to develop data on truck trip-chaining and logistics patterns in the state.

Analysis of Truck Travel Characteristics in Florida

The truck trip database developed from four months of ATRI's truck GPS data was used to analyze a variety of truck travel characteristics in the state of Florida. The truck travel characteristics analyzed include trip duration, trip length, trip speed, time-of-day profiles, and OD flows. Each of these characteristics was derived at a statewide level as well as for different regions in the state—Jacksonville, Tampa Bay, Orlando, Miami, and rest of Florida—defined based on the freight analysis framework (FAF) zoning system.

In addition, the truck trips were used in conjunction with the GPS data to derive distributions of OD travel distances, travel times, and travel speeds between more than 1,200 TAZ-to-TAZ OD pairs in the FLSWM. Comparing the minimum truck travel times measured using GPS data for the 1,200 OD pairs with free flow travel times used as inputs to FLSWM indicated that the FLSWM travel times are systematically underestimated when compared to the truck travel times measured from ATRI data. A similar comparison with the travel times extracted from Google Maps suggested that the Google Maps travel times also underestimate (albeit not as much the FLSWM travel times) truck travel times between origins and destinations. This is most likely because the travel times used as inputs for the FLSWM and those reported by Google Maps are predominantly geared toward passenger cars that tend to have higher travel speeds and better acceleration characteristics. ATRI's truck GPS data, on the other hand, provide an opportunity to accurately measure travel times exclusively for trucks (and for different times of the day).

In addition to the measurement of OD truck travel distances, travel times, and speeds, the project team performed an exploratory analysis of truck travel routes for more than 1,600 trips between 10 OD pairs in FLSWM. A preliminary exploratory analysis suggested that a majority of trips between any OD pair tend to travel by largely similar routes (i.e., the variability in route choice is not high for the 10 OD pairs examined in this study). Specifically, considerable overlap was observed among the routes across a large number of trips between an OD pair. This observation has interesting implications for future research on understanding and modeling truck route choice. While this study did not delve further into understanding the route choice patterns of long-haul trucks, this is an important area for future research using the truck GPS data from ATRI.

Assessment of ATRI's Truck GPS Data and Its Coverage of Truck Traffic in Florida
This project resulted in a better understanding of ATRI's truck GPS data in terms of its coverage of truck traffic in the state of Florida. This includes deriving insights on (a) the types of trucks (e.g., heavy trucks and medium trucks) present in the data, (b) the geographical coverage of the data in Florida, and (c) the proportion of the truck traffic flows in the state covered by the data.

Based on discussions with ATRI and anecdotal evidence, it is known that the major sources of ATRI data are freight shipping companies that own large trucking fleets, which typically comprise tractor-trailer combinations (or Federal Highway Administration [FHWA] vehicle type classes 8–13). However, a close observation of the data, from following the trucks on Google Earth and examining travel characteristics of individual trucks, suggests that the data include a small proportion of trucks that are likely to be smaller trucks that do not necessarily haul freight over long distances. The project used simple rules to divide the data into two categories: (1) long-haul trucks or heavy trucks (considered to be FHWA vehicle classes 8–13), and (2) short-haul trucks or medium trucks. Specifically, trucks that did not make at least one trip of 100-mile length in a two-week period and those that made more than 5 trips per day were considered short-haul or medium trucks. Out of a total of 169,714 unique truck IDs in the data, about 4.6 percent were labeled as short-haul trucks (or medium trucks) and separated from the remaining long-haul trucks (or heavy trucks). In future work, it will be useful to derive better definitions of heavy trucks and medium trucks. Whereas heavy trucks are of primary interest to FLSWM for updating and validating its freight truck model components (assuming these are the long-haul freight carrying trucks), medium trucks are also of potential use for updating the non-freight truck model components in FLSWM. Further, extracting sufficient data on medium trucks potentially can help understand truck movement within urban regions as well, because a considerable proportion of truck traffic in urban areas tends to comprise medium trucks.

ATRI's truck GPS data represent a sample of truck flows within, coming into, and going out of Florida. This sample is not a census of all trucks traveling in the state. Also, it is unknown what proportion of heavy truck flows in the state is represented by this data sample. To address this question, truck traffic flows implied by one-week of ATRI's truck GPS data were compared with truck counts data from more than 200 Telemetered Traffic Monitoring Sites (TTMS) in the state. The results from this analysis suggest that**,** at an aggregate level, the ATRI data provide 10.1 percent coverage of heavy truck flows observed in Florida. When the coverage was examined separately for different highway facilities (based on functional classification), the results suggest that the data provide a representative coverage of truck flows through different types of highway facilities in the state.

The coverage of ATRI data was examined for different geographical regions in Florida by examining the spatial distribution of the number of truck trips generated at TAZ-level and at county-level geography. In addition, the percentage of heavy truck traffic covered by ATRI data at different locations was examined. All these examinations suggest potential geographical differences in the extent to which ATRI data represent heavy truck traffic volumes at different locations in the state. For instance, truck trips generated from Polk County were much higher than those generated from Hillsborough and Miami-Dade counties. Further, the percentage of heavy truck traffic covered by ATRI data in the southern part of Florida (within Miami) and the southern stretch of I-75 is slightly lower compared to the coverage in the northern and central Florida regions. Such geographical differences (or spatial biases) potentially can be adjusted by combining ATRI's truck GPS data with observed data on truck traffic flows at different locations in the state (from FDOT's TTMS traffic counting program).

OD Tables of Statewide Truck Flows

An important outcome of the project was to use ATRI's truck GPS data in combination with other available data to derive OD tables of freight truck flows within, into, and out of the state of Florida. The OD flow tables were derived at the following levels of geographic resolution:

a) TAZs of the FLSWM, where Florida and the rest of the country are divided into about 6,000 TAZs,
b) County-level resolution, where Florida is represented at a county-level resolution and the rest of the country is represented at a state-level resolution, and
c) State-level resolution, where Florida and the rest of the country are represented at a state-level resolution.

As part of this task, first, the truck trip database developed from four months of ATRI's GPS data was converted into OD tables at the TAZ-level spatial resolution used in the FLSWM. Such an OD table derived only from the ATRI data, however, is not necessarily representative of the freight truck flows in the state. This is because the ATRI data does not comprise the *census* of trucks in the state. Besides, it is not necessarily a random sample and is likely to have spatial biases in its representation of truck flows in the state. To address these issues, the OD tables derived from the ATRI data were combined with observed truck traffic volumes at different locations in the state (and outside the state) to derive a more robust OD table that is representative of the freight truck flows within, into, and out of the state. To achieve this, a mathematical procedure called the Origin-Destination Matrix Estimation (ODME) method was employed to combine the OD flow table generated from the ATRI data with observed truck traffic volume information at different locations within and outside Florida. The OD flow table estimated from the ODME procedure is likely to better represent the heavy truck traffic volumes in the state, as it uses the observed truck traffic volumes to weigh the ATRI data-derived truck OD flow tables.

Explorations of the Use of ATRI's Truck GPS Data for Other Applications
In addition to the above, this project conducted preliminary explorations of the use of ATRI's truck GPS data for the following applications:

a) Analysis of truck flows out of two ports in Florida—Port Blount Island in Jacksonville and Port Everglades in Fort Lauderdale,
b) Analysis of routing patterns of trucks that used the US 301 roadway to travel between I-95 around Jacksonville and I-75 around Ocala, and
c) Analysis of changes in truck routing patterns during the closure of a stretch of I-75 near Ocala due to a major multi-vehicle crash in January 2012.

Note that these applications were only preliminary explorations conducted as proofs of concept. Future work can expand on these explorations to conduct full-scale applications.

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CHAPTER 1 : INTRODUCTION

1.1 Background

Freight is gaining increasing importance in transportation planning and decision making at all levels of the government, particularly MPOs, states, and at the federal level. An accelerated growth in the volume of freight shipped on American highways has led to a significant increase in truck traffic. This has put enormous pressure on national highways, impacting traffic operations, safety, highway infrastructure, port operations, and distribution center operations. Traffic congestion, in turn, impedes the speed and reliability of freight movement on the highway system and leads to direct economic costs for producers and consumers, passenger traffic congestion, safety issues, and environmental impacts.

As freight movement continues to grow within and between urban areas, appropriate planning and decision making processes are necessary to mitigate the above-mentioned impacts. However, a main challenge in establishing these processes is the lack of adequate data on freight movements such as detailed origin-destination (OD) data, truck travel times, freight tonnage distribution by OD pairs, transported commodity by OD pairs, and details about truck trip stops and paths. As traditional data sources on freight movement are either inadequate or no longer available (e.g., the Vehicle Inventory and Use Survey), new sources of data must be investigated.

Recognizing the need for better freight data, several efforts are underway to exploit advanced technologies and form innovative partnerships with freight stakeholders to gather freight movement data. Many trucking companies use advanced vehicle monitoring (AVM) systems that allow remote monitoring of their fleets using Geographical Positioning Systems (GPS) technology-based Automatic Vehicle Location (AVL) systems. To tap into such truck GPS data sources, private-sector truck data providers have formed innovative partnerships with freight carriers and other freight stakeholders to collect the GPS data and provide it to public agencies while protecting the confidentiality of the data. Notable among such efforts is a joint venture by the American Transportation Research Institute (ATRI) and the Federal Highway Administration (FHWA) to develop and test a national system for monitoring freight performance measures (FPM) on key corridors in the nation. This FPM data system is built based on data obtained from trucking companies that use GPS-based AVM/AVL technologies to remotely monitor their trucks. ATRI's FPM database contains GPS traces of a large number of trucks as they traveled through the national highway system. This provides unprecedented amounts of data on freight truck movements throughout the nation (and Florida). Such truck GPS data potentially can be used to support planning, operation, and management processes associated with freight movements. Further, the data can be put to better use when used in conjunction with other freight data obtained from other sources.

ATRI's truck GPS data is being used increasingly for a variety of freight performance measurement and planning applications in the recent past. The applications include, but are not limited to, identifying and prioritizing major freight bottlenecks on the nation's highways (Short et al., 2009) and regional and statewide truck flow modeling (Bernardin et al., 2011; Kuppam et al., 2014). For the state of Florida, ATRI's truck GPS provides a significant opportunity to develop data on statewide truck flow patterns, freight performance measurement, and a variety of other applications. Since a majority of freight being shipped across the nation (and Florida) is via the truck mode, ATRI's truck GPS data are likely to be of significant value in providing the data needed for understanding statewide freight movement by the truck mode.

The Florida Department of Transportation (FDOT) is developing a program to develop data on and understand statewide freight movements, including the freight flows between different origins and destinations in the state, the freight flows coming into and going out of the state, the performance of the transportation system in accommodation freight movement, and freight flows into and out of major freight activity centers in the state. As part of this program, FDOT uses FHWA's freight analysis framework (FAF) and other data sources to understand current and future commodity flows in the state. For example, FDOT is developing methods to disaggregate FAF data to obtain commodity flows at smaller geographies such as counties and census tracts. The FDOT program hopes to relate such disaggregate commodity flow data to the information gathered from the ATRI data on truck movements to understand how these commodities are transported between different origins and destinations. In another ongoing project, FDOT is developing a next-generation multimodal freight forecasting model system for long-term freight planning in Florida. FDOT intends to validate and calibrate this model with an independent source of data on OD truck flows in the state.

1.2 Project Objectives

The overarching goal of this project was to investigate the use of ATRI's truck GPS data for statewide freight performance measurement, statewide freight truck flow analysis, and other freight planning and modeling applications. The project aimed to develop supporting methods and procedures to use the data, and combine the data with other data sources, for different freight movement modeling and planning applications. The specific objectives of the project are identified next.

1.2.1 Objective 1: Derive Freight Performance Measures for Florida's Freight-intensive Highways

The first objective of the project was to use ATRI's truck GPS data to derive freight performance measures for Florida's freight-intensive highways. To this end, the project involved the development of data on average truck speeds on each (and every) mile of Florida's Strategic Intermodal System (SIS) highway network for different time periods in the day. These data were developed and submitted in a GIS shape file that can be used in an ArcGIS environment to identify the major freight bottlenecks on Florida's SIS highway network. In addition to the development of average speed measures, the project developed example applications of ATRI's truck GPS data for measuring truck speed reliability and for highway freight bottleneck analysis.

1.2.2 Objective 2: Develop Methods to Convert ATRI's Raw GPS Data Streams into Truck Trips

The raw GPS data streams from ATRI need to be converted into a truck trip format to realize the full potential of the data for freight planning applications. Therefore, the second objective of the project was to convert the raw GPS data into a data base of truck trips. Development of such a truck trip database involved the determination of truck starting and ending instances and locations, trip distance, total trip duration, and duration of intermediate stops (e.g., at traffic signals and rest stops) in the trip. In addition, the process involved resolution of potential anomalies in GPS data, such as data-discontinuities due to loss of satellite signals. This task involved the development of algorithms and a software code (written in Java programming language) to convert the raw GPS data streams into a truck trip format. These algorithms were then applied to four months of raw GPS data from ATRI, comprising a total of 145 million raw GPS data records, to develop a large database of truck trips traveling within, into, and out of the state. The resulting database comprised more than 1.2 million truck trips traveling within, into, and out of the state.

1.2.3 Objective 3: Analyze Truck Travel Characteristics in Florida

The third objective of the project was to use ATRI's truck GPS data to analyze truck travel characteristics in the state of Florida. To this end, the project involved an analysis of the truck trip data derived from the four months of ATRI's truck GPS data. The truck travel characteristics analyzed included trip duration, trip length, trip speed, time-of-day profiles, and OD flows. Each of these characteristics was derived at a statewide level and for different regions in the state—Jacksonville, Tampa Bay, Orlando, Miami, and rest of Florida—defined based on the freight analysis framework (FAF) zoning system. Furthermore, the task involved deriving and analyzing the OD travel distances, travel times, and travel routes between a selected set of OD pairs in the state.

1.2.4 Objective 4: Assess ATRI's Truck GPS Data and Its Coverage of Truck Traffic in Florida

The fourth objective was to assess ATRI's truck GPS data in Florida to gain an understanding of its coverage of truck traffic in the state of Florida. This included deriving insights on (a) the types of trucks (e.g., heavy trucks and light trucks) present in the data, and (b) the geographical coverage of the data in Florida, and (c) the proportion of the truck traffic flows in the state covered by the data.

1.2.5 Objective 5: Derive Statewide Truck Trip Flow OD Tables for the Traffic Analysis Zone (TAZ)-level Spatial Resolution in the Florida Statewide Model (FLSWM)

An important objective of the project was to use ATRI's truck GPS data in combination with other available data sources to derive origin-destination (OD) tables of freight truck flows within, into, and out of the state of Florida. As part of this task, first, the truck trip database developed from four months of ATRI's GPS data was converted into OD tables at the TAZ-level spatial resolution used in the Florida Statewide Model (FLSWM). Such an OD table derived only from the ATRI data, however, was not necessarily representative of the freight truck flows in the state. This is because the ATRI data did not comprise the *census* of trucks in the state; the data comprised only a sample of trucks traveling in the state. Although it is a large sample, it is not necessarily a random sample and is likely to have spatial biases in its representation of truck flows in the state. To address these issues, the OD tables derived from the ATRI data need to be combined with observed truck traffic volumes at different locations in the state (and outside the state) to derive a more robust OD table that is representative of the freight truck flows within, into, and out of the state. To achieve this, a mathematical procedure called the Origin-Destination Matrix Estimation (ODME) method was employed to combine the seed OD flow matrix generated from the ATRI data with observed truck traffic volume information at different locations within and outside Florida.

1.2.6 Objective 6: Explore the Use of ATRI's Truck GPS Data for Other Applications of Interest to Florida

Another objective of the project was to explore the use of ATRI's truck GPS data for a variety of applications of interest to Florida other than those mentioned above. Specifically, exploratory analysis tasks were provided on an ongoing basis as needed by FDOT. These included (a) analysis of truck flows out of two ports in Florida—Port Blount Island in Jacksonville and Port Everglades in Fort Lauderdale, (b) analysis of routing patterns of trucks that used the US 301 roadway to travel between I-95 around Jacksonville and I-75 around Ocala, and (c) analysis of changes in truck routing patterns during the closure of a stretch of I-75 near Ocala due to a major multi-vehicle crash in January 2012. Note here that these applications are only exploratory in nature and conducted only as proofs of concept. Future work can expand on these explorations to conduct full-scale applications of the above mentioned tasks.

1.3 Structure of the Report

The research conducted for the above-mentioned objectives and the project outcomes and findings are described in subsequent chapters.

Chapter 2 presents a brief overview of ATRI's truck GPS data. In addition, the chapter describes the procedures and outcomes of the freight performance measurement task described in objective 1. The chapter is accompanied by an appendix (Appendix A) to provide an overview of the exploratory tasks described in objective 6.

Chapter 3 presents the procedures and algorithms used to convert the raw GPS data streams into a large database of truck trips in Florida (objective 3).

Chapter 4 presents an analysis of the truck travel characteristics using the truck trip database developed from four months of raw GPS data (objective 4). This chapter is accompanied by an appendix to present examples of truck route choice patterns between several OD pairs as well as distributions of truck travel times between those same OD pairs.

Chapter 5 presents an assessment of ATRI's truck GPS data in Florida, specifically in terms of its coverage of truck traffic flows in the state of Florida as well as different geographical locations (objective 5). This chapter is accompanied by an appendix that presents an analysis of the seasonality of the observed truck traffic counts obtained from the Telemetered Traffic Monitoring Sites (TTMS) data collected by FDOT.

Chapter 6 presents the development of statewide OD truck flows using ATRI data in combination with other data sources for the TAZ-level spatial resolution in the FLSWM. The ODME procedure used for this purpose, the observed truck traffic volume data within and outside Florida, and the results from the procedure are presented in this chapter.

Chapter 7 summarizes the work conducted, the findings and benefits of the study, and identifies opportunities for future research and implementation.

CHAPTER 2 : OVERVIEW OF ATRI DATA AND ITS APPLICATIONS FOR FREIGHT PERFORMANCE MEASUREMENT

2.1 Introduction

This chapter provides a background on ATRI’s truck GPS data. In addition, the chapter provides examples of the applications of the data for highway freight performance measurement (section 2.2), with a focus on the performance measures (i.e., average truck speeds) developed for Florida’s Strategic Intermodal System (SIS) highway network.

2.2 Background on ATRI's Truck GPS Data

The American Transportation Research Institute (ATRI) collects truck position data throughout the U.S. and North America from a large sample of trucks that use onboard, wireless communications systems. This information has been collected for FHWA as part of their Freight Performance Monitoring System (FPMS) (Jones et al., 2005) for the purpose of monitoring truck travel speeds in freight-significant corridors. The ATRI database contains consecutive truck GPS data for several locations in the nation from 2002 through the most recent month of 2014. In the state of Florida, the ATRI database contains truck GPS data from 2005 through the most recent month of 2014. For the majority of analysis conducted in this project, ATRI used data in Florida from the calendar year 2010.

At a minimum each record within the database contained the following information:

- Unit Information: A unique identifier for the transponder/truck,
- Geographic Information: The latitude and longitude data that identify where a truck position record was recorded, and
- Temporal Information: The time at which a truck position record was recorded, in the following format – MM-DD-YYYY HH:MM:SS.

Additionally, many of the records contain information such as spot speed and heading. Spot speed is the “instantaneous” speed of the truck at the location where its movement is recorded. A sample record looks as below:

Unique Truck ID	Time/Date Stamp	Latitude	Longitude	Heading	Speed
12232123	05-03-2011 01:55:55	33.915932	-84.494760	N	25

Note that the “Unique Truck ID” is a random digit identifier that cannot be used to identify the actual vehicle or to trace the carriers that provided the data. The original truck GPS identification numbers were converted to random digit identifiers and destroyed to protect the confidentiality of the carriers. Therefore, ATRI is unable to provide information about individuals trucks (other than GPS records), such as the commodity carried, weight or volume carried, purpose of travel, and the type of truck. However, since the focus of FPMS was truck travel speeds on freight-significant corridors, and the trucks traveling in these corridors tend to be predominantly tractor-trailer combination trucks, ATRI indicated that the data comprise predominantly tractor-trailer combination trucks (also called heavy trucks from here forward). Most such trucks can be categorized as classes 8–13 of FHWA’s vehicle classification scheme, as shown in Figure 2.1. It will be discussed in Chapter 5 that an unknown but small portion of the data comprise trucks of lower classification (Class 7 or below), such as single unit trucks that might serve the purpose of freight distribution in urban areas and across smaller distances.

To protect confidentiality of the data, ATRI required USF to sign a non-disclosure agreement (NDA). According to the NDA, the raw GPS data shared by ATRI with USF was to be used only for the purpose of analysis by USF researchers. The raw data must not be shared with anyone outside the research team. However, the agreement allows for the aggregate results and data products from the research to be submitted to FHWA as long as the locations of the trip origins, destinations, and intermediate locations are not revealed in a high spatial resolution. Once the NDA was in place, ATRI started sharing the raw truck GPS data with USF. The data were shared through a secure FTP site that was used throughout the project for transferring data.

In this project, the research team worked with Florida-specific data for the year 2010. Specifically, most of the tasks were carried out using ATRI's truck GPS data for a certain time period in the year 2010. For example, for generating of average truck travel speeds on the Florida network, three months of data in the year 2010 were used. For other tasks, such as generating OD flows of truck travel in the state, four months of data were used.

For any given time period (say, a week), the first step in the process of extracting a Florida dataset involved isolating all the unique truck IDs with GPS positions in Florida during that time period (i.e., all trucks found in Florida during that period). Subsequently, all the GPS data for those unique IDs were extracted, not only within the boundaries of Florida but also throughout North America. Thus, the database can be used to derive information on truck travel within Florida as well as that coming into and going out of Florida. For example, Figure 2.2 shows a sample of truck GPS records in Florida found during a certain time period in ATRI's database. Figure 2.3 shows all of ATRI's truck GPS data in North America with the same unique truck IDs found in Florida during that time period (i.e., the truck IDs in Florida from the data in Figure 2.2).

Since analyzing large streams of data was complex and time consuming, most procedures developed in the project were first developed for smaller-size datasets —specifically, data for one week time periods—and then employed (and if needed modified) for larger datasets.

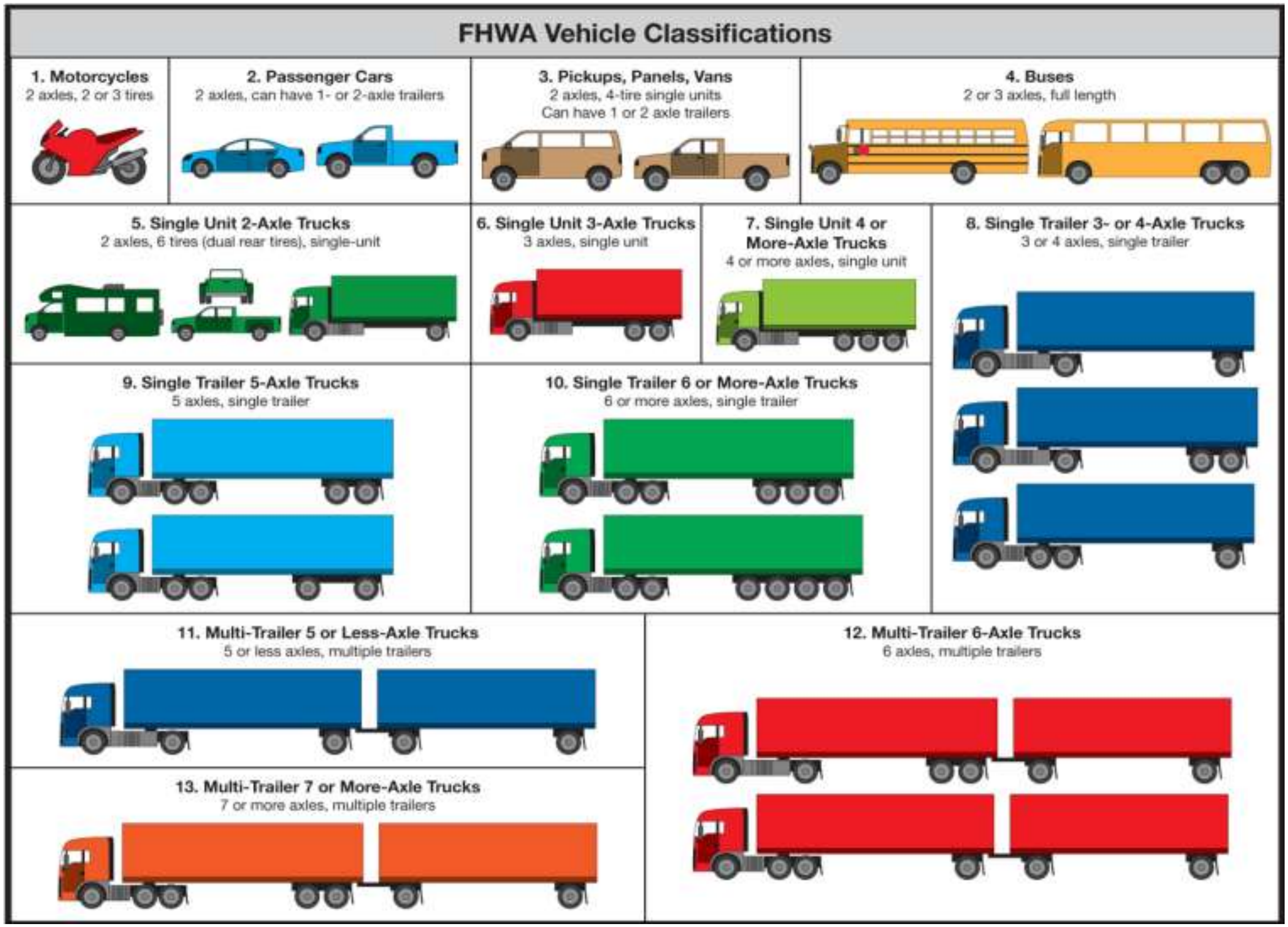


Figure 2.1 FHWA Vehicle Classifications

Source: http://onlinemanuals.txdot.gov/txdotmanuals/tri/images/FHWA_Classification_Chart_FINAL.png, accessed on 5-13-2014.

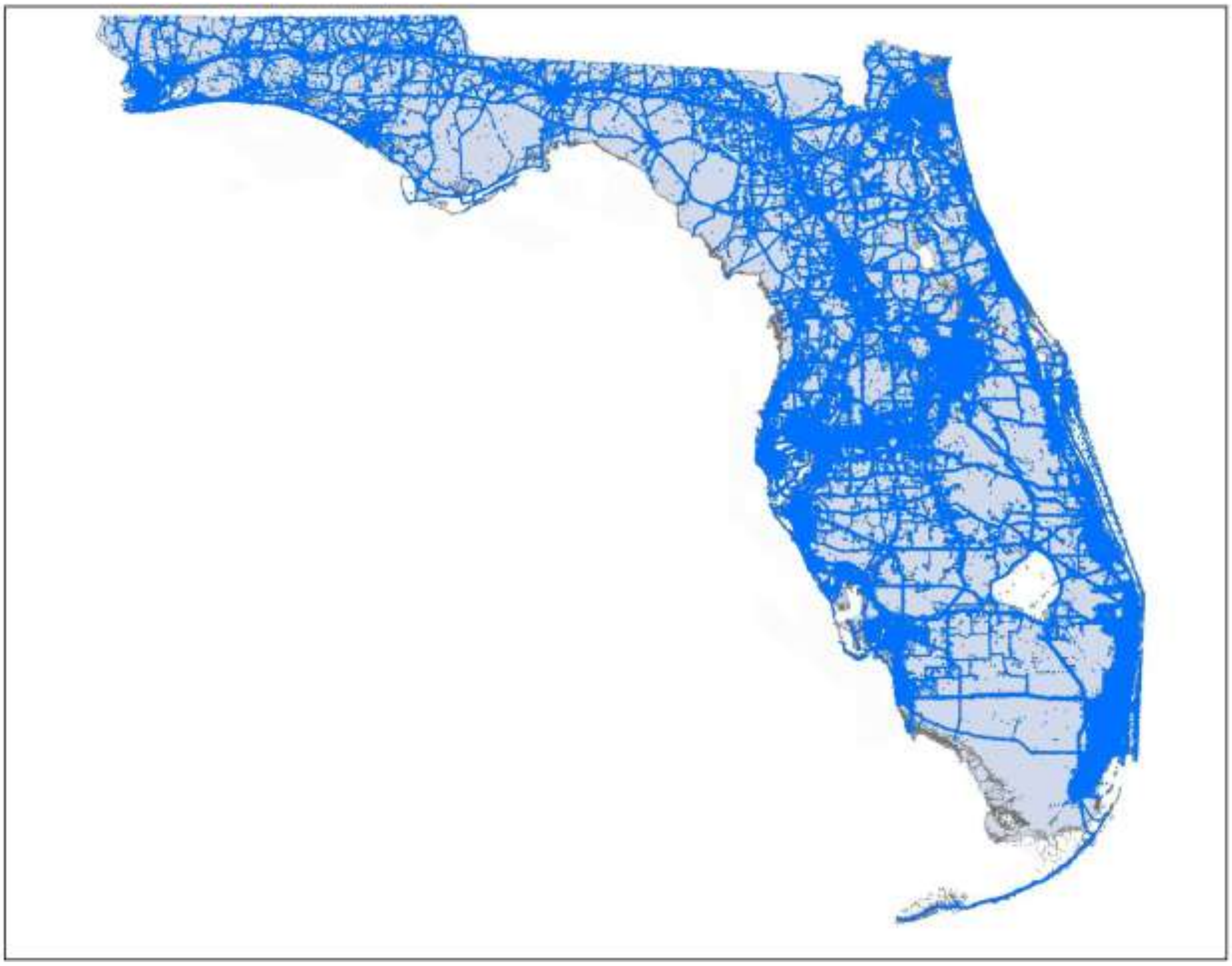


Figure 2.2 Sample of Truck GPS Record Positions in Florida

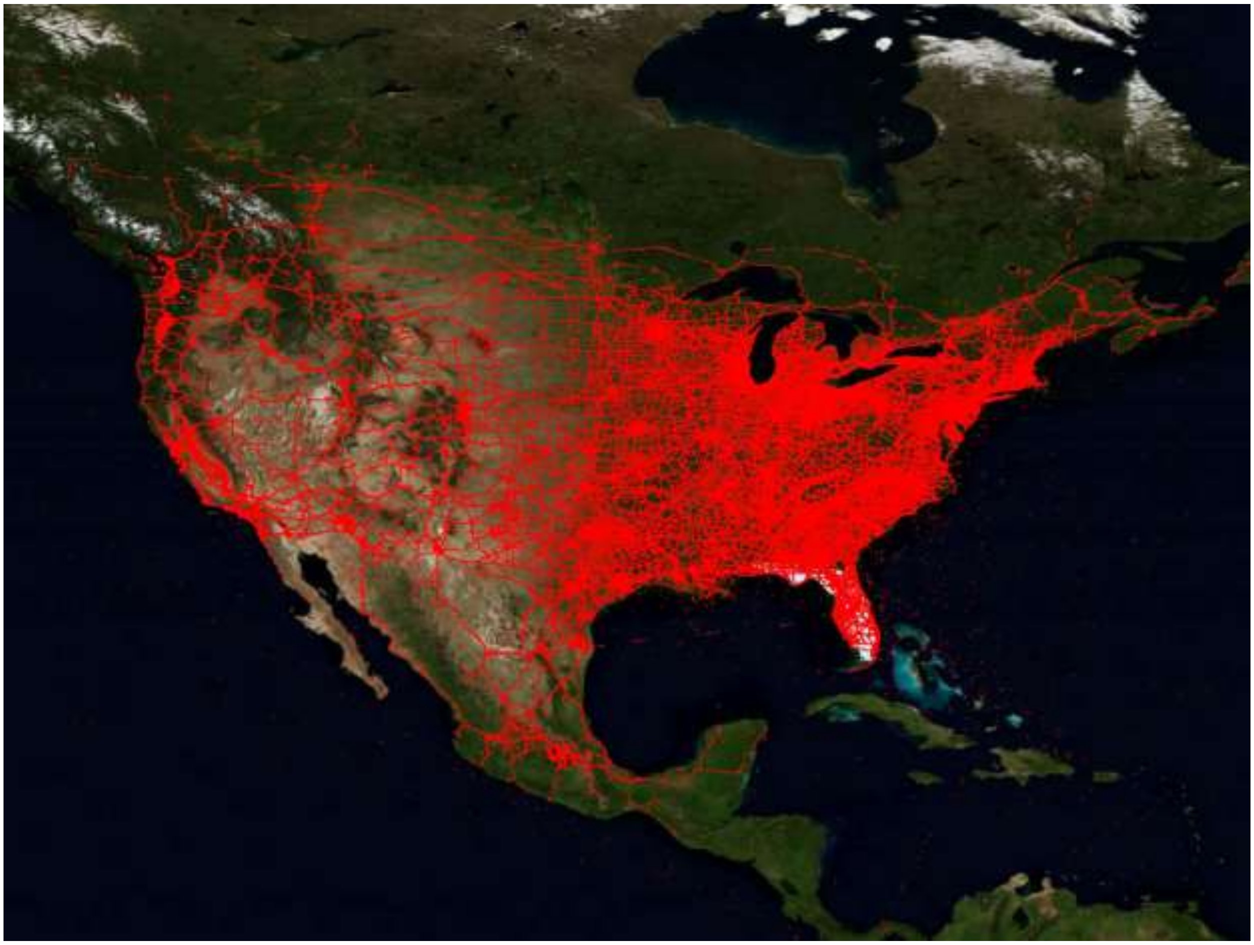


Figure 2.3 Truck GPS Record Positions throughout North America for Same Sample of Trucks in Florida from Figure 2.2

2.3 Applications of ATRI's Truck GPS Data for Freight Performance Measurement

2.3.1 Freight Performance Measures: Average Truck Speeds on SIS Highways

The ATRI dataset can be processed into measurements of average speeds for freight-significant corridors. In this project, ATRI's truck GPS data in Florida were used to measure average speeds on each mile of Florida's SIS highway network for different time periods of the day. Three months of data in the year 2010 were used to generate the speeds.

The first step in generating the average truck speed information for SIS highways was to identify truck GPS data points that fell on the SIS highway network segments. This required a GIS layer of highly accurate and a bidirectional roadway network (i.e., a network that recognizes divided highways—for example, a section of interstate 4 between Tampa and Orlando, as two different segments, one in each direction) to select only those GPS data points that fell on the SIS highway network. Extracting data that was not on the network (for example, parked at a facility near the network) could produce less-reliable results.

The research team received from FDOT two different sources of network geometry in a shape file format—(1) SIS network, and (2) Navteq network. After preliminary assessment by the research team, it was determined that neither network was accurate enough for the purpose of this task.[1] Therefore, using these two networks as reference and by tracing the truck GPS points on selected roadways, the ATRI team created a highly-accurate network geometry of Florida's SIS highways. The shape file of this network has a vector spatial representation and the geographic coordinate reference GCS_WGS_1984. The network geometry data were organized into roadway segments that were generally 1.0 miles in length in rural areas and 0.5 miles in length in urban areas. The final network geometry comprised 9,750 individual segments covering 9,042 miles of multidirectional roadways on SIS.

Next, the truck GPS dataset was further narrowed to include only those data points that fell along Florida's SIS road network (using the ATRI-created network geometry). Using the geographic coordinates of the truck GPS points, each truck data point was assigned a unique segment ID that linked each point to a specific highway facility. A spatial join of the truck GPS dataset to the network accomplished this task. The truck GPS dataset was processed into measurements of average speed. With the network divided into segments and the truck GPS data assigned a unique segment ID, the data for each segment were aggregated and sorted into the following five time bins:

- AM Peak: 6:00 a.m. – 9:59 a.m.
- Mid-day: 10:00 a.m. – 2:59 p.m.
- PM Peak: 3:00 p.m. – 6:59 p.m.
- Off-peak: 7:00 p.m. – 5:59 a.m.
- Average of all hours: 12 a.m. – 11:59 p.m.

Average speeds were then calculated for each corridor segment during each time period. ATRI used several additional sources of data, such as maximum speed limits and Average Annual Daily Truck Traffic (AADTT) to validate the average speed FPMs. The resulting shape file, with information on average weekday speeds on each mile of the SIS highway network for different time periods of the day, was submitted to FDOT. The shape file can be used in a GIS workspace for visualizing average truck speeds and identifying locations affected by congestion. As an illustration, Figure 2.4 shows the average AM Peak speed for each segment in the SIS highway network based on data from weekdays in 2010. Segments with slower average speeds are shown in shades of red, and those with faster average speeds are shown in shades of green. Figure 2.5 displays the shape file and its functionality when deployed in ESRI's ArcGIS desktop. In this example, one segment is highlighted, and an information box displays the unique attributes for that individual segment.

[1] The SIS network provided by FDOT was not multidirectional, so it could not be used for measuring speeds by direction. The Navteq network was multidirectional. However, at some locations, the network geometry was not aligned with the true location of the roadway.

Figure 2.4 Average Truck Speeds for AM Peak Time Period on Florida's SIS Highways

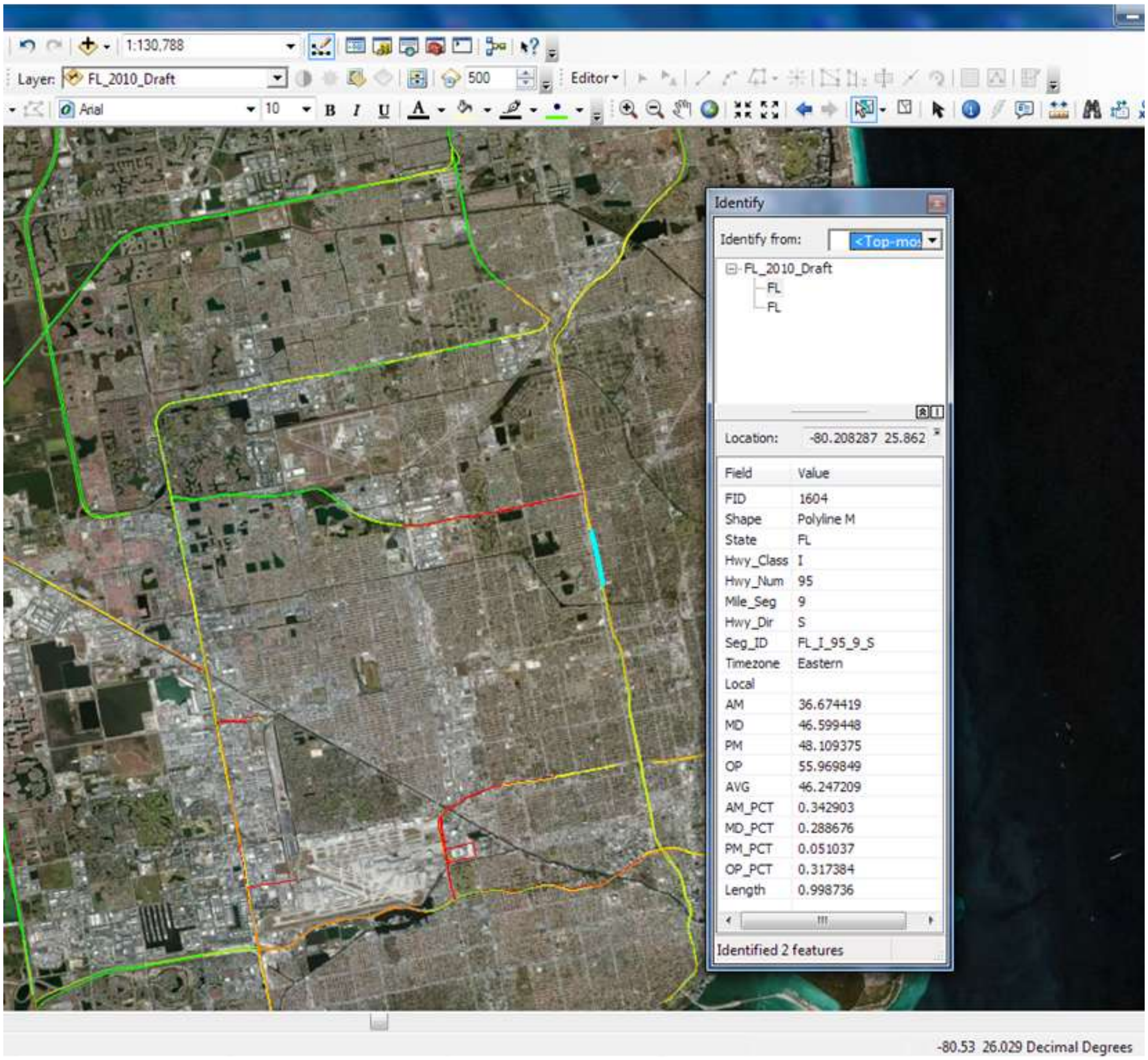


Figure 2.5 Average Truck Speeds for Different Time Periods in the Day for a One-Mile Segment in the Miami Region

The performance measurements (i.e., average truck speeds), if produced for each hour, can be used to analyze specific roadway segments and networks during a given time period. As an illustration, Figure 2.6 displays average speeds in one-hour time periods across one-mile segments along a stretch of I-95 in Fort Lauderdale**.** Such information can be used to understand the spatial and temporal extent of congestion faced by trucks on freight significant corridors.

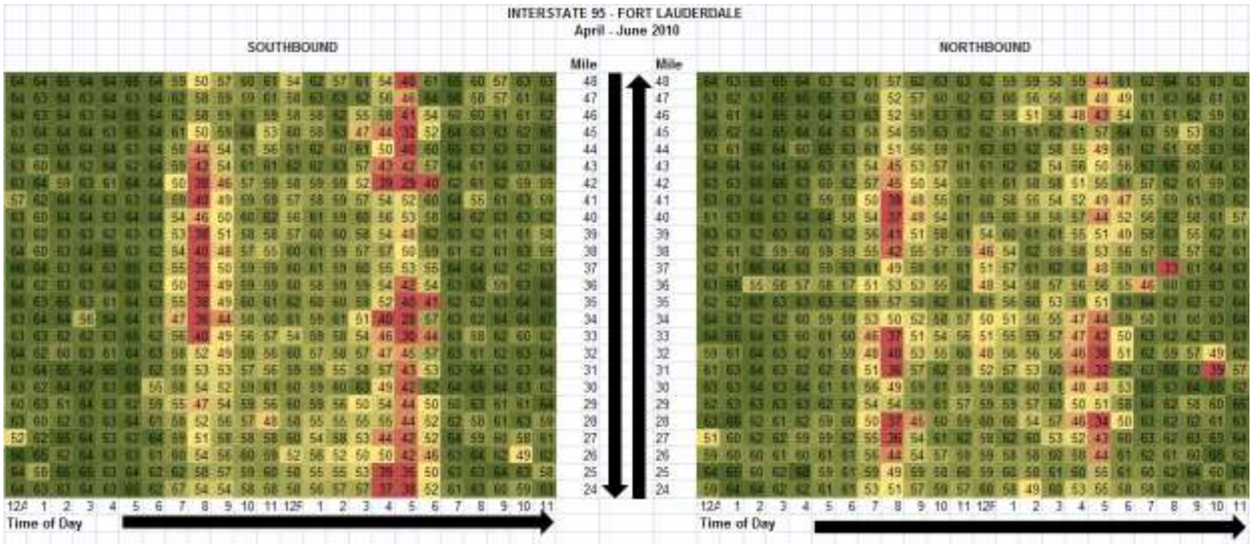


Figure 2.6 Average Speeds by Hour for Miles 24-48 on I-95 in Fort Lauderdale, Florida

2.3.2 Freight Performance Measures: Truck Speed Reliability Measurements

Since the ATRI data contain truck GPS data for extended time periods, the data can be used to measure the reliability of truck movement (i.e., to develop measures of variability in truck speeds) on freight-significant corridors in the state. Two widely-used measures of reliability include the Travel Time Index (TTI) and Planning Time Index (PTI). The TTI is the ratio of the average speed for a given highway segment at a particular time of day to the functional free-flow speed of the same segment of highway. The higher the index, the longer it takes, on average, to travel the segment of highway at that time of day compared to if traffic was moving at free flow. The PTI is the ratio of the "worst-case scenario" average travel speed for a given highway segment at a particular time of day to the functional free-flow speed of the same segment of highway. The worst-case scenario is defined as the 95th percentile of average speeds during a given time period (with lower speeds being a higher percentile rank). The higher the index, the more time is needed for motorists to plan for a 95 percent on-time arrival.

Eight urban freeway corridors from southeast Florida (Figure 2.7) were selected for reliability (of truck speeds) measurement demonstration in this study. Table 2.1 presents reliability measures along each of these eight urban segments, presented separately by direction. It can be observed from the table that the reliability was lowest during the PM peak periods.

Figure 2.7 Highway Corridors Selected for Truck Speed Reliability Measurements

Table 2.1 Truck Speed Reliability Measures for Eight Miami Corridors

Miami, FL - April-June 2010			Travel Time Index				Planning Time Index			
Polyline	Freeway Section (sorted from most congested to least congested)	Length (mi)	Morning Peak (6a-9a)	Midday (9a-4p)	Evening Peak (4p-7p)	Average Peak Period	Morning Peak (6a-9a)	Midday (9a-4p)	Evening Peak (4p-7p)	Average Peak Period
1	I-95 NB: SR 91 to SR 84	12.2	1.16	1.10	1.18	1.17	1.69	1.35	2.04	1.82
	I-95 SB: SR 84 to SR 91	12.2	1.12	1.16	1.36	1.19	1.68	1.77	3.12	2.12
2	I-95 NB: I-195 to SR 91	8.2	1.09	1.17	2.07	1.68	1.38	2.40	10.00	6.56
	I-95 SB: SR 91 to I-195	8.2	1.36	1.27	1.33	1.36	3.41	2.93	4.16	3.49
3	I-95 NB: US 1 to I-195	5.1	1.21	1.18	1.65	1.38	3.17	1.64	4.31	3.62
	I-95 SB: I-195 to US 1	5.1	1.25	1.18	1.39	1.27	3.13	2.24	4.57	3.31
4	I-75 NB: SR 821 to I-595	13.3	1.04	1.05	1.15	1.06	1.11	1.15	1.66	1.21
	I-75 SB: I-595 to SR 821	13.3	1.09	1.06	1.09	1.09	1.35	1.16	1.28	1.33
5	SR 826 NB: SR 836 to I-75	8.3	1.12	1.18	1.86	1.53	1.50	1.67	5.20	3.56
	SR 826 SB: I-75 to SR 836	8.3	1.28	1.31	1.51	1.32	2.18	2.57	7.59	3.10
6	SR 91 NB: SR 821 to SR 852	2.9	1.35	1.18	1.29	1.33	3.15	2.30	3.97	3.36
	SR 91 SB: SR 852 to Sr 821	0.3	1.29	1.21	1.17	1.26	5.96	4.15	1.81	4.93
7	I-75 NB: SR 826 to SR 821	4.9	1.05	1.05	1.08	1.06	1.10	1.08	1.10	1.10
	I-75 SB: SRI 821 to SR 826	4.8	1.42	1.15	1.08	1.30	6.65	2.91	1.29	4.73
8	SR 826 EB: I-75 to I-95	8.3	1.35	1.15	1.21	1.31	2.94	1.58	2.74	2.88
	SR 826 WB: I-95 to I-75	8.3	1.40	1.23	1.32	1.38	3.42	2.28	3.64	3.46

2.3.3 Identification and Analysis of Freight Bottlenecks

Identification and prioritization of highway bottlenecks offer a better understanding of when, where, and possibly why congestion is occurring. As an illustration, Figure 2.8 provides an example where the freight performance measures (average truck speeds) are fused with the FAF data on truck volumes to identify important bottlenecks for freight movement along Florida's interstate highways. Specifically, the color coding displays average speeds on interstate highways in Florida during the PM peak period. The FAF data on AADTT for the same roadways are displayed using variations in the thickness of the highway segments. Such analyses can be conducted to identify and prioritize the locations with combinations of greater congestion and truck travel demand.

Figure 2.8 Fusion of ATRI's Freight Performance Measures FAF Data on Truck Volumes to Identify Important Bottlenecks for Freight Movement

As another illustration, Figure 2.9 shows an example of a Florida urban interchange that ranked in the top 100 freight bottlenecks in the nation. In this study (ATRI, 2009), each bottleneck was given a "freight congestion index value"[2] that was calculated based on congestion at the location (measured by the extent to which the measured truck speeds are below free-flow speeds) and the freight demand at the location (measured by the hourly freight truck volume). Subsequently, the different locations were rank-ordered based on the congestion index value. Such analysis can be conducted for Florida to identify and rank-order the highway bottlenecks in the state for prioritization of funding toward fixing highway freight bottlenecks in the state.

[2] A complete description of the methodology for identifying and rank-ordering the bottlenecks is available at http://www.atri-online.org/fpm/ResearchMethodology.pdf, accessed on 3-10-2014.

Furthermore, one can analyze the specific segments of the bottleneck to identify which segments or directions of an interchange, for instance, have the worst congestion.

2009 Bottleneck Analysis of 100 Freight Significant Highway Locations

Tampa , FL: I-4 at I-275

Bottleneck Summary

The bottleneck location is shown in **Figure 1**.
The speed profile is shown in **Figure 2**.

Average Speed	45
Peak Average Speed	36
Nonpeak Average Speed	50
Nonpeak/Peak Speed Ratio	1.37
Congestion Index	**260,041**
Ranking (out of 100)	**49**

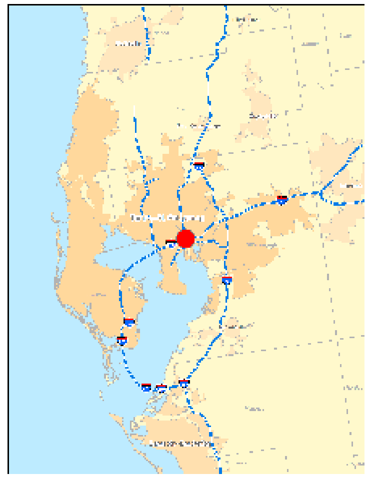


Figure 1: Location Map

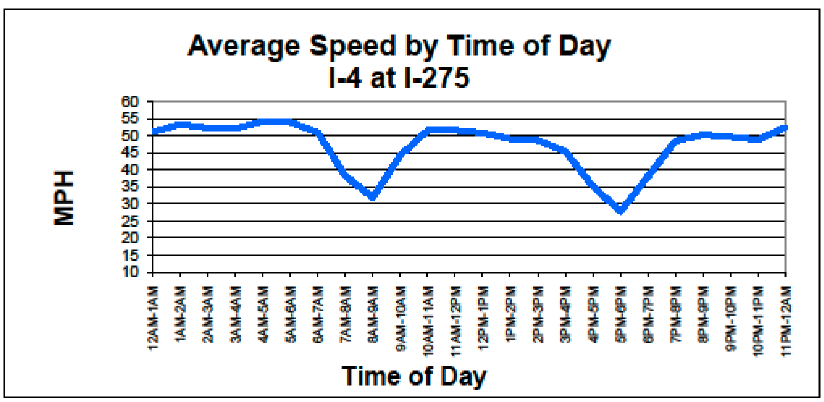


Figure 2: Speed Profile

Figure 2.9 Bottleneck Analysis for I-4 at I-275 in Tampa

Source: ATRI (2009) Bottleneck Analysis of 100 Freight Significant Highway Locations. Available at: http://atri-online.org/2010/05/08/944/, accessed on 3-10-2014.

CHAPTER 3 : CONVERSION OF ATRI TRUCK GPS DATA TO TRUCK TRIPS

3.1 Introduction

As discussed in the previous chapter, ATRI data comprised large streams of GPS records of truck movements in North America. The raw GPS data streams from ATRI needed to be converted into a truck trip format to realize the full potential of the data for freight flow analysis, modeling, and planning applications. Development of such a truck trip database involved the determination of truck starting and ending instances and locations, trip distance, total trip duration, and duration of intermediate stops (e.g., at traffic signals and rest stops) in the trip. Doing so required separation of valid pickup/delivery stops from congestion stops, stops at traffic signals, and stops to meet hours of service regulations,[3] making use of land-use information and GIS analysis tools along with carefully-considered assumptions. In addition, the process involved resolution of potential anomalies in GPS data, such as data discontinuities due to loss of satellite signals. This chapter describes the algorithms and procedures developed in the project to convert the raw GPS streams provided by ATRI data into a database of truck trips. The next section provides a brief description of ATRI's truck GPS data used in the project. Section 3.3 describes the algorithms and procedures. Section 3.4 presents the results from the algorithms.

3.2 ATRI's Truck GPS Data

In this project, ATRI provided more than 145 million raw GPS records of truck movements from four months—March, April, May, and June—in 2010 for the state of Florida. Specifically, for each of these four months, all trucks from ATRI's database that were in Florida at any time during the month were extracted. Subsequently, the GPS records of those trucks were extracted for time periods ranging from two weeks to an entire month as they traveled within Florida as well as in other parts of North America. This allows the examination of truck movements within Florida as well as truck flows into (and out of) Florida from (to) other locations in the nation.

Each GPS record contained information on its spatial and temporal location along with a unique truck ID that did not change across all the GPS records of the truck for a certain time period varying from one day to over one month (at least two weeks for most trucks in the data). In addition to this information, a portion of the GPS records database contained spot speeds information (i.e., the instantaneous speed of the truck for each GPS record), and the remaining portion of the database did not contain spot speed information. In the remainder of this report, the former type of data is called data with spot speeds and the latter type is called data without spot speeds. The data with spot speeds and the data without spot speeds were separately delivered to USF, presumably because they come from different fleets of trucks based on the type of GPS units/technology used to monitor the trucks. The frequency (i.e., ping rate) of the GPS data streams varied considerably, ranging from a few seconds to over an hour of interval between consecutive GPS records. Table 3.1 shows the distribution of the time gap between consecutive GPS readings in one week of data during the month of May 2010. Whereas a large

[3] Long-haul drivers make en-route stops for long durations to rest before resuming further driving. Hours-of-service regulations in 2010 by the Federal Motor Carrier Safety Administration (FMCSA) required an 11-hour maximum daily driving limit. Specifically, truck drivers were allowed to drive up to 11 consecutive hours only after10 hours of off-duty time (or rest). Therefore, not all stops of longer duration are valid pickup/delivery stops. See http://www.fmcsa.dot.gov/regulations/hours-of-service for more information on FMCSA's hours-of-service regulations for different years.

proportion (79.7%) of data with spot speeds comprised GPS streams at less than 15-minute interval, a considerable proportion (29.5%) of data without spot speeds had GPS streams at greater than 1-hour intervals.

Table 3.1 Distribution of Time Gap between GPS Readings in a Week of Truck GPS Data

	% of Consecutive GPS Readings in Data	
	Data with Spot Speeds	***Data without Spot Speeds***
< 1 minute	12.4%	21.5%
1–5 minutes	25.5%	15.0%
5–10 minutes	17.8%	8.5%
10–15 minutes	24.0%	4.9%
15–30 minutes	12.4%	9.7%
30 minutes–1 hour	2.8%	10.9%
1–2 hours	1.7%	27.8%
> 2 hours	3.4%	1.6%

For each GPS record, ATRI extracted and provided to USF information on how far the location is from the nearest interstate highway. In addition, ATRI shared with USF a geographic file (i.e., GIS shape file) containing polygons of major truck stops (such as rest stop areas, weigh stations, welcome centers, and wayside parking) within and outside Florida.

3.3 Algorithm Description

The overall procedure to convert ATRI's truck GPS data into a database of truck trips can be described in the following five broad steps. Each of the broad steps is detailed in this section.

1) Clean, read and sort the GPS data for each truck ID into a time series, in the order of the date and time of the GPS records.
2) Identify stops (i.e., trip-ends or trip origins and destinations) based on spatial movement, time gap, and speed between consecutive GPS points.
    a) Derive a preliminary set of trips based on a minimum stop dwell-time buffer value (i.e., eliminate stops of duration less than dwell-time buffer value). Use 30 minutes dwell-time buffer in the beginning.
    b) Combine very small trips (< 1 mile trip length) with preceding trips or eliminate them.
    c) Eliminate poor-quality trips based on data quality issues such as large time gaps between GPS records and incomplete trips (i.e., trips spanning beyond the temporal limits of the study period).
3) Eliminate trip-ends in rest areas and other locations that are unlikely to involve a valid pickup/delivery.
    a) Overlay trip ends on a geographic file of rest areas, wayside stops, and similar locations.
    b) Eliminate stops in close proximity of interstate highways, which are most likely to be rest areas or wayside parking stops.

c) Join consecutive trips ending and beginning at such stops.

4) Find circular (i.e., circuitous) trips based on the ratio between air distance to roadway network distance. Use raw GPS data between the origin and destination of circular trips to split them into appropriate number of shorter, non-circular trips by allowing smaller dwell-time buffers at the destinations. To do this, implement step 2 with a smaller dwell-time buffer (15 minutes) and go through steps 3 and 4 to find any remaining circular trips. Repeat the process with a dwell-time buffer of 5 minutes to split remaining circular trips.
5) Conduct additional quality checks and eliminate trips that do not satisfy quality criteria.

3.3.1 Clean and Sort Data

The raw GPS data were first screened for basic quality checks such as the presence of spatial and temporal information and the presence of at least one day of data for each truck ID. Truck IDs that did not have GPS data for at least a span of one day or that had too few GPS records were removed. For such trucks, it was difficult to extract trips because most of the data were likely to be lost in the form of incomplete trips, i.e., trips without a valid origin and/or destination in the data. The cleaned data were then sorted in a time series for each truck, beginning from the GPS record with the earliest date and time stamp.

3.3.2 Identify Truck Stops (i.e., Truck Trip-ends) to Generate Truck Trips

This step comprised a major part of the procedure to convert raw GPS data into truck trips. The high-level details of the algorithmic procedure in this step are presented in Figure 3.1. Following is a list of the terms used in the algorithm along with their definitions:

1) *Travel distance* (td): Spatial (geodetic) distance between two consecutive GPS records.
2) *Travel time* (trt): Time gap between the two consecutive GPS records.
3) *Average travel speed* (trs): Average travel speed between consecutive GPS records (td/trt).
4) *Trip length* (tl): Total distance traveled by the truck from origin of the trip to the current GPS point. This becomes equal to trip distance, when the destination is reached.
5) *Trip time* (tpt): Total time taken to travel from origin of the trip to the current GPS point.
6) *Trip speed* (tps): Average speed of the trip between the origin and the current GPS point.
7) *Origin dwell-time* (odwt): Total time duration of stop at the origin; i.e., when the truck is not moving (the wait time for the truck before starting its trip)
8) *Destination dwell-time* (ddwt): Total duration the truck stops at the destination of a trip.
9) *Stop dwell-time* (sdwt) – Duration of an intermediate stop (e.g., traffic stop).
10) *Total stop dwell-time* (tsdwt): Total duration at all intermediate stops during the trip.

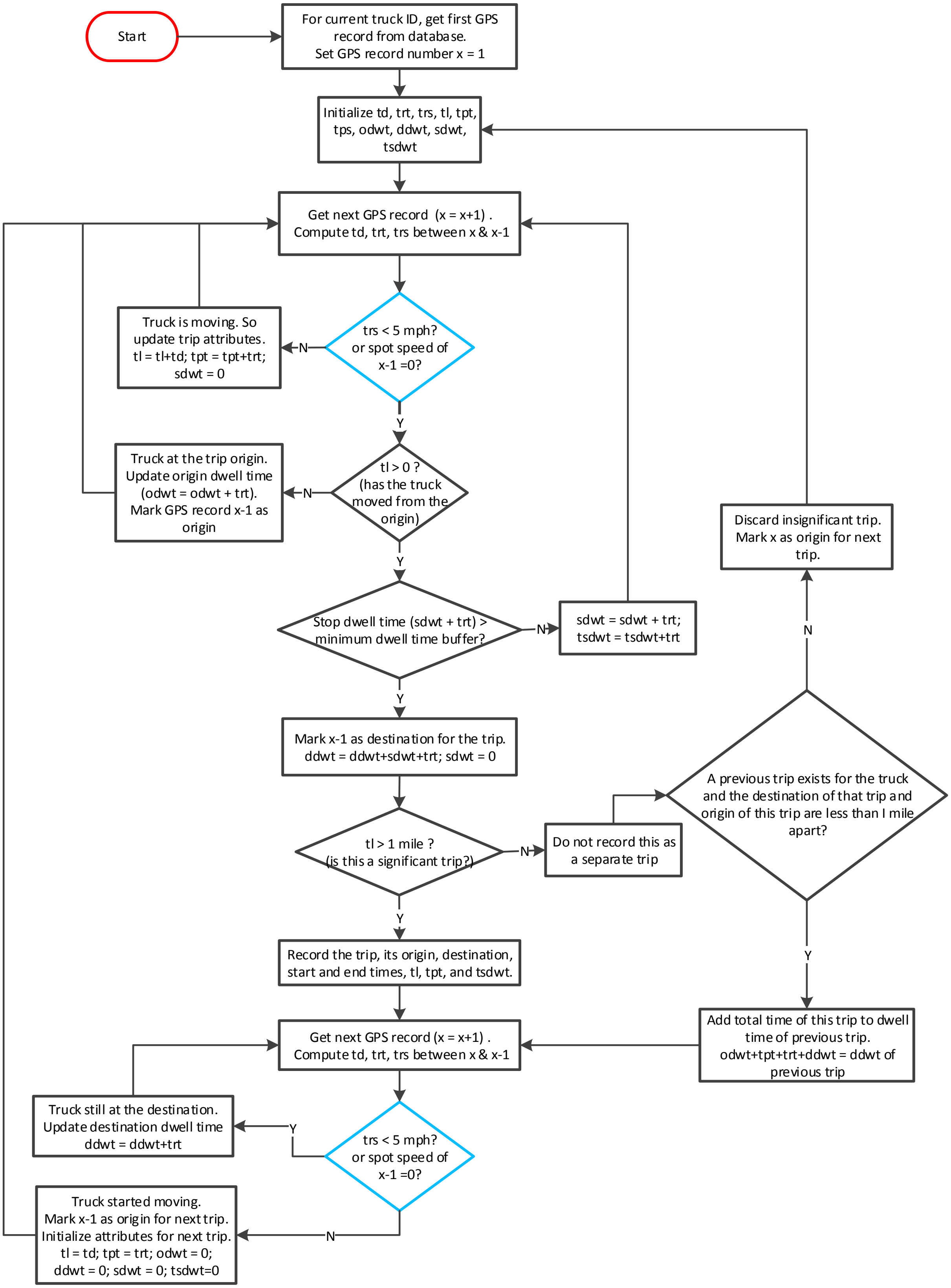


Figure 3.1 Algorithm for Identifying Truck Trip Ends from Raw GPS Data

The first three terms—td, trt, and trs—are measures of movement between consecutive GPS data points. The next three terms—tl, tpt, and tps—are measures of total travel between the trip origin and the current GPS data point. When the truck destination is reached, these measures are for the entire trip beginning from its origin to the destination. The last four terms—odwt, ddwt, sdwt, and tsdwt—are dwell-times (i.e., stop durations) at different stages during the trip. odwt is the dwell-time at the origin of a trip, ddwt is the dwell-time at the destination of the trip, sdwt is the dwell-time at an intermediate stop (e.g., traffic stop) that is not the destination of the trip, and tsdwt is the sum of dwell-time at all intermediate stops during the trip.

For each truck ID, the algorithm begins with reading its first GPS record and initializing all the terms—td, trt, trs, tl, tpt, tps, odwt, ddwt, sdwt, and tswdt. Then, the algorithm reads the next record and computes average travel speed between the two records to verify if the truck is moving or if it is at rest. The subsequent parts of the algorithm are described below.

3.3.2.1 Determining Truck Stops and Moving Instances

An important component of the algorithm involved determining whether a truck was at a stop (i.e., rest) or in motion. As can be observed from the flowchart (Figure 3.1), the primary condition used to determine whether a truck was at a stop (which could be an origin, a destination, or simply an intermediate stop) or it was moving was based on the average travel speed between consecutive GPS data points. A cut-off speed of 5 mph was used; if the average travel speed between consecutive GPS records was less than 5 mph (i.e., if trs < 5 mph), then the truck was assumed to have stopped. As mentioned earlier, a portion of the data contained spot speeds (i.e., instantaneous speeds), and remainder of the data did not contain information on spot speeds. We used the data with spot speeds to test different cut-off values on the travel speed between two consecutive GPS data points. Besides, other recent studies that converted ATRI's truck GPS data into trips (Bernardin et al., 2011; Kuppam et al., 2014) also used a 5-mph cut-off to determine whether a truck is moving or if it is at rest.

For data with spot speeds, the average travel speed criterion (i.e., if trs < 5 mph) was used and was checked if the spot speed was zero. If one of these two criteria was satisfied, the truck was assumed to be at rest. It was important to check for small travel speeds between consecutive GPS data points (i.e., if trs < 5 mph), even in data with spot speeds. When the time gap between two consecutive GPS data points that are moving (i.e., spot speed > 0) was large enough, the only way to determine if the truck stopped between two points was by checking its travel speed between the two points. Limited tests on data with spot speeds suggested that it was sufficient to use the average travel speed criterion (i.e., without checking for spot speeds), increasing confidence in the quality of trips derived from the data without spot speeds.

An alternative approach to determine truck stops was to use a minimum distance criterion (i.e., assuming the truck to be at a stop if it did not move beyond a certain distance, i.e., distance cut-off value). However, since the time gap between consecutive GPS records varied considerably—ranging from a second to several hours—it was difficult to use a single distance cut-off for determining truck stops.

3.3.2.2 Separating Intermediate Stops from Trip Destinations

Checking for average travel speeds between consecutive GPS records helped in identifying if the truck was at rest or moving. However, truck being at rest did not necessarily indicate whether it was at a valid origin or destination or if it was at an intermediate stop. The intermediate stops could be due to a number of reasons, including stops at traffic signals and traffic congestion (these stops typically tend to be of a few minutes duration), stops at gas stations for refueling purposes, wayside stops for drivers' quick relaxation and other purposes such as restroom visits, and rest stops of long duration to comply with hours of service.

To identify and eliminate many such intermediate stops, once the algorithm detected a stop (i.e., trs < 5 mph or spot speed =0) for a trip in progress (i.e., tl > 0), it started accruing the stop dwell-time (sdwt) based on the time elapsed between successive GPS data points (sdwt = sdwt + trt). If the truck started moving again (i.e., if trs > 5 mph or spot speed > 0) before the stop dwell-time reached the minimum dwell-time buffer value, then the stop was considered an intermediate stop, and the algorithm proceeded to find another stop. On the other hand, if the stop dwell-time exceeded the minimum dwell-time buffer value, then the stop was considered a candidate for valid destination, and the stop dwell-time (sdwt) was considered as part of the destination dwell-time (ddwt), by updating ddwt as sdwt + trt. Subsequently, if the length of this trip (tl) was greater than 1 mile (if not it was considered an insignificant trip and not recorded), the trip was recorded, along with its origin, destination, start/end times, trip length, and the total time the truck stopped at all intermediate locations between origin and destination (tsdwt).[4] The destination dwell-time of the trip was then updated using subsequent GPS records (i.e., ddwt = ddwt + trt) until the truck started moving again (i.e., trs > 5 mph or spot speed > 0). Once the truck started moving (see the bottom left portion of the flowchart in Figure 3.1), the origin of a potential next trip was marked, and the algorithm proceeded to find the next truck stop, as can be observed from the looping of the bottom portion of the algorithm to the top portion (on the left side of Figure 3.1).

A major determinant of the quality of outputs from the above procedure depended on the dwell-time buffer (i.e., the minimum stop duration required for a truck stop to be called a destination). Some previous studies (Ma et al., 2011) considered stops of less than 3 minutes' duration as intermediate stops while other studies (Bernardin et al., 2011; Kuppam et al., 2014) considered stops of less than 5 minutes' duration as intermediate stops. In this study, however, based on discussions with ATRI and our own tests using Google Earth (i.e., by observing the land-uses of stops made by trucks and the duration of those stops), larger dwell-time buffers were used. This was because the focus of this research was to extract truck OD flows over long-haul distances of concern for Florida's statewide freight model. While most intermediate stops in urban areas tend to be of smaller duration (e.g., most traffic signal cycles tend to be of less than 3 minutes' duration), not all stops of larger duration tend to be for commodity pickups and/or deliveries. Intuition suggests that 5 minutes is not sufficient for picking up or delivering many types of goods. Besides, refueling stops, stops at weighing stations, and quick relaxation or restroom stops tend to be longer than 5 minutes. And, of course, truck stops for the purpose of complying with hours of service regulations tend to be of several hours duration.

[4] Most previous studies do not record the total stop dwell-time (tsdwt) — a useful attribute for truck trips, especially for understanding how the duration of intermediate stops varies with trip length and other relevant factors.

To arrive at an appropriate dwell-time buffer, we compared the trip outputs using different values of dwell-time buffer—5, 10, 15, 30, and 45 minutes and 1 hour—with the land-uses of the trip ends in Google Earth. Dwell-time buffers of short durations such as 5 minutes or 10 minutes were resulting in false identification of too many intermediate stops as truck origins and/or destinations, while dwell-time buffers of too long durations led to missing valid origins/destinations at pickup/delivery locations such as distribution centers. Further, using smaller dwell-time buffers was leading to a larger share of short-length trips (because a long trip between an origin and destination was broken down into several short trips). Besides, for low-frequency data where the consecutive GPS records have large time gaps, small dwell-time buffers cannot be relevant (for example, testing for a 5-minute dwell time would not give different results than testing for a 15-minute dwell-time buffer if the raw GPS records are spaced at 15-minute interval). After testing for different values of dwell-time buffers, we realized that no dwell-time buffer value was perfect, and a trade-off had to be made between minimizing false identification of unnecessary intermediate stops as trip ends, on one hand, and skipping of valid origins and destinations on the other. After extensive tests via following trucks on Google Earth, a 30-minute dwell-time buffer was used as a beginning point to separate intermediate stops from trip destinations.

The 30-minute dwell-time buffer helped in avoiding most intermediate stops, including traffic and congestion stops, wayside stops, gas refueling stops, and short stops at rest areas. But it would not help eliminate longer duration stops at rest areas, including those made to comply for hours-of-service regulations. Another issue was that the 30-minute dwell-time buffer led to skipping of some valid origins or destinations that involved smaller dwell-times. These two issues are addressed latter.

3.3.2.3 Dealing with Insignificant Trips

Trips that were too short in length were not recorded as independent trips. The minimum acceptable trip length was assumed to be one mile. Therefore, if a trip was of length less than one mile, it was discarded unless the trip occurred in the same area of the previous trip's destination. In this case, the insignificant trip's time was simply added to the previous trip's destination dwell time (see bottom right portion of the algorithm in Figure 3.1). For example, if the destination of a trip is large in size (such as a port), it might happen that the truck moves within the port for less than one mile, leading to insignificant trips. Such movement was not considered a new trip but, since the truck would still be at the same destination as the previous trip (port), it was incorporated into the previous trip's destination dwell time.

3.3.2.4 Quality Control Checks in the Algorithm

Figure 3.1 does not present all details of the algorithm to make it easier for readers to understand the main components of the algorithm and for ease in presentation. These details include the following quality checks embedded into the algorithm.

Dealing with large time gaps between consecutive GPS records: The ping rate in the data (i.e., the frequency at which GPS positions are recorded) varied considerably, ranging from a few seconds to several hours. Data with large time gaps between consecutive records could be due to many reasons, including loss of GPS signals (e.g., in tunnels and mountains) and malfunctioning of the GPS device. In such cases, the extracted trips tend to be of lower quality because it is difficult to use only the spatial and temporal movement information to ascertain what happened in the time gap. On the other hand, it is also possible that some GPS units (depending on the type of equipment) may not record truck positions for an extended time period simply because the truck engine is switched off. In such situations, the truck is simply not making any movements for an extended time period. Therefore, if the time gap between two consecutive records was greater than 2 hours and if the trip was in progress (i.e., the travel speed between the two records was greater than 5 mph), such a trip was discarded. However if the speed was less than 5 mph, then the truck was assumed to be at rest (i.e., not moving) for the entire time gap.

Trips spanning beyond the temporal limits of the study period: It is not necessary that the GPS records of a truck begin with a trip origin and end with a trip destination. For many trucks, the first several records indicated that the truck was in motion (because the trip started before the first available GPS record for the truck) and/or the last records belonged to a trip that ended after the last GPS record. Such incomplete trips found at the edges of study periods were discarded.

The above quality checks were implemented in the algorithm every time a GPS record was read and the travel distance (td), travel time (trt), and average travel speed (trs) were computed between consecutive records. In addition to the above quality controls embedded within the algorithm, quality checks were conducted on the trips output at the end of the procedure. Specifically, trip speeds, trip time, and distance were examined for manifestations of any anomalies such as GPS jumps and jiggles. GPS jumps happen when GPS records show unrealistically large movements within short durations, which manifest as trips with unrealistically large speeds. Such trips were eliminated based on average trip speeds and travel time. Specifically, only those trips within an average speed of 80 mph (between origin and destination) were retained. Further trips that were too short in time (i.e., trips of travel time less than a minute) also were removed.

3.3.3 Eliminate Trip Ends in Rest Areas

The above-described algorithm eliminates unwanted trip ends (such as traffic stops and refueling stops) to some extent. However, the algorithm does not eliminate unwanted trip ends in rest areas and other locations (e.g., wayside stops) with dwell times larger than the dwell-time buffer used in the algorithm. To address this issue, the trip ends derived from the above step were overlaid on a geographic file of rest stops provided by ATRI containing polygons of rest areas, commercial truck stops, weigh stations, wayside parking, etc., throughout the nation. All the trip ends falling in these polygons were eliminated by joining consecutive trips ending and beginning in those polygons.

Doing the above helped in eliminating a large number of unwanted trip ends in rest areas, wayside parking areas, and other such locations. However, further scrutiny suggested that a good portion of trip ends were still in rest areas and similar locations. This is because the data in the geographic file of rest stops provided by ATRI were not necessarily exhaustive of all rest areas and other such stops (not for pickup/delivery) in the nation. To eliminate the remaining trip ends in rest areas, the research team used information on the distance of each trip end from the nearest interstate highway. When a random sample of 200 rest areas from the shape file provided by ATRI were examined *vis-à-vis* their distance from the highway network, a vast majority of the rest areas were found in very close proximity to interstate highways (45% were within 800 feet distance of an interstate highway). Therefore, all trip ends within a buffer of 800 feet from interstate highways were treated as stops at rest areas or wayside parking areas. Any consecutive trips ending and beginning in the same location were joined to form a single trip.

The natural next question was how the 800-feet value was determined. We examined if treating all trip ends within a close proximity of interstate highways as rest stops helps in removing additional unwanted stops while not removing true origin or destination stops. To examine this, the movement of 40 trucks was traced for at least two weeks on Google Earth and observed the land-uses of their stop locations. For each of these 40 trucks, the number of valid trip ends noticed in Google Earth were recorded and then compared with the number of trips output from the algorithm after eliminating trip ends that were in the rest stops polygons of the shape file provided by ATRI and those that were within a given proximity of interstate highways. This was tested for different buffers around interstate highways—half mile, quarter mile (1320 feet), 1000 feet, 800 feet, and 500 feet. As expected, no single buffer was ideal; using a large buffer led to elimination of too many valid origins/destinations, and using a small buffer led to the presence of too many invalid origins/destinations such as rest areas or wayside parking areas. However, using 800 feet provided a good trade-off between losing valid origins/destinations and counting invalid origins/destinations.

3.3.4 Find Circular Trips and Split Them into Shorter Valid Trips

Recall from Section 3.3.2.2 that a 30-minute dwell-time buffer was used to separate intermediate stops from valid trip destinations. Among the other dwell-time buffers examined, the 30-minute buffer struck a good balance between removing intermediate stops (such as traffic signal stops, congestion stops, and refueling stops) and skipping valid destinations (of less than 30 minutes dwell time) en-route. However, it would be useful to recover such valid destinations of less than 30 minutes.

When the trip outputs from the algorithm with a 30-minute dwell-time buffer were examined, some trips had origins and destinations that were too close to each other, although the roadway network distance of those trips measured in the algorithm (using GPS data) was large. Some trips, for example, had their origin and destination in the same location, although the distance traveled by the truck on the roadway network was large. One reason for this was because the algorithm was skipping some valid destinations (of less than 30 minutes dwell time) en-route (and if the trucks were changing the travel direction after the skipped destinations).

One way to identify if a trip extracted from the algorithm had any valid destinations en-route that have been skipped was to check its circuity ratio, the ratio between the air distance between origin and destination and the roadway network distance between origin and destination. The value of the circuity ratio can range from 0 to 1. If a truck travels in a straight line between its origin and destination, its circuity ratio would be 1. However, most trips on the highway transportation network tend to travel more than the air distance between the origin and destination. At the same time, if the ratio is too small, there is a high chance that the truck stopped en-route at valid destinations, albeit for shorter durations than 30 minutes. Intuitively, it is unlikely that trucks detour significantly between the origin and destination only for the sake of traveling to intermediate rest stops. Figure 3.2 shows an example of such a trip whose origin and destination locations (marked by blue circles) are too close to each other, although the distance traveled by the truck on the network along the route shown in red in the figure is more than 100 miles. In this example, the truck stopped at three other locations between the origin and destination (marked by yellow circles) for less than 30 minutes. The land-uses of these stops, when examined on Google Earth, were all valid destinations such as warehouses and large grocery stores. When several other such examples were examined, it became more apparent that trips with a small circuity ratio had skipped en-route stops of duration smaller than 30 minutes, and most of these stops were valid destinations. After extensive testing, through tracing raw GPS data of trips with different circuity ratio values, a cut-off value of 0.7 was determined. All trips extracted from the algorithm with a circuity ratio less than 0.7 were considered to be circular trips with a high chance of a skipped valid destination en-route.

The circular trips were then separated for further processing. Specifically, the procedure went back to the raw GPS data of the trips with a circuity ratio less than 0.7 and re-applied the algorithm in Figure 3.1 with a smaller dwell-time buffer (15 minutes). This helped in splitting the circular trips into multiple potentially-valid trips. Specifically, each circular trip was broken into an appropriate number of shorter, non-circular trips by allowing smaller stop dwell-time buffers at the destinations. The trip outputs from this process were, again, checked for circuity. For any remaining trips with a circuity ratio of less than 0.7, the algorithm in Figure 3.1 was reapplied on the corresponding raw data, albeit with a smaller dwell-time buffer (5 minutes). In the example in Figure 3.2, this iterative process would result in four separate trips, each with a circuity ratio greater than 0.7, instead of a single trip with a small circuity ratio.

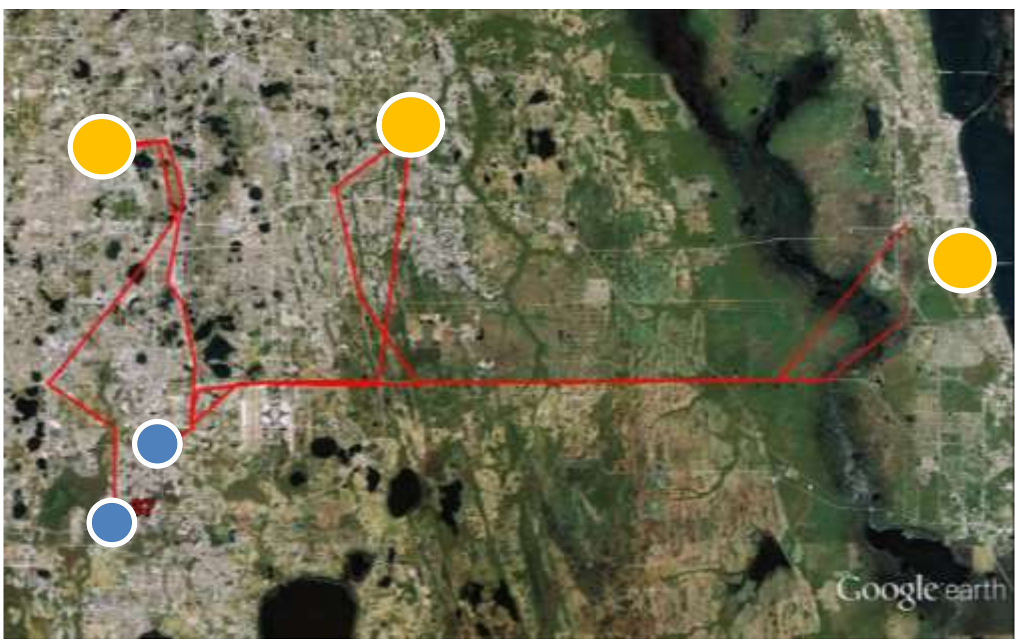


Figure 3.2 Example of a Circular Trip Extracted from the Algorithm with 30-Minute Dwell-time Buffer

An example of the results from this procedure is in order here. Applying the algorithm in Figure 3.1 with a dwell-time buffer of 30 minutes and the subsequent step (eliminating trip ends in rest areas and in close proximity of interstate highways) to one month of ATRI's GPS data (May 2010) resulted in a total of 252,000 trips. Of all these trips, 183,000 (72.6%) had circuity ratios greater than or equal to 0.7. After splitting the remaining 69,000 trips (with circuity ratio < 0.7) into smaller trips by reapplying the algorithm in Figure 3.1 with a minimum dwell-time buffer of 15 minutes, about 123,000 trips were extracted. About half of these trips had a circuity ratio of at least 0.7. For the other half, the algorithm in Figure 3.1 was repeated with a minimum dwell-time buffer value of 5 minutes. This resulted in more than 87,000 trips, of which 38,000 trips had a circuity ratio of at least 0.7. The remaining 49,000 trips, with a circuity ratio smaller than 0.7, were discarded. In all, the final number of trips extracted for the month of May 2010 was 183,000 + 62,000 + 38,000 = 283,000.

The above-described iterative procedure of checking for circuity and splitting circular trips into multiple valid trips using smaller dwell-time buffers helped in two ways: (a) it helped capture trips with valid destinations of short dwell times, and (b) it helped remove any remaining circular trips, some of which were likely to have resulted from joining consecutive trips within a close proximity of interstate highways, as described in the previous section.

3.4 Results

The above-discussed procedure was applied to four months of raw data (March–June 2010) comprising more than 145 million raw GPS records. This resulted in more than 2.7 million truck trips. Of these, more than 1.27 million trips had at least one end in Florida. Table 3.2 shows a summary of the raw data and the trips derived from the data. Summaries are provided for each month of the data, separately for data with spot speeds and data without spot speeds. The number of trips extracted, the number of unique truck IDs to which these trips belonged, and the average trip distance and trip speeds (without considering duration at rest stops) are presented for three different types of trips—(a) all trips including those outside Florida, (b) FL-link trips (trips with at least one end in Florida), and (c) FL-only trips (trips with both origin and destination in Florida).

Note from the table that the trips extracted from data without spot speeds were longer than those from data with spot speeds. For a certain type of data (e.g., for data with spot speeds), the average trip distances and trip speeds were similar across the four months. Besides, the average trip speeds appeared to be similar across different datasets and for different months. A detailed analysis of the characteristics of the trips extracted in this project is presented in the next chapter.

The trip outputs from the procedures discussed in this chapter were subject to a variety of quality checks, some of which are discussed here. The land uses of the OD locations of a random sample of 232 trips extracted from the algorithms were examined on Google Earth. More than 90 percent of the 464 trip ends were in locations that are highly likely to involve goods pickups/deliveries, such as distribution centers, manufacturing companies, industrial areas, ports, retail stores, shopping centers, and agricultural lands. Of the remaining locations, 24 were on highways (that are not interstate highways) without nearby freight-related land uses, 3 were in rest areas, and 9 were in gas stations. Most of the 24 trip ends on highways were truck stops of longer than 30 minutes. In future work, eliminating truck stops in close proximity to major highways (in addition to interstate highways) potentially can improve the results. For stops at gas stations, however, particularly those of greater than 30 minutes' duration, it is difficult to decipher if they are made for refueling purposes or for fuel delivery services. In addition to trip end locations, the accuracy of temporal attributes (i.e., trip start and end times) was assessed. The trip start times output from the algorithm were found to be accurate for more than 95 percent of the trips, and the trip end times were accurate for all trips. Overall, while scope exists for improving the algorithms in this chapter (e.g., by using detailed land-use information), the quality of trips extracted suffices for the purpose of estimating statewide TAZ-to-TAZ truck flows.

Table 3.2 Summary of Truck Trips Extracted from Four Months of ATRI's Truck GPS Data

		Data with Spot Speeds			Data without Spot Speeds			All Data		
		All Trips	FL-link Trips	FL-only Trips	All Trips	FL-link Trips	FL-only Trips	All Trips	FL-link Trips	FL-only Trips
March 2010	Number of GPS records	13,271,519			25,750,534			39,022,053		
	Number of trips extracted	284,092	145,245	119,602	449,074	195,298	128,178	733,166	340,543	247,780
	Number of unique truck IDs	7,406	6,594	4,815	47,523	39,277	25,979	54,929	45,871	30,794
	Average trip length (miles)	188	135	59	258	225	78	231	187	69
	Average trip time (minutes)	212	162	83	315	286	120	275	233	102
	Average trip speed (mph)	41	37	34	40	38	33	40	38	33
April 2010	Number of GPS records	12,920,919			22,818,557			35,739,476		
	Number of trips extracted	283,673	144,526	118,288	397,098	175,717	116,647	680,771	320,243	234,935
	Number of unique truck IDs	7,434	6,645	4,848	42,493	35,337	23,786	49,927	41,982	28,634
	Average trip length (miles)	185	135	58	255	223	78	226	183	68
	Average trip time (minutes)	209	162	82	311	283	119	268	228	100
	Average trip speed (mph)	41	37	34	40	38	33	40	38	34
May 2010	Number of GPS records	13,252,936			21,741,597			34,994,533		
	Number of trips extracted	283,017	145,946	119,359	360,734	159,992	104,148	643,751	305,938	223,507
	Number of unique truck IDs	7,327	6,527	4,676	36,888	30,046	19,287	44,215	36,573	23,963
	Average trip length (miles)	187	134	58	262	230	76	229	184	66
	Average trip time (minutes)	210	161	80	320	291	117	272	229	97
	Average trip speed (mph)	41	37	34	40	38	33	40	38	34
June 2010	Number of GPS records	13,740,038			21,511,076			35,251,114		
	Number of trips extracted	293,266	148,895	120,950	356,727	156,227	101,513	649,993	305,122	222,463
	Number of unique truck IDs	7,525	6,736	4,882	36,438	29,731	19,113	43,963	36,467	23,995
	Average trip length (miles)	186	135	57	257	225	77	225	181	66
	Average trip time (minutes)	210	161	80	316	287	118	268	226	97
	Average trip speed (mph)	41	38	34	40	38	33	40	38	34
All Four Months	Number of GPS records	53,185,412			91,821,764			145,007,176		
	Number of trips extracted	1,144,048	584,612	478,199	1,563,633	687,234	450,486	2,707,681	1,271,846	928,685
	Number of unique truck IDs	13,087	11,728	8,416	156,627	128,275	83,443	169,714	140,003	91,859
	Average trip length (miles)	186	135	58	258	226	77	227	184	67
	Average trip time (minutes)	210	162	81	315	287	119	271	229	99
	Average trip speed (mph)	41	37	34	40	38	33	40	38	33

CHAPTER 4 : CHARACTERISTICS OF TRUCK TRIPS DERIVED FROM ATRI DATA

4.1 Introduction

This chapter presents an analysis of the truck trip data derived from the four months of ATRI's truck GPS data described earlier. The truck travel characteristics analyzed included trip duration, trip length, trip speed, time-of-day profiles, and origin-destination flows. Each of these characteristics was derived at a statewide level and for different regions in the state—Jacksonville, Tampa Bay, Orlando, Miami, and rest of Florida—defined based on the freight analysis framework (FAF) zoning system. Several of these characteristics are provided in Appendix B. Furthermore, the chapter presents an analysis of Origin-to-Destination (OD) travel distances, travel times, and travel routes between a selected set of TAZ-to-TAZ OD pairs. Appendix C augments this chapter by providing route choice and travel time distributions derived from the data for 10 different OD pairs.

4.2 Trip Length, Trip Time, Trip Speed, and Time-of-Day Distributions

Figure 4.1 shows the trip length distribution of more than 2.7 million trips derived from the data. As can be observed, a considerable proportion of the trips are within 50 miles' length. Figure 4.2 shows the trip duration distribution of these trips. Two types of trip durations are reported: (1) total trip time and (2) trip time in motion. Total trip time is the time between trip start and trip end, including the time spent at rest stops. Trip time in motion excludes the time spent at rest stops and other long-duration stops. Note that trip time in motion includes time at smaller duration (< 5 minutes) stops such as traffic stops to reflect congestion effects. Figure 4.3 shows the trip speed distribution considering the two types of trip times discussed above. Specifically, the average trip speed considers all stops between trip start and trip end, and trip speed in motion excludes stops of longer duration (e.g., rest stops) but considers stops of smaller duration.

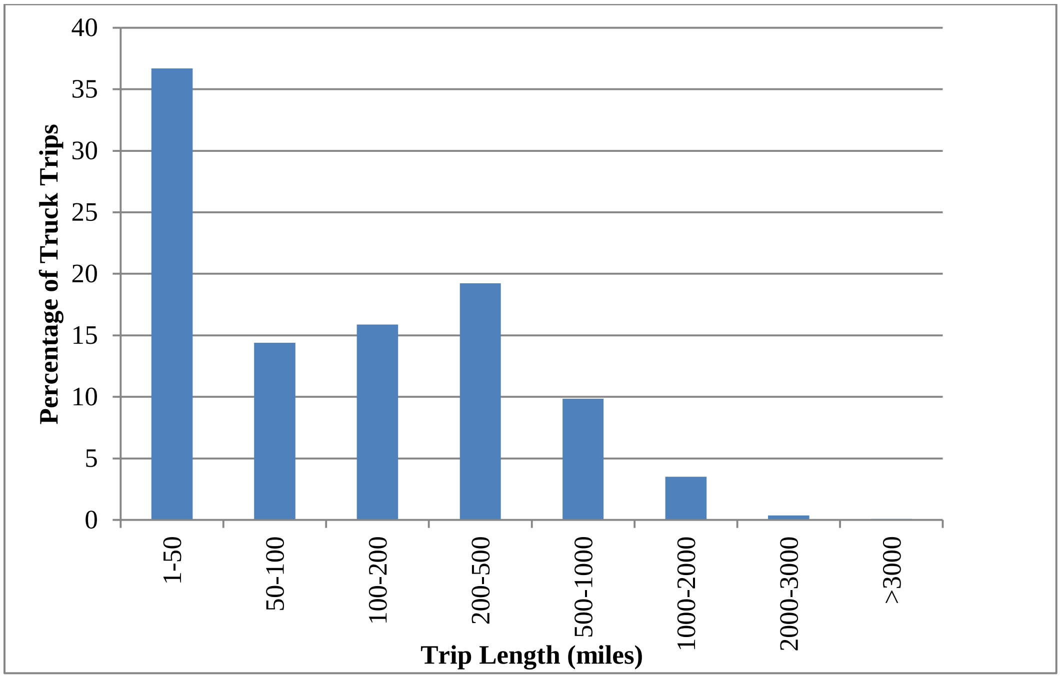


Figure 4.1 Trip Length Distribution of All Trips Derived from Four Months of ATRI Data

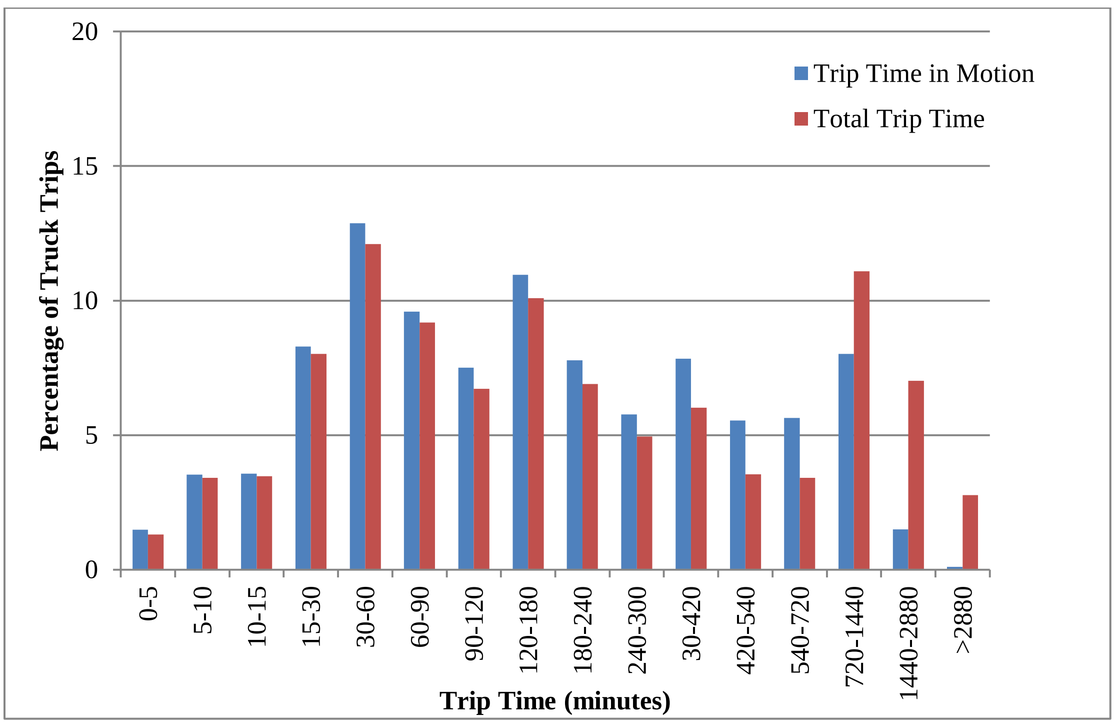


Figure 4.2 Trip Time Distribution of All Trips Derived from Four Months of ATRI Data

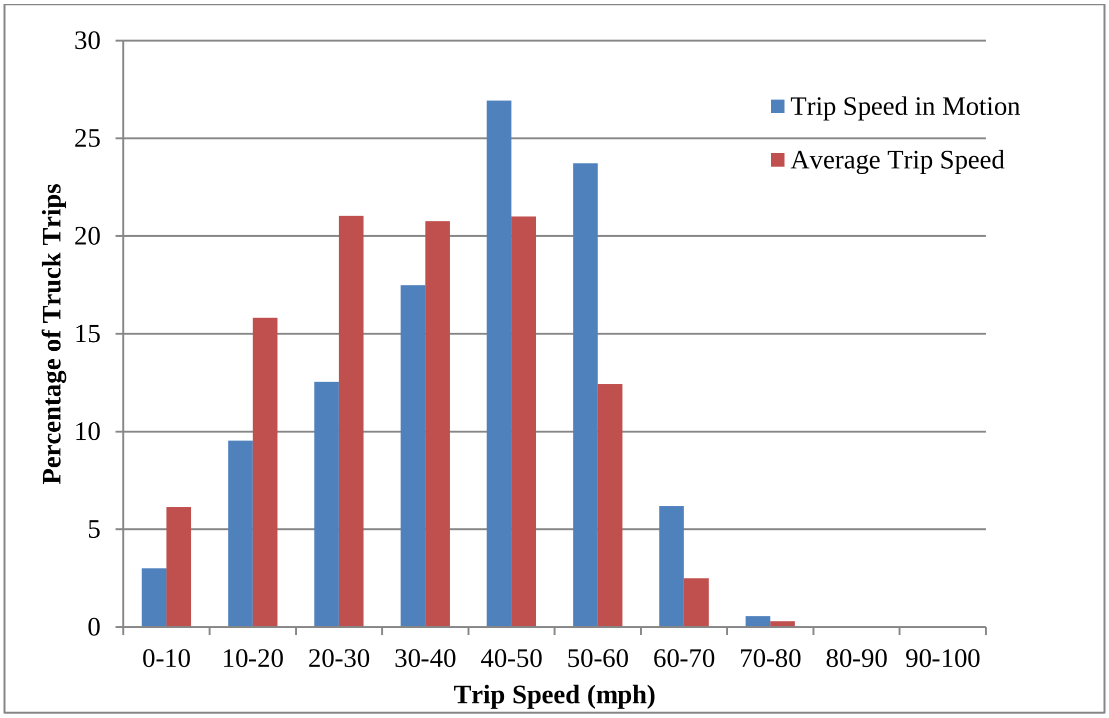


Figure 4.3 Trip Speed Distribution of All Trips Derived from Four Months of ATRI Data

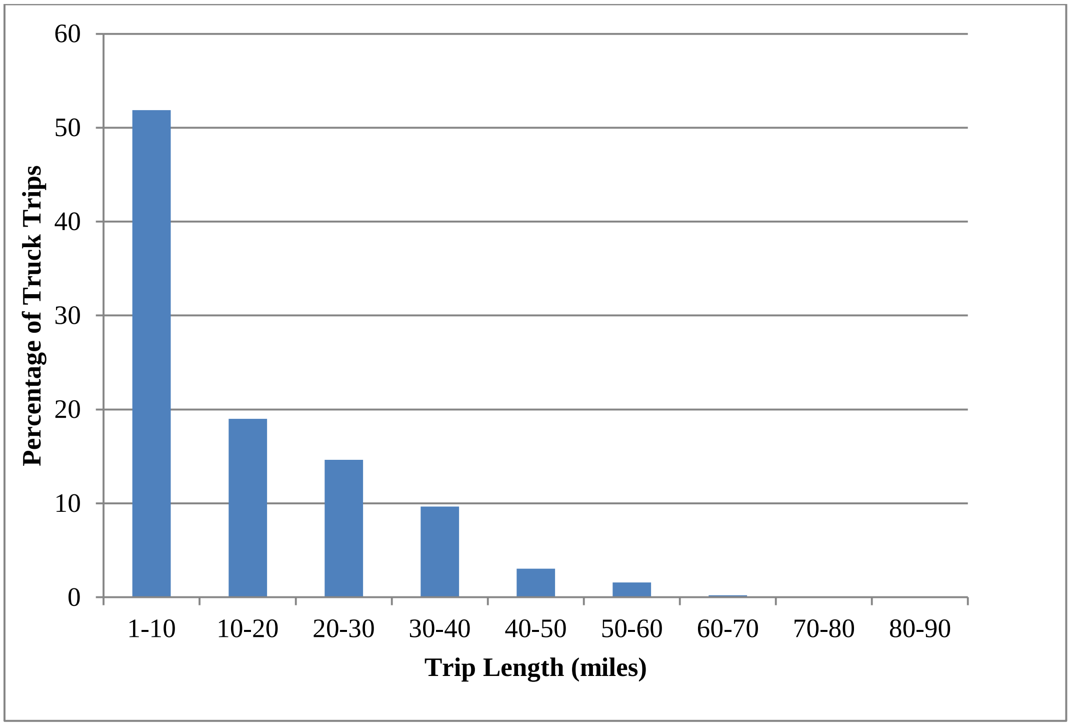
Appendix B provides the distributions of trip length, duration, speed, and time-of-day[5] profiles for different segments of the 2.7 million trips discussed above. The different segments include trips starting and ending in different FAF zones in Florida—Jacksonville FAF zone, Tampa FAF zone, Orlando FAF zone, and Miami FAF zone. Following are the specific counties in each of these FAF zones:

- Jacksonville FAF zone: Baker, Clay, Duval, Nassau, St. Johns
- Miami FAF zone: Broward, Miami-Dade, Palm Beach
- Orlando FAF zone: Flagler, Lake, Orange, Sumter, Osceola, Seminole, Volusia
- Tampa FAF zone: Hernando, Hillsborough, Pasco, Pinellas

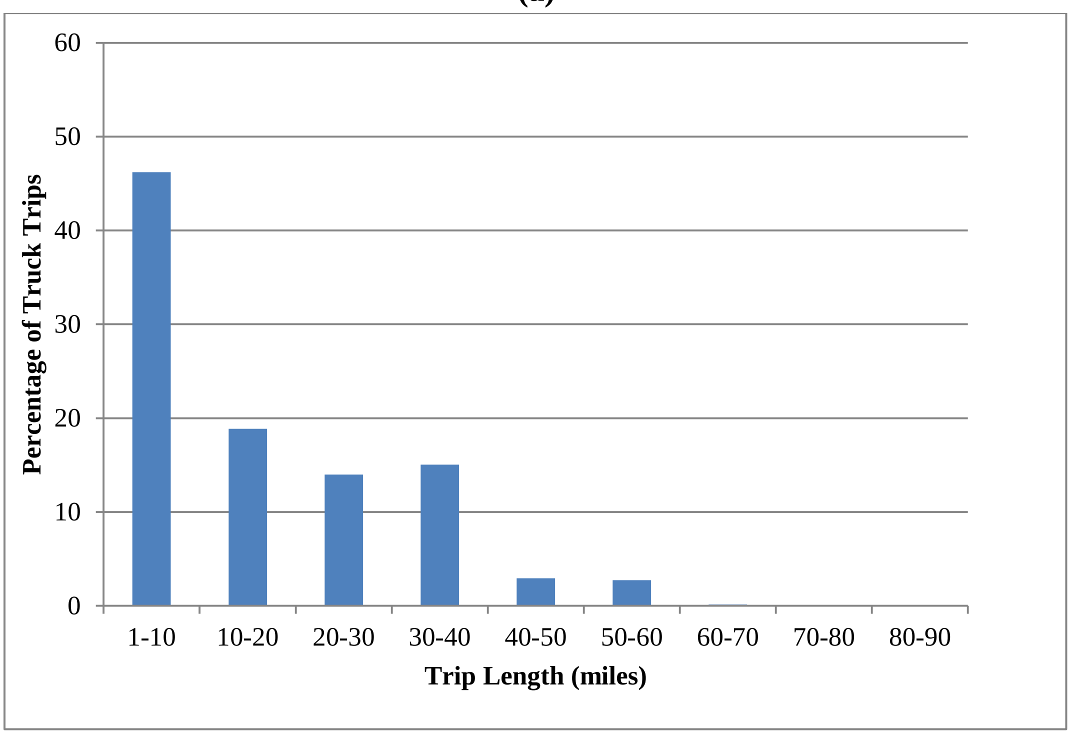
The distributions are provided separately for weekday and weekend trips. Such distributions potentially can be used for modeling heavy truck trip characteristics within the major regional models in the state. In addition to the above distributions, for each urbanized county in each of these FAF zones, the top 10 origins and destinations are provided at the state-level and the county-level geography. As an example, the truck trip characteristics for the Tampa FAF zone are provided in Figures 4.4 through 4.9, and those for other FAF zones are provided in Appendix B. It is interesting to note that the time-of-day profiles for all the four FAF zones in Florida showed a single peak during the late morning period as opposed to a bi-modal peak typically observed for passenger travel for morning and evening peak periods.

[5] Note: Time-of-day of a trip is determined based on the hour in which the midpoint of the trip falls.

The appendix provides truck trip characteristics for the following trip segments as well: (a) trips that start and end in Florida (Internal–Internal trips for Florida), (b) trips that start in Florida but end outside Florida (Internal–External trips), and (c) trips that start outside Florida and end in Florida (External–Internal trips). As an illustration, Figures 4.10 and 4.11 show the top 10 destination states for trips starting from Florida and the top 10 origin states for trips ending in Florida, respectively.

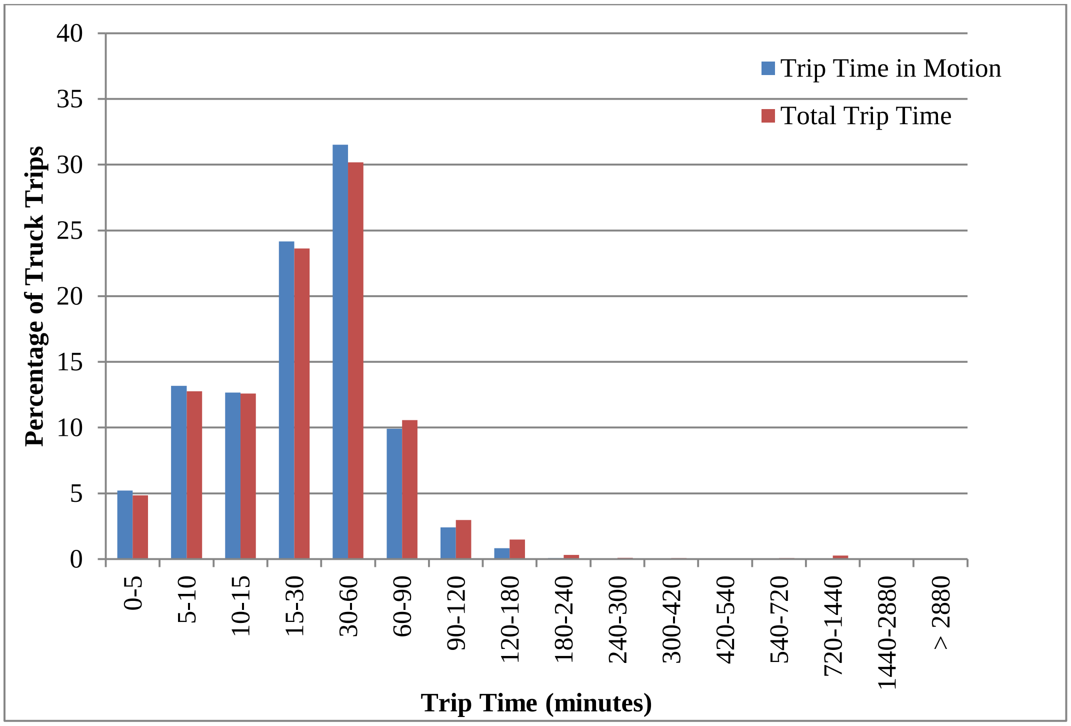


(a)

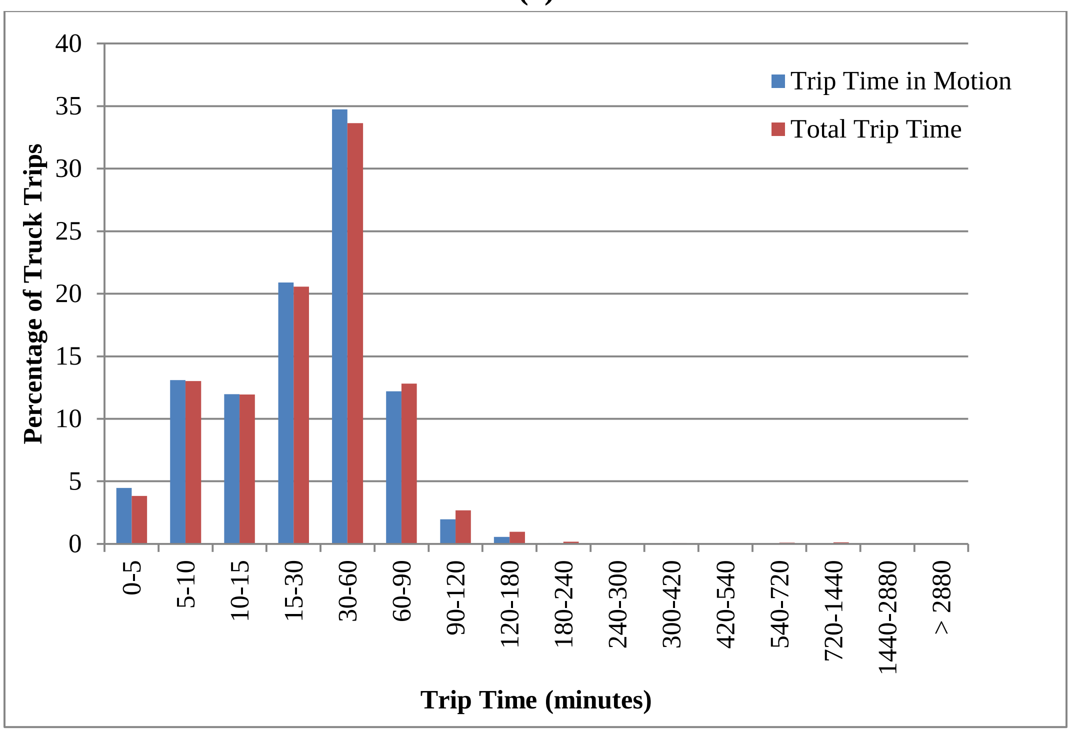


(b)

Figure 4.4 Trip Length Distribution of Trips Starting and Ending in Tampa FAF Zone during (a) Weekdays (61,465 trips), and (b) Weekend (7,780 trips)

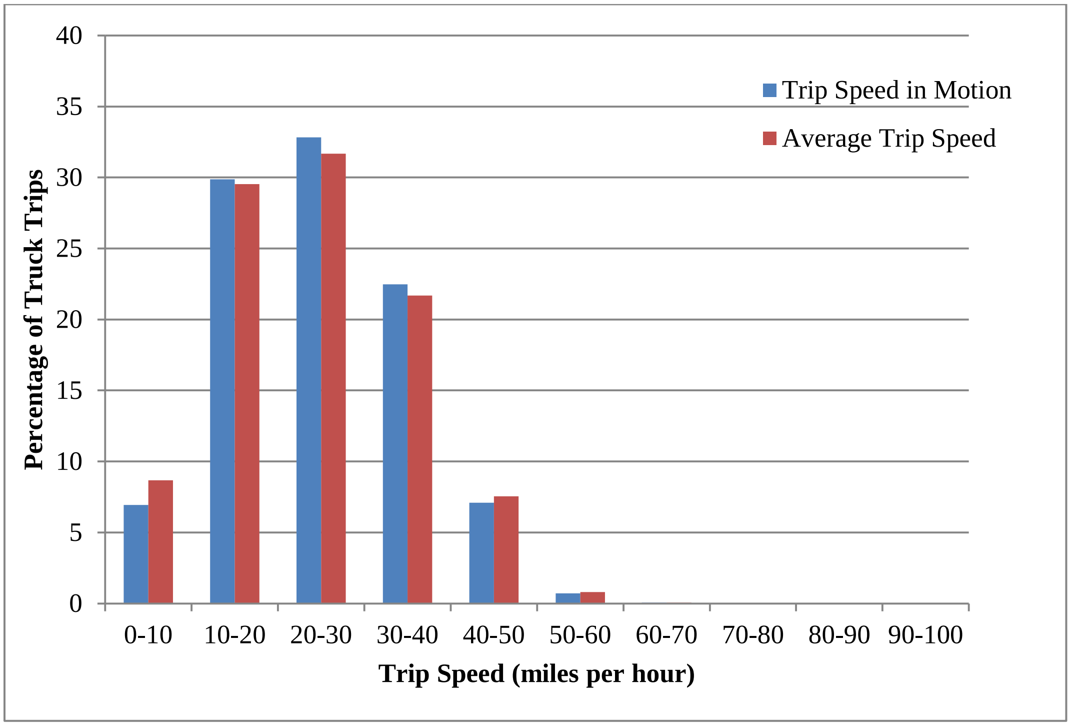


(a)

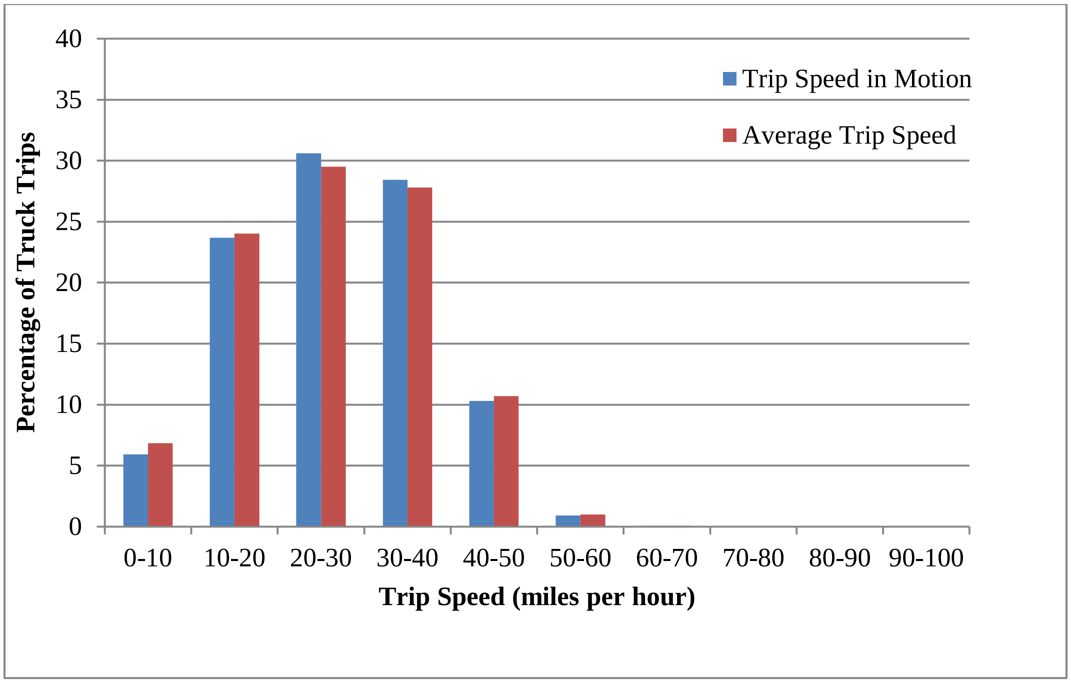


(b)

Figure 4.5 Trip Time Distribution of Trips Starting and Ending in Tampa FAF Zone during (a) Weekdays (61,465 trips), and (b) Weekend (7,780 trips)

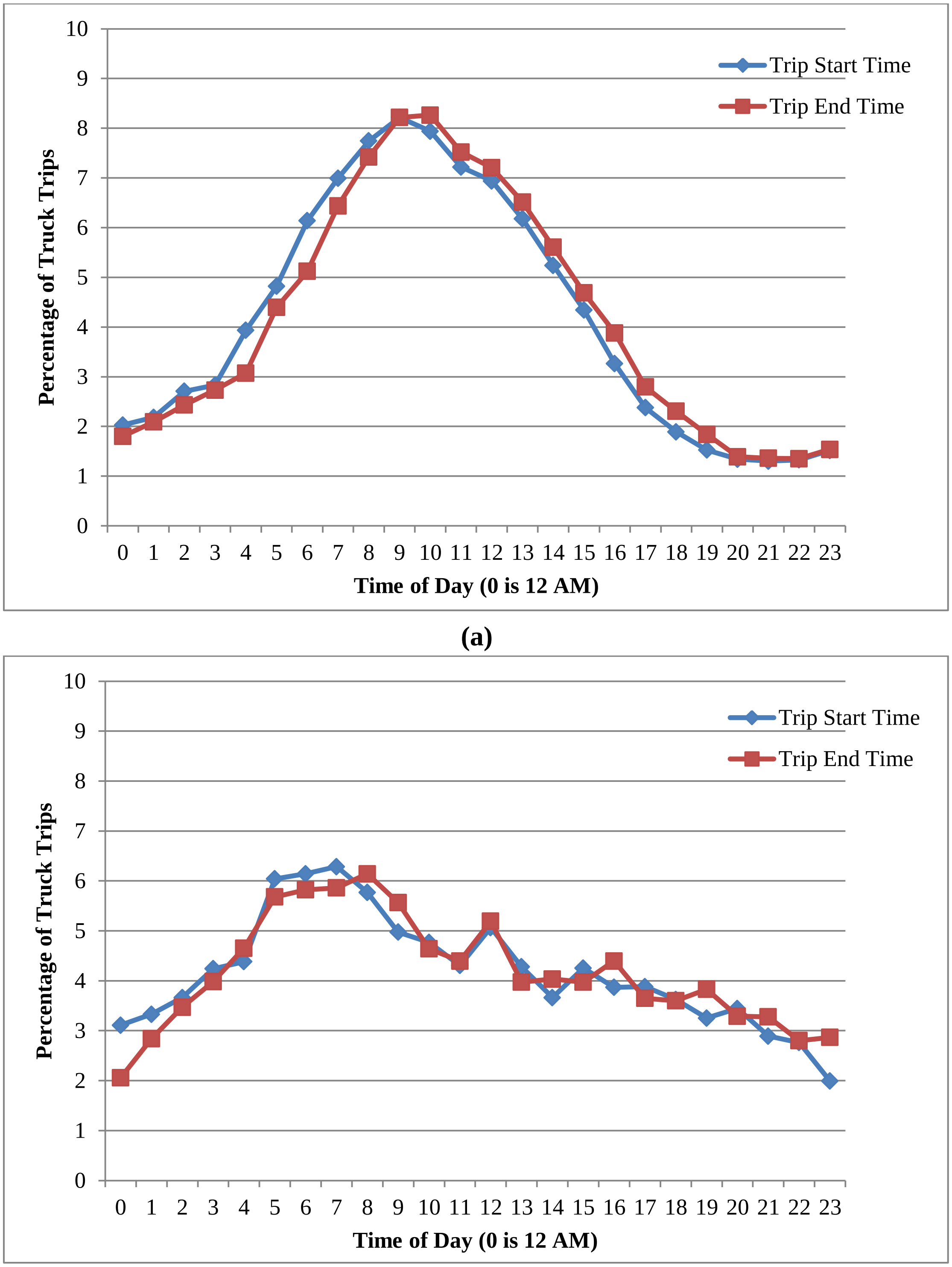


(a)



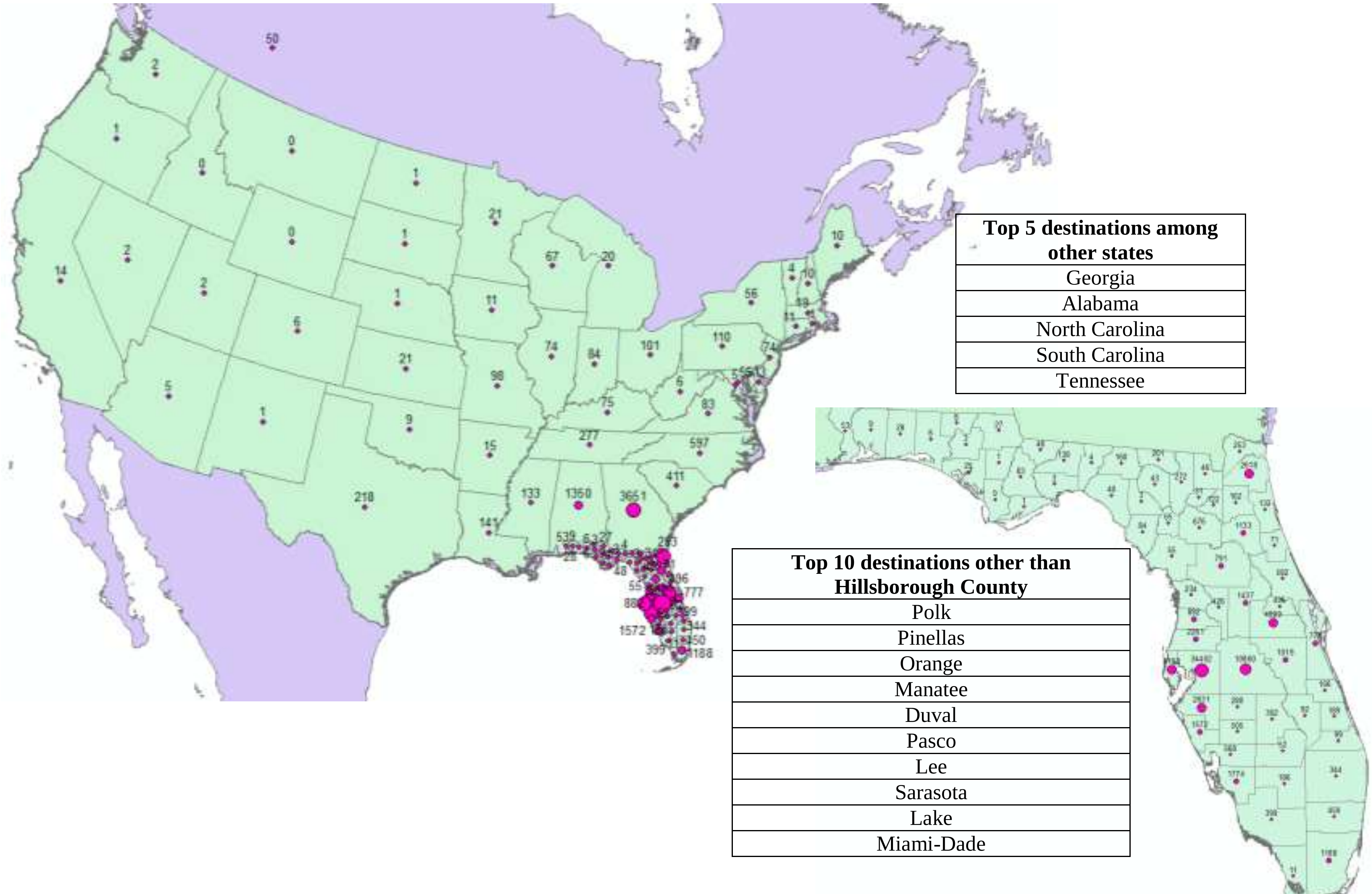
(b)

Figure 4.6 Trip Speed Distribution of Trips Starting and Ending in Tampa FAF Zone during (a) Weekdays (61,465 trips), and (b) Weekend (7,780 trips)



(b)

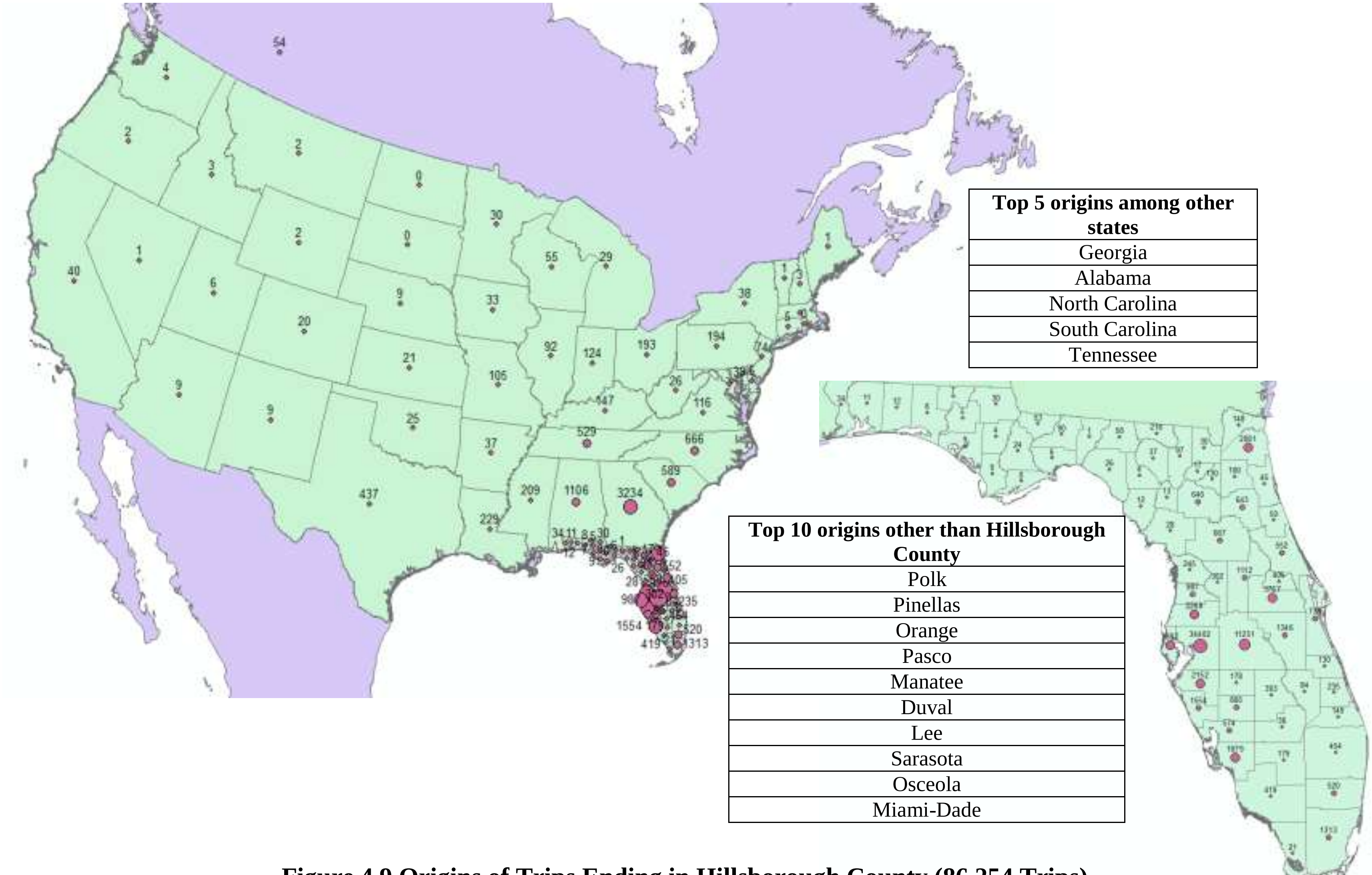
Figure 4.7 Time-of-Day Profile of Trips Starting and Ending in Tampa FAF Zone during (a) Weekdays (61,465 trips), and (b) Weekend (7,780 trips)



Top 5 destinations among other states
Georgia
Alabama
North Carolina
South Carolina
Tennessee

Top 10 destinations other than Hillsborough County
Polk
Pinellas
Orange
Manatee
Duval
Pasco
Lee
Sarasota
Lake
Miami-Dade

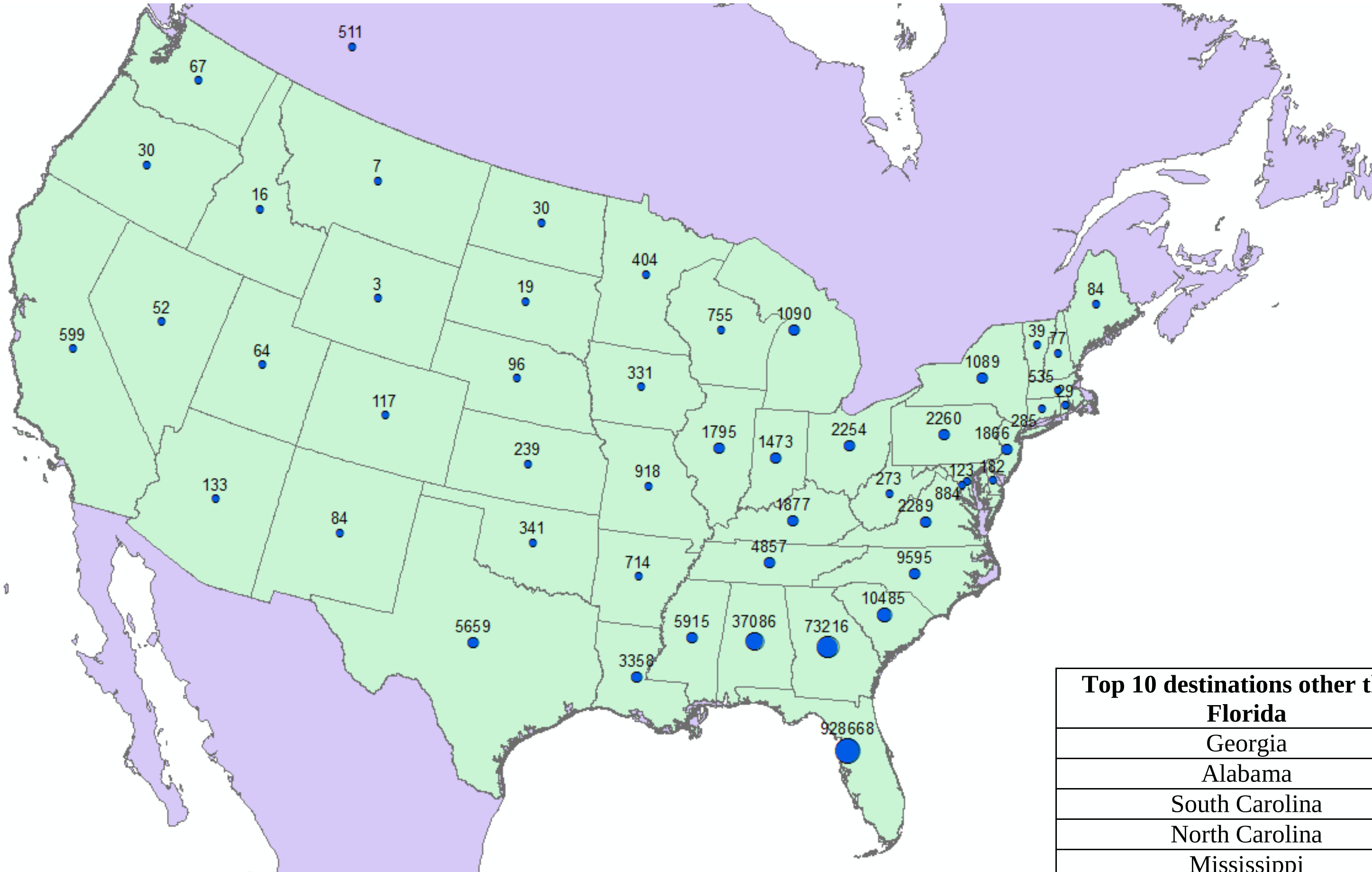
Figure 4.8 Destinations of Trips Starting in Hillsborough County (87,701 Trips)



Top 5 origins among other states
Georgia
Alabama
North Carolina
South Carolina
Tennessee

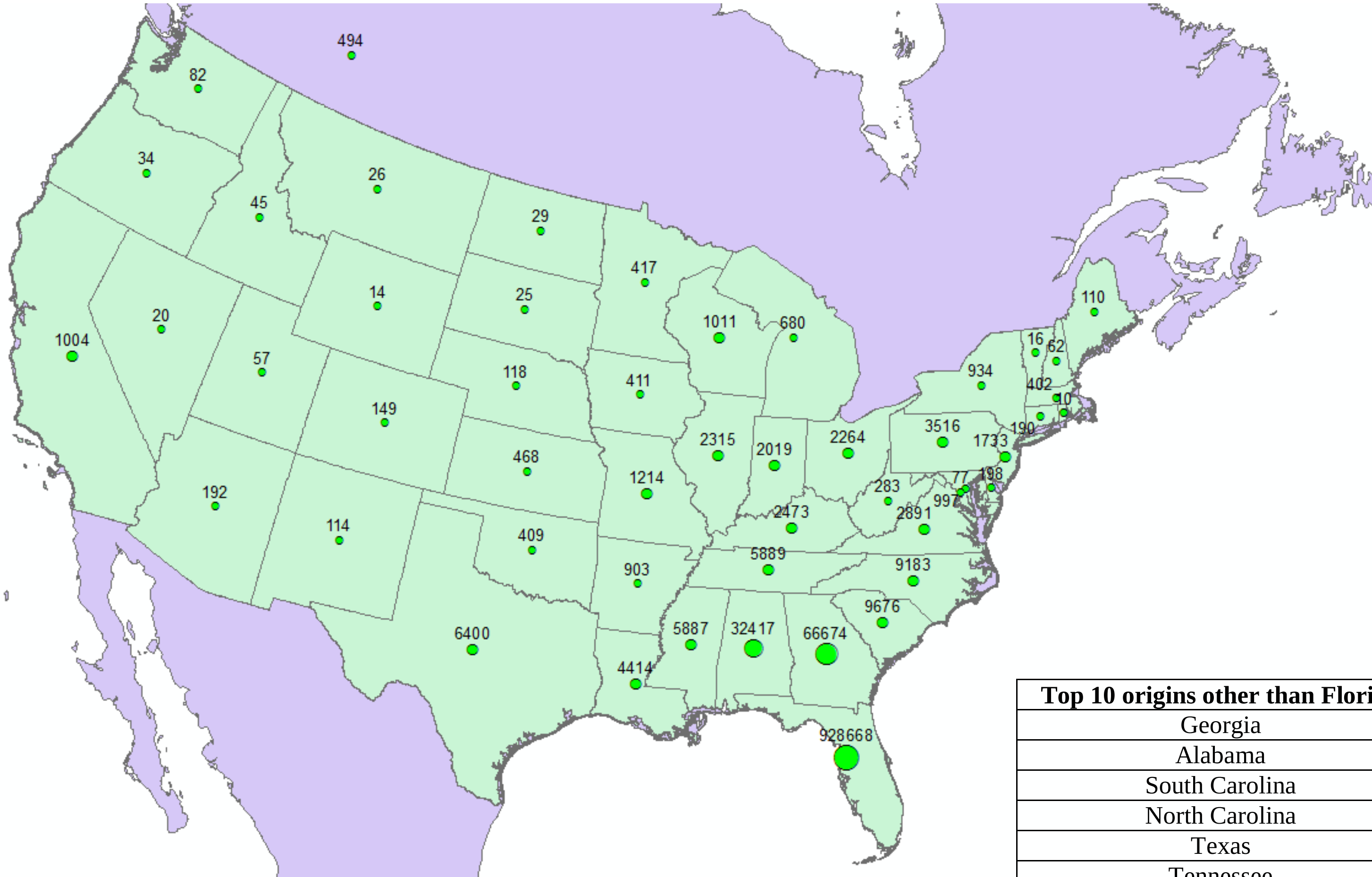
Top 10 origins other than Hillsborough County
Polk
Pinellas
Orange
Pasco
Manatee
Duval
Lee
Sarasota
Osceola
Miami-Dade

Figure 4.9 Origins of Trips Ending in Hillsborough County (86,254 Trips)



Top 10 destinations other than Florida
Georgia
Alabama
South Carolina
North Carolina
Mississippi
Texas
Tennessee
Louisiana
Virginia
Pennsylvania

Figure 4.10 Destinations of Trips Starting in Florida (1,102,873 Trips)



Top 10 origins other than Florida
Georgia
Alabama
South Carolina
North Carolina
Texas
Tennessee
Mississippi
Louisiana
Pennsylvania
Virginia

Figure 4.11 Origins of Trips Ending in Florida (1,097,614 Trips)

4.3 Origin-Destination Truck Travel Time and Route Measurements

One of the tasks in the project involved the exploration of the use of ATRI's truck GPS data to generate information on truck travel time and routes between several locations (i.e., origin-destination pairs) in the state. Such information can be used in future studies to analyze the route choice behavior of trucks, to inform truckers of the time that can be expected to travel between given OD pairs, and, potentially, to derive travel time reliability measures. In addition, truck travel time skims between OD pairs can be generated for use in the Florida Statewide Model (FLSWM).

The travel time skims currently used for the FLSWM are based on free-flow speeds. It will be useful to update these travel time skims using the GPS data, because the GPS data potentially can provide a better estimate of travel times. However, it is a cumbersome task to estimate the travel times for each (and every) OD pair in the FLSWM. Given there are about 6,000 zones in the FLSWM, it would be 6000 × 6000 OD pairs (i.e., 36 million OD pairs). Thus, it is not feasible to estimate travel times separately for each OD pair using GPS data. It is feasible to measure the travel times for a smaller number of OD pairs. The estimated travel times have been compared with the travel time skims currently used in the FLSWM and with the travel times reported in Google Maps. Based on these comparisons, an assessment was made on the currently used travel time skims in the FLSWM along with recommendations for future work on estimating travel time skims for the FLSWM.

4.3.1 Factors Influencing Travel Distance and Travel Time Measurements from ATRI's GPS Data

A variety of factors influence measurement of travel distance and travel time measurements from GPS data. These are discussed below.

<u>Route Choice</u>: Between any given OD pair with several truck trips extracted from the ATRI data, it was observed that not all trips took the same route. Differences in the paths taken by the trucks lead to differences in travel distances and travel times across different trips between the same OD pair.

<u>Ping rate of GPS data</u>: Ping rate is the time gap between two consecutive GPS records. The simplest method to measure OD travel distances using GPS data was by adding up distances between every two consecutive GPS records, starting from the first GPS record at the origin and ending with the last GPS record at the destination.[6] The accuracy of the OD travel distances measured using this method depends on how closely located are the consecutive GPS records (or the ping rate of the GPS data). For GPS data with larger ping rates, the travel distance was underestimated, since the air-field distance between consecutive GPS records was smaller than or equal to the network distance. In ATRI's truck GPS data, the data without spot speeds had much higher ping rates (i.e., larger gap between consecutive GPS data points) than the data with spot speeds. Therefore, only the data with spot speeds were used for measuring travel distances and travel times and for deriving travel routes. Figure 4.12 shows the distribution of ping rates from one week of ATRI data with spot speeds and without spot speeds (one distribution for each type

[6] Better methods involve map-matching of the GPS coordinates to the roadway network and then measuring the distance along the network.

of data). Within the data with spot speeds, only those trips with a maximum of 15 minute ping rate were selected.

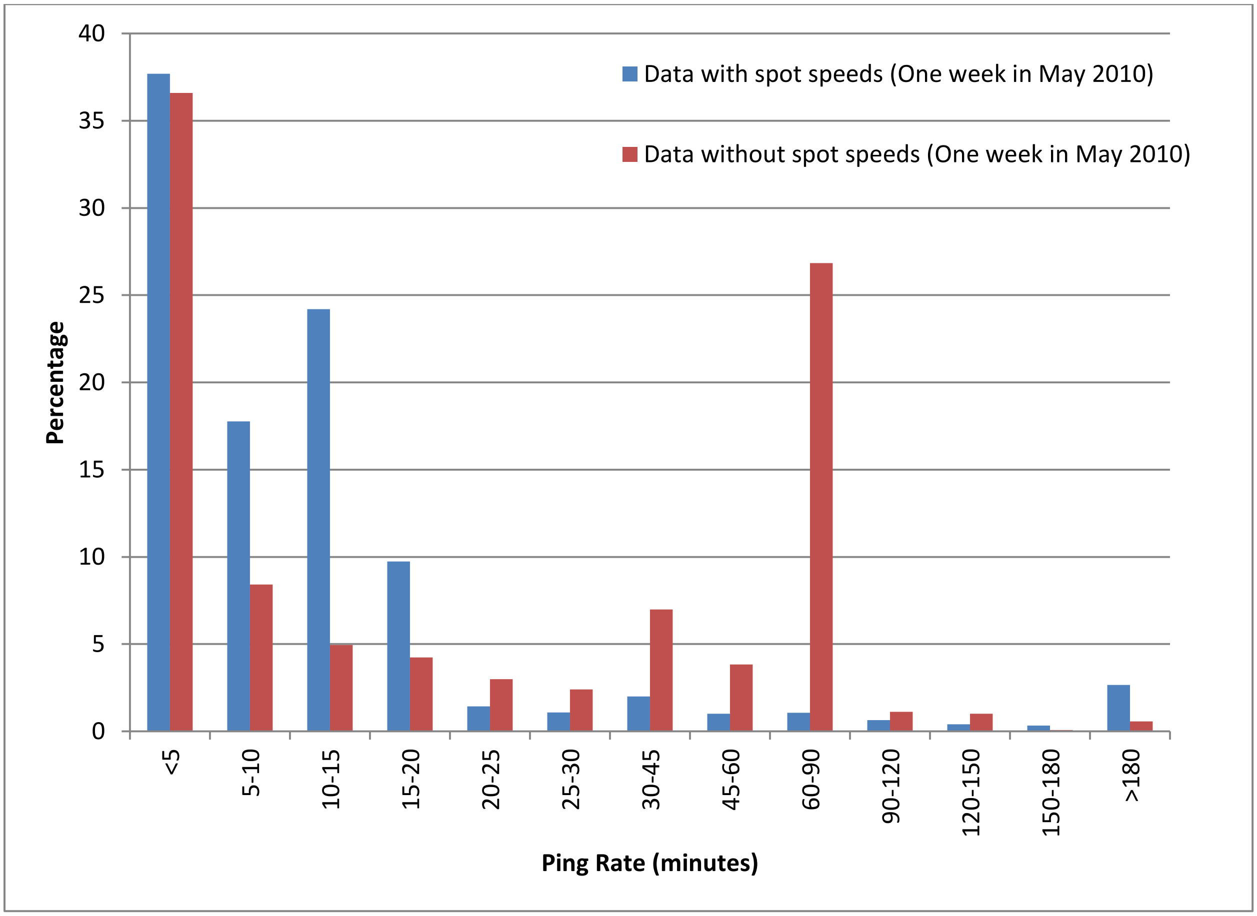


Figure 4.12 Distribution of Ping Rates from One Week of ATRI Data with and without Spot Speeds (May 2010)

TAZ size: The size of TAZ at the origin and/or destination ends of the trip did not actually influence the travel time measured from the GPS data, because the GPS data provided more spatially detailed information (i.e., longitude and latitude) on trip ends. However, when comparing the distances measured from the ATRI data with those from the distance measurements in FLSWM, the TAZ size influenced the distance measured in FLSWM. This is because in FLSWM the TAZ-to-TAZ distance is measured based on centroid-to-centroid distance. In GPS data, not all trips end at the centroid. Therefore, depending on where the trips end in a TAZ, the differences between the trip distances and times measured in GPS data to those from the FLSWM may vary considerably. To minimize this variation, OD pairs that have at least one end in Florida were selected (because the TAZs outside Florida are larger in size than those inside Florida).

Time of day: Due to temporal variation of traffic congestion, the time-of-day during which a trip is taken influences the travel time of the trip. In this study, the following time periods were defined based on the midpoint of the trips:

- AM peak trips: trips with their midpoints between 6 a.m. and 9 a.m. (Florida time),
- Mid-day trips: trips with their midpoints between 9 a.m. and 4 p.m. (Florida time),
- PM peak trips: trips with their midpoints between 4 p.m. and 7 p.m. (Florida time), and
- Night-time trips: trips with their midpoints between 7 p.m. and 6 a.m. (Florida time).

Number of trips (extracted from GPS data) between OD pairs: For constructing statistically-representative distributions of travel time between OD pairs, and for capturing the variance in route choices and congestion effects, OD pairs with at least 20 trips extracted from the ATRI data were selected for further analysis.

Table 4.1 shows the distribution of different OD pairs in FLSWM by the number of trips extracted (from four months of ATRI data). A total of 327,326 OD pairs had at least one trip extracted from the entire four months of ATRI data—with spot speeds and without spot speeds. After eliminating the OD pairs with only trips from data without spot speeds, 126,138 OD pairs had at least one trip extracted from data with spot speeds. Subsequently, eliminating OD pairs with both ends outside Florida resulted in 75,089 OD pairs with at least one trip from data with spot speeds (with at least one end in Florida). From these OD pairs, only 1,237 OD pairs with at least 20 trips in the data were selected (shown in grey-shaded cells in the table). More than 60,000 trips were extracted from the data with spot speeds between these 1,237 OD pairs, with at least one end in Florida and with at least 20 trips. For these trips, we were confident about the measurement of travel distances and travel times and the extracted travel routes.

Table 4.1 Distribution of OD Pairs Based on Number of Trips Extracted from ATRI Data

Number of Trips from ATRI Data	# OD Pairs Based on All Trips from ATRI Data with & without Spot Speeds	# OD Pairs Based on Trips from ATRI Data with Spot Speeds	All Trips from ATRI Data with Spot Speeds with at Least One End in Florida
1–5	286,579	110,269	68,128
5–10	18,059	7,297	3,864
10–20	11,166	4,543	1,860
20–30	4,026	1,512	495
30–40	2,143	764	243
40–50	1,219	412	132
>=50	4,134	1,341	367
Total	327,326	126,138	75,089

4.3.2 Truck Travel Distance, Travel Time, and Travel Route Measurements for 1,237 OD pairs

For the 1,237 OD pairs discussed above, the distributions of truck travel distance and travel times were derived and summarized in an Excel file. The file consists of the following information for each OD pair:

- Origin and destination locations (FLSWM TAZ numbers, county, and state),
- OD travel distance and free-flow travel time used as input to FLSWM, and
- Distributions of OD travel distance, travel time in motion (i.e., travel time excluding large duration stops at rest stops etc.), and corresponding travel speeds derived from the ATRI data, expressed as minimum, average, and maximum values, along with 5th, 10th, 15th, 50th and 85th percentile values.

In addition to travel distance and travel route measurements, the travel routes for a large number of trips between these OD pairs were derived in the form of on-route network links between the origin and destination TAZs. Specifically, the travel route information was extracted for 36,703 trips between 725 OD pairs within Florida. For each of these trips, the travel route is provided in the following fashion:

- Origin TAZ,
- Destination TAZ, and
- Several GPS coordinates that fall on-route between the origin TAZ and the destination TAZ, with each GPS coordinate representing the centroid of a network link on-route between the origin TAZ and the destination TAZ[7]

The travel routes, travel distances, and travel times were examined in more detail for a sample of 10 OD pairs. The 10 OD pairs were selected strategically to include a randomly selected sample of 2 OD pairs in each of the following five travel distance bands: within 100 miles, 100 to 200 miles, 200-500 miles, 500-1000 miles, and above 1000 miles. For each of these OD pairs, the route choice of all trips extracted from the data are depicted as on-route GPS coordinates in Appendix C. Specifically, Figures C.1 through C.10 show maps with the route choices, one figure for each OD pair. For illustration, the travel routes for 365 truck trips extracted from the ATRI data between a sample OD pair are presented in Figure 4.13, in the form of on-route GPS points between the origin and destination TAZs.

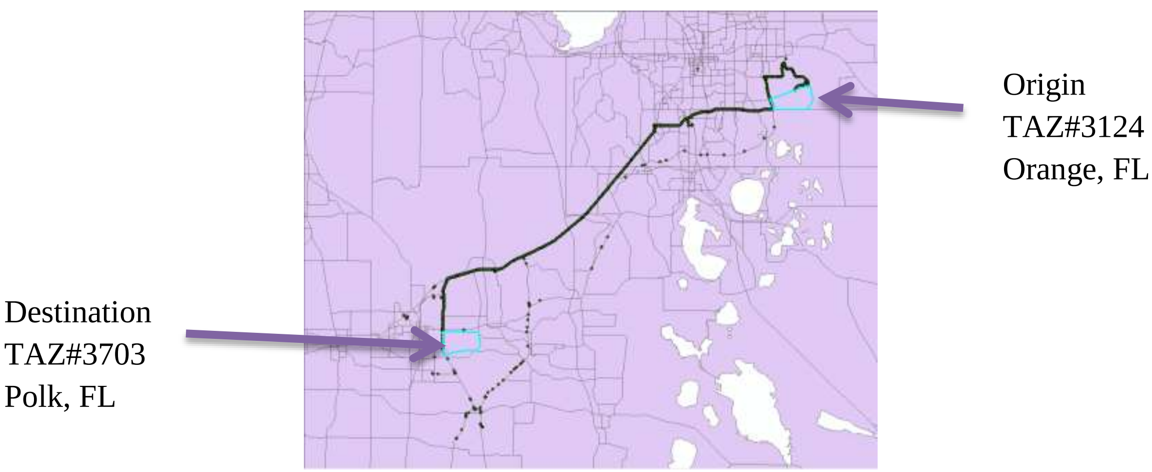


Figure 4.13 Route Choice for 365 Trips between a Sample OD Pair (3124-3703)

[7] The FLSWM network was used for this purpose. Specifically, for each trip, each on-route GPS coordinate of the trip was replaced by another GPS coordinate representing the centroid of the nearest network link.

One can observe from Figure 4.13 and other figures in Appendix C that a large proportion (if not all) of trips between an OD pair tend to travel by largely similar routes. Even if the trips may not travel by the exact same route, considerable overlap can be observed among the routes across a large number of trips between an OD pair. Upon further examination of truck travel routes for a few randomly-sampled OD pairs (not shown in figures), it can be seen that truck travel routes tend to exhibit higher variability for travel over shorter distances within urban areas than for travel over longer distances. These observations have interesting implications for future research on understanding and modeling truck route choice. While this study did not delve further into understanding the route choice patterns of long-haul trucks, this is an important area for future research using the truck GPS data from ATRI.

For the same set of 10 OD pairs, the distributions of travel times (i.e., travel time in motion including stops of smaller duration such as traffic stops and fueling stops but excluding significant stops such as rest stops) and travel distances measured from ATRI's truck GPS data are shown in Table 4.2 along with the travel times and travel distances used as inputs for the FLSWM and those measured in Google Maps. The measurement of travel distances and travel times on Google Maps for each OD pair was done for the same route taken by the shortest trip extracted from ATRI's GPS data for that same OD pair. Several observations can be made from the table, as discussed below.[8]

First, the travel distances (for the shortest trips) measured from the ATRI data were smaller than those in the FLSWM and Google Maps. This was likely because the travel distances computed from the GPS data were straight line approximations (and therefore, underestimations) of the distances between consecutive GPS points. However, such underestimation of network distances using the GPS data was smaller for shorter length trips. The reader will note that underestimating distances should not influence the measurement of travel times using GPS data. While the distance between consecutive GPS points was approximated (and thereby underestimated) as a straight line distance, the time between consecutive GPS points was simply the time gap between the consecutive time stamps (which depends on the actual route taken to travel between the two coordinates).

[8] To augment this table, Appendix C provides histograms of OD travel time distributions for the same 10 OD pairs. Specifically, the distributions for three different types of travel times are provided: (1) total travel time, which measures the time between trip start and tripe end including the time spent at all intermediate stops such as rest stops, traffic congestion stops, and fueling stops; (2) travel time in motion ,including non-significant stops, which measures the travel time excluding significant stops such as rest stops but includes non-significant stops, such as traffic congestion stops and fueling stops; and (3) travel time in motion excluding non-significant stops, which excludes the time spent at all intermediate stops including rest stops, traffic congestion stops, and fueling stops. These distributions are provided for different time periods of the day such as AM peak, mid-day, PM peak, and night time.

Table 4.2 Travel Time and Travel Distance Measurements for a Sample of 10 OD Pairs

OD pair	Travel Time (minutes)							Travel Distance (miles)						
	FLSWM	Google Maps	ATRI data (Travel time in motion excluding traffic stops and other small duration stops)					FLSWM	Google Maps	ATRI data				
			Shortest	15th percentile	50th percentile	85th percentile	Average			Shortest	15th percentile	50th percentile	85th percentile	Average
3124-3703	64	67	70	81	89	102	92	66.7	69.2	62.2	64.9	66.8	69	67.4
4526-1863	54	67	62	65	74	94	80	55	56.4	55	57.2	57.8	59	59.3
2228-4227	104	106	122	154	174	194	175	117.3	116	113.4	117.5	121	124.5	121.2
3662-3124	117	123	137	144	154	167	156	130.1	133	124.5	131.5	133.4	136.6	133.8
5983-792	209	224	231	252	260	278	267	247	244	240.2	243	248.5	250	249.1
2420-4147	211	237	228	248	269	291	269	265	223	203	207	209.1	211.3	209.6
4035-5819	497	553	631	645	683	723	689	652	654	649	650.1	653.4	675.5	660.1
5073-6117	425	534	494	573	664	805	678	555	543	462	558	604.3	669.6	605.7
413-6086	810	891	993	1063	1224	1347	1217	1130	1064	1120	1133	1164.1	1249	1192.6
2355-6176	952	1159	1344	1361	1422	1475	1426	1338.8	1289	1335	1340.5	1354.3	1388	1359.3

Second, the shortest travel times measured using GPS data were considerably higher than those used as inputs into the FLSWM or those measured in Google Maps. To examine this further for a larger sample of OD pairs, the travel times measured using the data were plotted against those measured from Google Maps and those used in FLSWM for 100 OD pairs. Figure 4.14 shows the plot comparing the travel times measured using GPS data with those derived from Google Maps (on the same routes as in the GPS data and during the same time-of-day). In this figure, the travel times measured using GPS data exclude the time spent at all en-route stops including rest-stops and traffic signal stops. It can be observed that the truck travel times measured using GPS data were higher than those from Google Earth (on the same travel routes). The differences were higher for longer trips. These differences likely were because the travel times reported in Google Maps are not necessarily exclusively for trucks; they are based on a variety of different information sources, most of which are likely to be oriented toward passenger cars. ATRI's truck GPS data, on the other hand, were exclusively for trucks that tend to travel at a slower speed than cars due to at least the following three reasons: (a) trucks are not allowed to travel on the fastest lanes in many sections of the highway network, (b) trucks accelerate at a slower rate than cars, and (c) truck drivers are often instructed (and incentivized) by the trucking fleet owners to travel at moderate speeds for reducing fuel consumption and cost savings. Therefore, it is reasonable that the truck travel times measured using the GPS data were larger than the travel times measured by Google Maps.

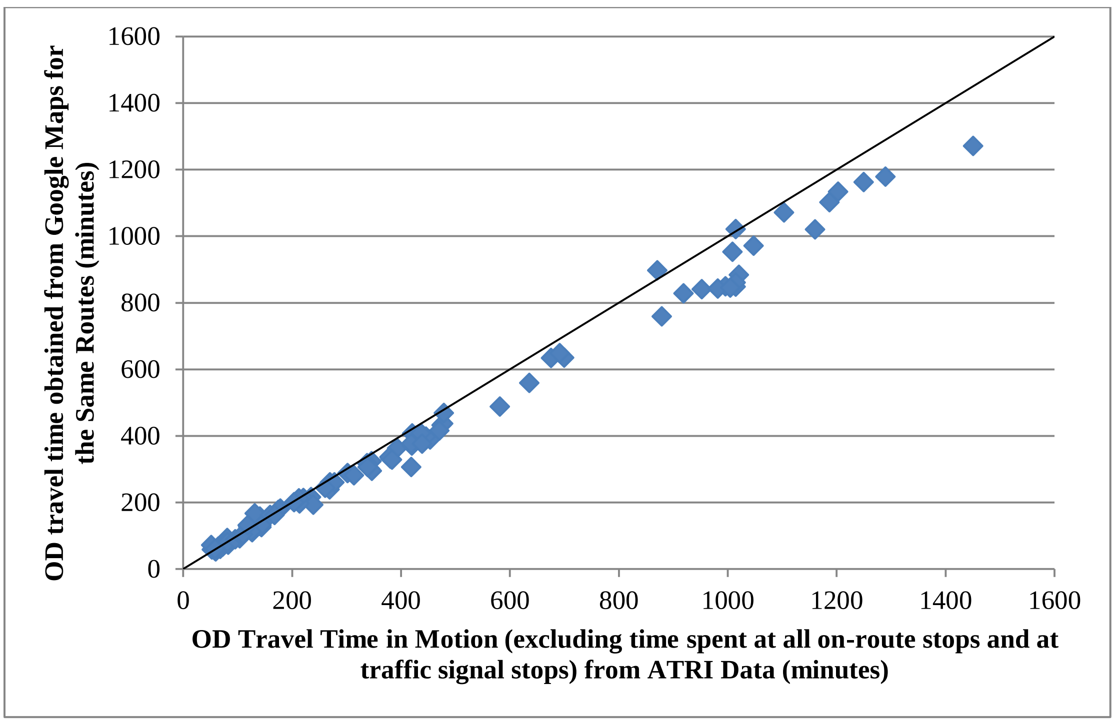


Figure 4.14 Comparison of OD Travel Times Measured in ATRI Data (excluding all stops en route) with Travel Times from Google Maps

Figure 4.15 shows a plot comparing the truck travel times measured using GPS data with travel times used as inputs for the FLSWM (i.e., the travel times from the travel time skim matrices). The truck travel times measured using GPS data were much higher than those in

FLSWM. The differences increase with increase in the trip length. These results suggested that the travel time skims used as inputs for the FLSWM, which are free-flow travel times for passenger cars derived from speed limits on individual links on the shortest path between the origin and destination, did not closely represent truck travel conditions on the network. In this context, ATRI's truck GPS data provides a significant opportunity to develop better information on truck travel time skims used as inputs for the FLSWM. In this project, the truck travel time information was derived for 1,237 OD pairs. Since there is a large number of OD pairs (more than 25 million within Florida) in the FLWSM, it is not feasible to rely on the GPS data alone to generate truck travel time information for all OD pairs. Instead, the travel time information derived in this project for 1,237 OD pairs potentially can be used in future work to derive (or impute) truck travel time information for all other OD pairs in the FLSWM. Such better truck travel time information can be used to replace the currently used passenger car travel time skim matrices used as inputs for the freight components of FLSWM.

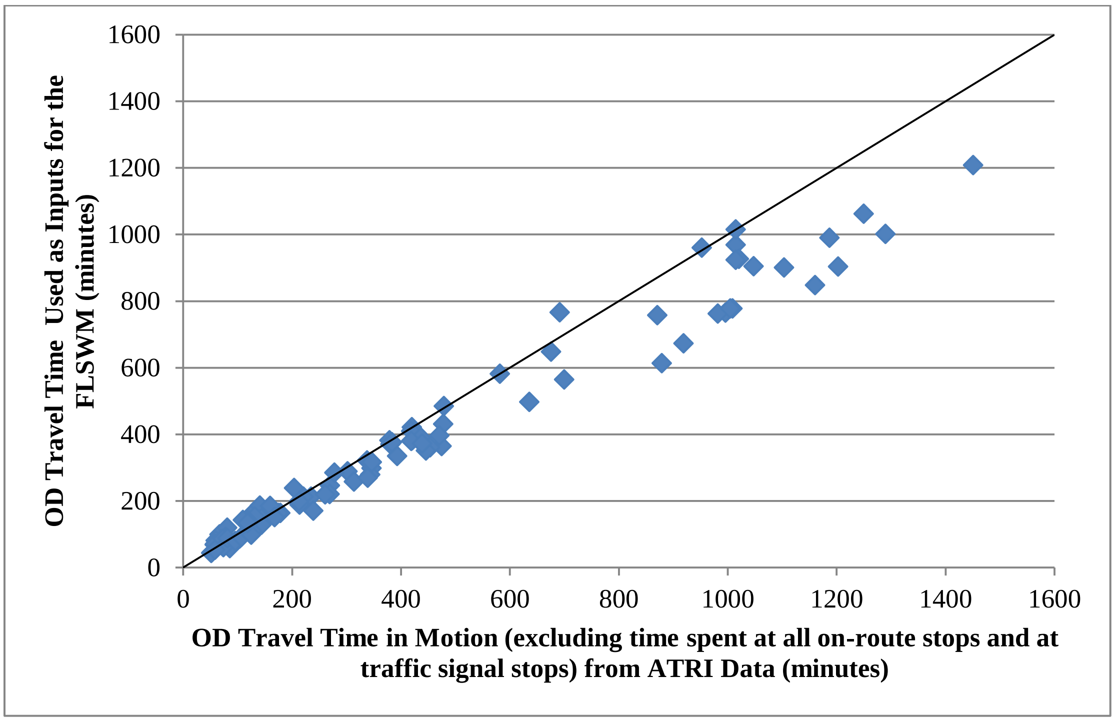


Figure 4.15 Comparison of OD Travel Times Measured in ATRI Data (excluding all stops en route) with Travel Times used in FLSWM

CHAPTER 5 : ASSESSMENT OF THE COVERAGE OF TRUCK FLOWS IN FLORIDA BY THE ATRI DATA

5.1 Introduction

ATRI's truck GPS dataset served as the source data for this analysis. While not a census of all truck movement within Florida, the substantial dataset proved valuable to understanding freight movement within the state. ATRI's truck GPS dataset, however, is not necessarily a random population of the trucks in the state. Therefore, this chapter provides an assessment of the type of trucks included in ATRI data and the geographic coverage of the data.

5.2 Truck Types in ATRI Data

Based on the discussions with ATRI and anecdotal evidence, it is known that the major sources of ATRI data are large trucking fleets, which typically comprise tractor-trailer combinations. According to the FHWA vehicle type classification, these are tractor-trailer trucks in class 8–13 categories.[9] However, a close observation of the data, through following the trucks on Google Earth and examining some travel characteristics of individual trucks, suggested that the data included a small proportion of trucks that did not necessarily haul freight over long distances. Since the data did not provide information on the vehicle classification of each individual truck, some heuristics were developed in the project to classify the trucks into heavy trucks and medium trucks. The heuristics, as explained below, are based on the travel characteristics of individual trucks over extended time periods (i.e., at least two weeks).

As discussed earlier, more than 2.7 million truck trips were derived from about four months of ATRI's raw GPS data for the year 2010. This database included 169,714 unique truck IDs. Since the raw GPS data for each truck were available for at least two weeks (up to one month, in most cases), trucks that did not make at least one trip of 100-mile length in a two-week period were removed from the data. In this step, 88,869 trips made by 7,018 unique truck IDs were removed. The median length of such removed trips was 20 miles, suggesting the short-haul nature of these trucks. Subsequently, trucks that made more than five trips per day were removed, assuming that these trucks are not freight-carrying, tractor-trailer combination trucks. In this step, 275,224 trips made by 918 unique truck IDs were removed. The median length of these trips was 16 miles. For the reader's information, a histogram of the distribution of the trucks in the database by their daily trip rates is provided in Figure 5.1.

[9] Most freight in the U.S. is carried by tractor-trailer trucks of five axles or more (i.e., class 9 or above) and some on tractor-trailer units of less than five axles (i.e., class 8 trucks). See page ES-7 of http://www.fhwa.dot.gov/policy/vius97.pdf .

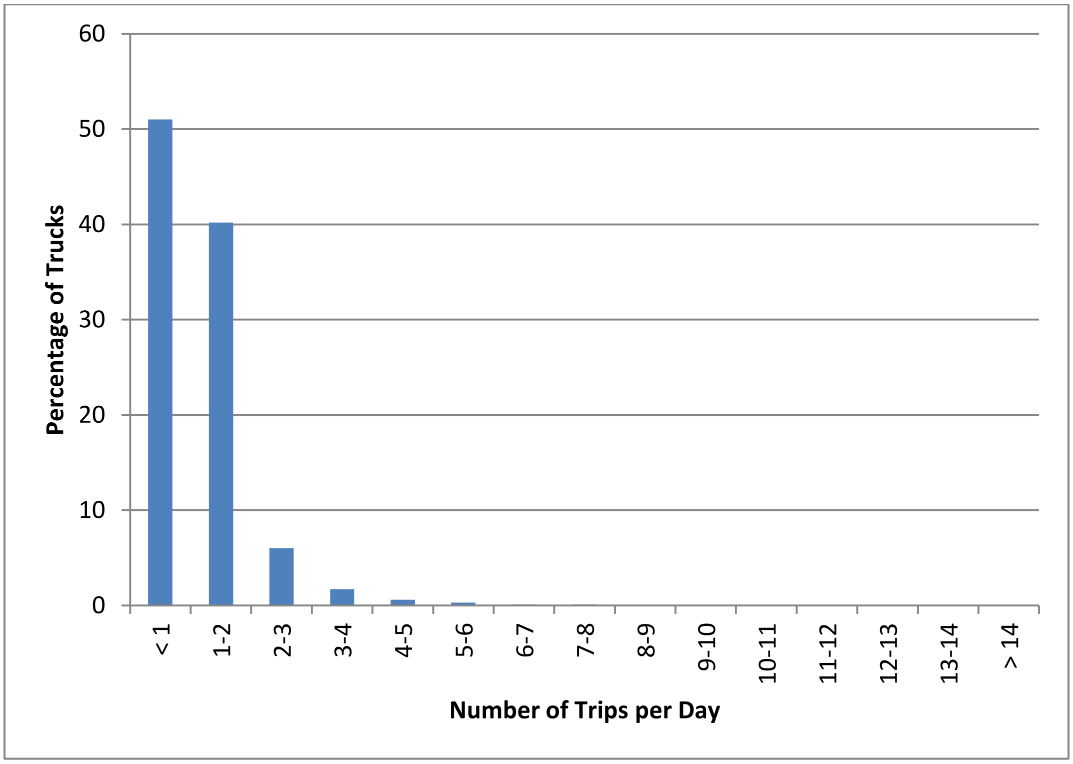


Figure 5.1 Distribution of Trucks by Daily Trip Rate

After the above-discussed procedures, more than 2.34 million trips extracted from GPS data of more than 161,776 unique truck IDs were considered as trips made by heavy trucks that carry freight. These trips were further used for OD matrix estimation later in the project. The trucks making these trips are considered to be long-haul trucks or heavy trucks (assumed to be FHWA vehicle classes 8–13). The remaining trucks (7,936 truck IDs) whose trips were removed from further consideration in OD matrix estimation were assumed to be short-haul trucks or medium trucks that serve the purpose of local delivery and distribution.

It is worth noting here that the procedures used in this project to separate heavy trucks from other trucks were simplistic. It is not necessary that only heavy trucks carry freight over long distances while only medium trucks serve the purpose of short-distance delivery and distribution services. Further research is needed to identify the composition of trucking fleet in the ATRI data and the purposes served by those trucks in the data.

5.3 What Proportion of Heavy Truck Traffic Flows in Florida Is Captured in ATRI's Truck GPS Data?

ATRI's truck GPS data represented a large sample of truck flows within, coming into, and going out of Florida. However, the sample did not necessarily comprise the entire population of truck flows. Also, it was unknown what proportion of truck flows in the state was represented by these data. To address this question, truck traffic flows in one week of ATRI's truck GPS data were compared with truck counts data from Florida Telemetered Traffic Monitoring Sites (TTMS) truck traffic counts for that same week. This section describes the procedure and results from this analysis.

One week of ATRI's truck GPS data, from May 9–15, 2010, were used to derive weekly ATRI truck traffic volumes through the FDOT TTMS traffic locations. Specifically, all truck GPS records available with ATRI for that week within Florida, as well as 60 miles beyond the Florida border into Alabama and Georgia, were used. Including GPS data points 60 miles beyond the Florida border helps account for truck trips coming into and going out of the state.

Generating data on weekly ATRI truck traffic volumes at each TTMS location required counting the number of times the trucks in the ATRI data crossed the location in the week. To do so, we first attempted to run the raw GPS data through map-matching algorithms embedded in the network analyst tool of ArcGIS. However, given the sheer size of the raw GPS data, it was practically infeasible to run all the raw GPS data through the ArcGIS map-matching tool.

To address the above issue, the raw GPS data records were reduced into a database of truck trip ends and intermediate GPS data points at a 5-minute interval (using the earlier discussed algorithms for converting the data into truck trips). Since the purpose was only to reduce the data to a manageable size and not to derive true pickup/delivery trip origins and destinations, any truck stop of more than 5 minutes dwell time was considered to be a trip end. A truck was considered to be "stopped" if either the spot speed was zero for at least 5 minutes or the average travel speed between consecutive GPS data points was less than 5 mph for at least 5 minutes. For each truck trip derived in this fashion, given its origin and destination location coordinates, intermediate GPS data points in "motion" were sampled from the raw data at a time interval of 5 minutes. An intermediate GPS data point was considered to be in motion if the truck was moving at a speed of greater than 5 mph. In all, the raw GPS data was reduced into a manageable GPS dataset comprising truck trip ends and intermediate GPS data points in motion at 5-minute time interval.

For each truck trip derived in the above-described fashion, the trip ends and intermediate GPS points were map-matched to the FLSWM highway network using the network analyst tool in ArcGIS. The map-matching algorithm snaps the GPS points to the nearest roadway links and also determines the shortest path between consecutive GPS data points. Since intermediate GPS data points between the trip ends were sampled at only a 5-minute interval, this procedure results in a sufficiently accurate route for the trip. The output from this process was an ArcGIS layer containing the travel routes for all trips generated from ATRI's one-week truck GPS data. This ArcGIS layer was intersected with another layer of FLSWM network containing the TTMS traffic counting stations (specified in the form of network links on which the TTMS stations were located). This helped estimate the number of truck trips (or individual trip routes) crossing each TTMS count station, which is nothing but the volume of ATRI trucks crossing the count stations.

Data on weekly heavy truck traffic volumes (for May 9–15, 2010) were extracted from FDOT's TTMS traffic counting data. Specifically, data on the total weekly volume of heavy trucks (i.e., class 8–13 trucks) were extracted. Figure 5.2 shows the TTMS locations in Florida and the range of heavy truck traffic volumes (average daily traffic volumes) at those locations. Highest tuck traffic volumes (i.e., around 5,000 heavy trucks per day) can be observed in the northern part of I-75 near and above Ocala and on I-95 near Jacksonville. The section of I-75 between Ocala and Tampa, I-4 between Tampa and Orlando, and the section of I-95 in southeast Florida have heavy truck volumes in the range of 3,000 to 4,000 trucks per day.

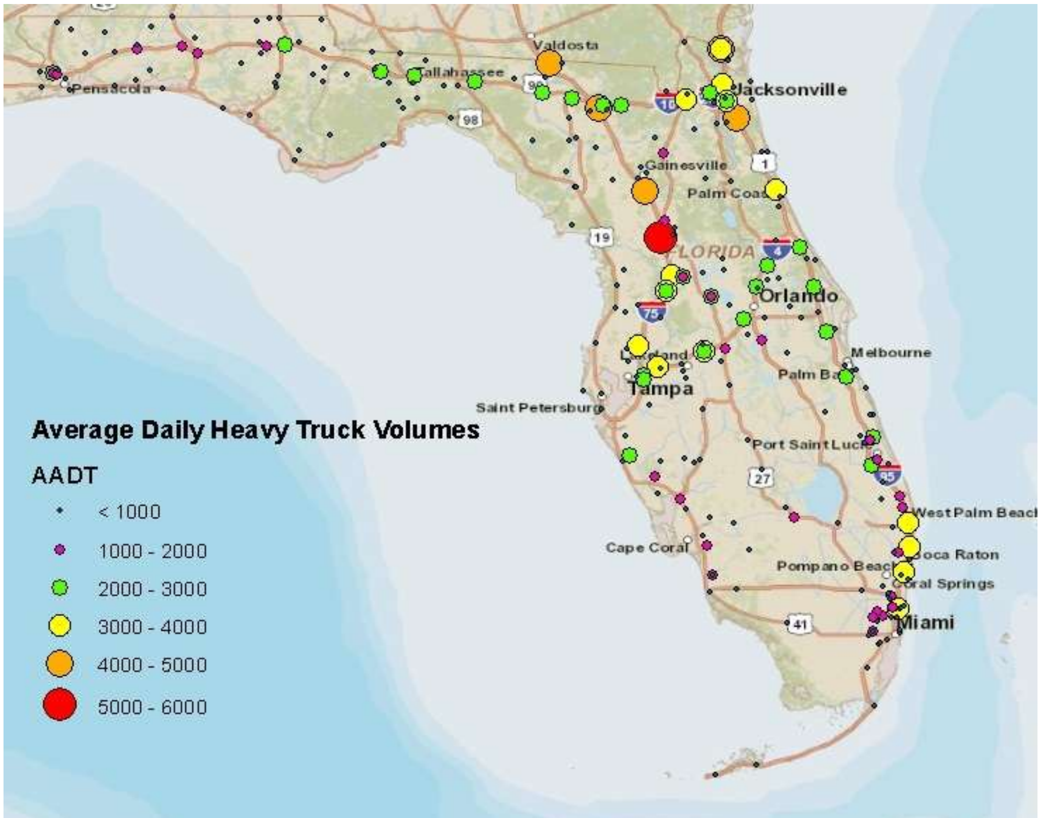


Figure 5.2 Observed Heavy Truck Traffic Flows at Different Telemetered Traffic Counting Sites (TTMS) in Florida

Out of more than 250 TTMS traffic counting locations in Florida, only 160 had traffic count data for all seven days in the week. Therefore, only these locations were selected for further analysis to compare the ATRI truck traffic volumes with observed TTMS truck traffic volumes at these locations. Figure 5.3 shows the results for each individual TTMS station. Specifically, the blue bars in the figure represent the observed heavy truck traffic volumes at those locations, and the red bars represent the ATRI truck traffic volumes through those locations. Clearly, at no single location did the ATRI data provide 100 percent coverage of the observed truck traffic flows. However, the data did provide some coverage of the heavy truck traffic flows at all locations.

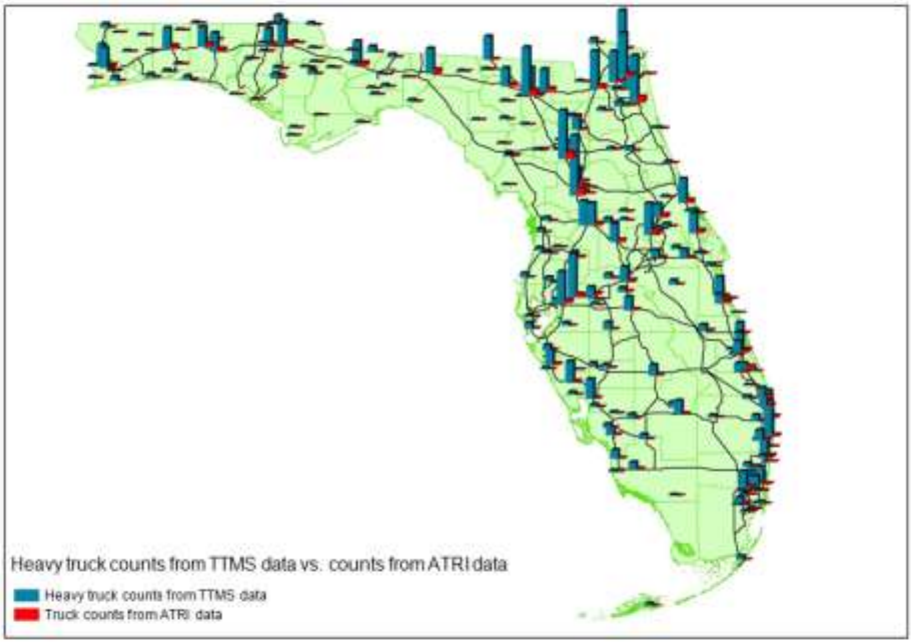


Figure 5.3 Heavy Truck (Classes 8–13) Counts from TTMS Data vs. Truck Counts from ATRI Data during May 9–15, 2010

Table 5.1 shows these results aggregated by the facility type. The second column in the table shows the number of TTMS traffic counting locations on different types of highway facilities (along with the corresponding percentages). The third column shows the observed TTMS volumes counted at these sites (along with the corresponding percentages), again, separately for each highway facility type. Notice that a bulk of heavy truck traffic (65.6%) was through locations on freeways and expressways that represent only 18.1 percent of the 160 TTMS sites considered in this analysis. The fourth column shows the truck traffic volumes counted in ATRI data using the previously-discussed map-matching procedure. As can be observed from the last row in this column, 163,467 ATRI truck crossings were counted at the160 TTMS locations. It is worth noting that the distribution of these ATRI truck traffic counts across different facility types was very similar to the distribution of TTMS truck counts across facility types. This can be observed by comparing the percentage numbers in the third and fourth columns. **This result suggests that the ATRI data provide a representative coverage of truck flows through different facility types in the state.** The last column expresses the ATRI truck traffic counts as a percentage of observed heavy truck traffic counts at the TTMS locations. For example 111,608 ATRI truck crossings were counted at TTMS locations on freeways and expressways. These constitute 10.5 percent of more than 1 million observed heavy truck traffic counts at these locations. These percentages provide an aggregate picture of the coverage provided by ATRI data of the heavy truck traffic flows in Florida. Overall, as can be observed from the last row in the last column of the table, it can be concluded that **the ATRI data provided 10.1 percent coverage of heavy truck flows observed in Florida**. This result was useful in many ways. First, this provided an idea of the extent of coverage of Florida's heavy truck traffic flows in the ATRI data. Second, the result could be used to weigh the seed matrix of ATRI truck trip flows (by 10.1 times) to create a weighted seed matrix that can be used as an input for the ODME process.

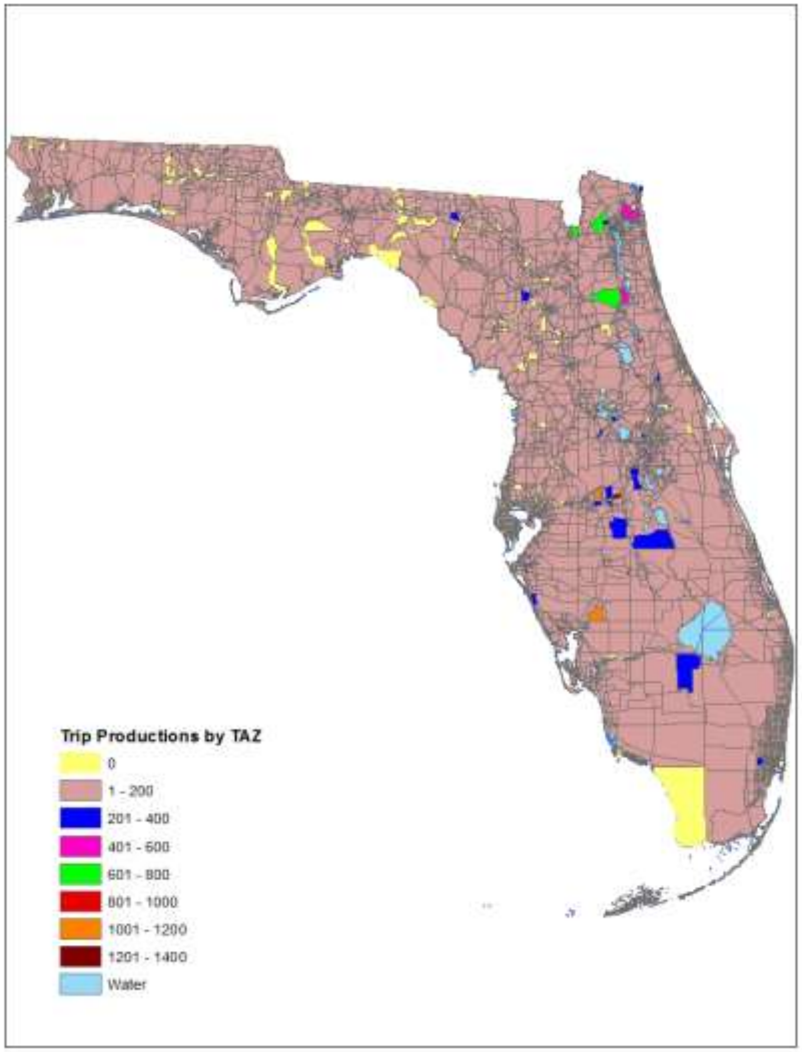
Table 5.1 Aggregate Coverage of Heavy Truck Traffic Volumes in Florida by ATRI Data (for One Week from May 9–15, 2010)

Facility Type	No. of TTMS Traffic Counting Stations	Observed TTMS Truck Traffic Volumes (Classes 8–13) during May 9–15, 2010	Truck Traffic Volumes in ATRI Data during May 9–15, 2010	% Coverage Assuming ATRI Data Comprises Trucks of Classes 8–13
Freeways & Expressways	29 (18.1%)	1,063,765 (65.6%)	111,608 (68.3%)	10.5%
Divided Arterials	64 (40.0%)	333,791 (20.6%)	30,472 (18.6%)	9.1%
Undivided Arterials	52 (32.5%)	101,066 (6.2%)	6,969 (4.3%)	6.9%
Collectors	8 (5.0%)	42,164 (2.6%)	5,127 (3.1%)	12.2%
Toll Facilities	7 (4.4%)	80,493 (5.0%)	9,291 (5.7%)	11.5%
Total	**160**	**1,621,279**	**163,467**	**10.1%**

5.4 Geographical Coverage of ATRI's Data in Florida

To understand the geographical coverage of ATRI's data in Florida, the number of trips originating from (i.e., trip productions) and the number of trips destining to (i.e., trip attractions) each traffic analysis zone (TAZ) of the FLSWM were plotted. Figure 5.4 shows the TAZ-level trip productions and attractions, and Figure 5.5 shows the county-level trip productions and attractions. Note that these trip productions and attractions were derived using the truck trips derived from four months of ATRI's truck GPS data. Since the trips were derived from four months of data (i.e., 122 days), the total trip productions and attractions derived from the data were first divided by 122 to get average daily trip productions and attractions. However, since the data were found to represent 10 percent of observed heavy truck traffic volumes in the state, the average daily trip productions and attractions were weighted by 10. Such weighted average daily trip productions and attractions are shown in Figures 5.4 and 5.5.

In Figure 5.4, the TAZs shaded in yellow color have zero trip productions (left side of figure) or zero trip attractions (right side) in ATRI's four-month GPS data. It can be observed that the Everglades region in the south and some TAZs in the northwest part of Florida have TAZs with no trips extracted from the data. It was reasonable that zero to limited heavy truck trips are produced from or attracted into the Everglades region. However, it was not clear if zero trip generation in some TAZs of northwestern Florida was a result of low penetration of data in those regions or if those TAZs have no freight truck trip flows. To investigate this further, the observed heavy truck traffic flows in the TTMS data (Figure 5.2) can be examined. Except on I-10, the northwestern region of the state did not have high truck traffic volumes. This suggests that zero trip generations in the ATRI data for several TAZs in the northwestern region was a reasonable representation of the truck flows in that region. Some TAZs in Duval (Jacksonville area), Putnam, Polk, and Desoto counties had higher trip generation according to the ATRI data. When examined closely, all these TAZs had major freight activity centers, such as distribution centers. However, major urban areas such as Miami, Tampa, and Orlando did not show TAZs with high trip generation. This was likely because the TAZs in these regions were smaller in size. Since the trip generations were not normalized by the area of the TAZ, it was difficult to make further inferences on the reasonableness of the TAZ-level trip generations.



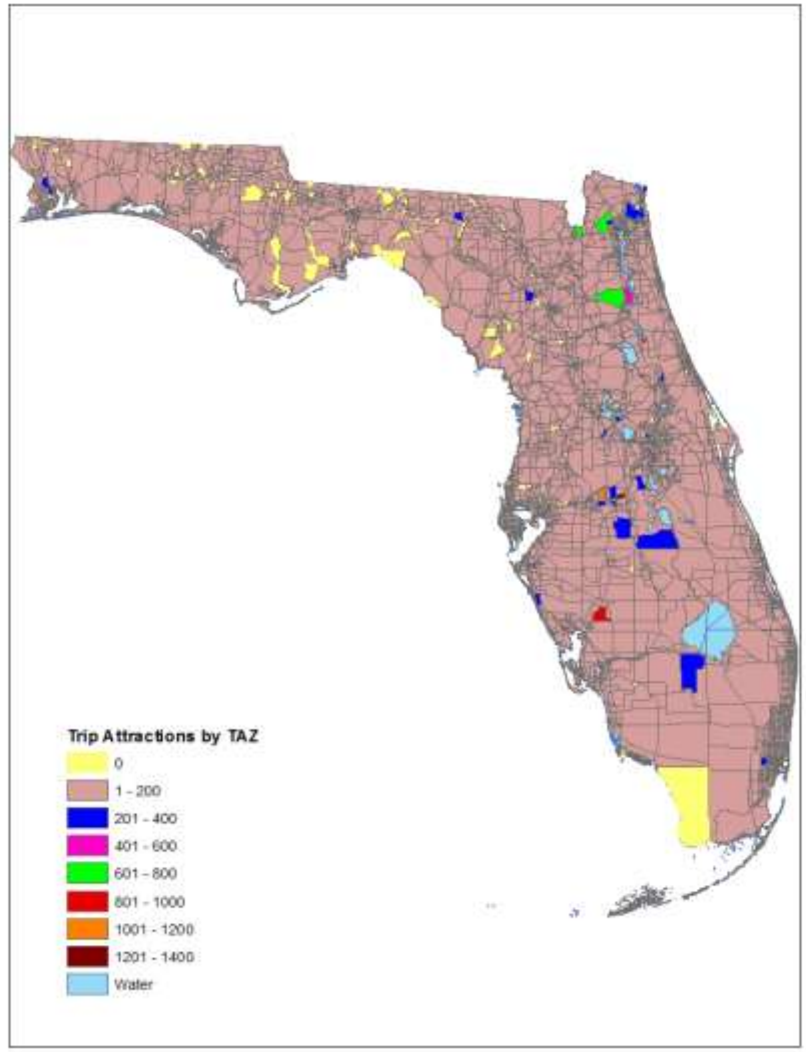


Figure 5.4 FLSWM TAZ-Level Trip Productions and Attractions in the ATRI Data (4 Months of Data Factored to One Day)

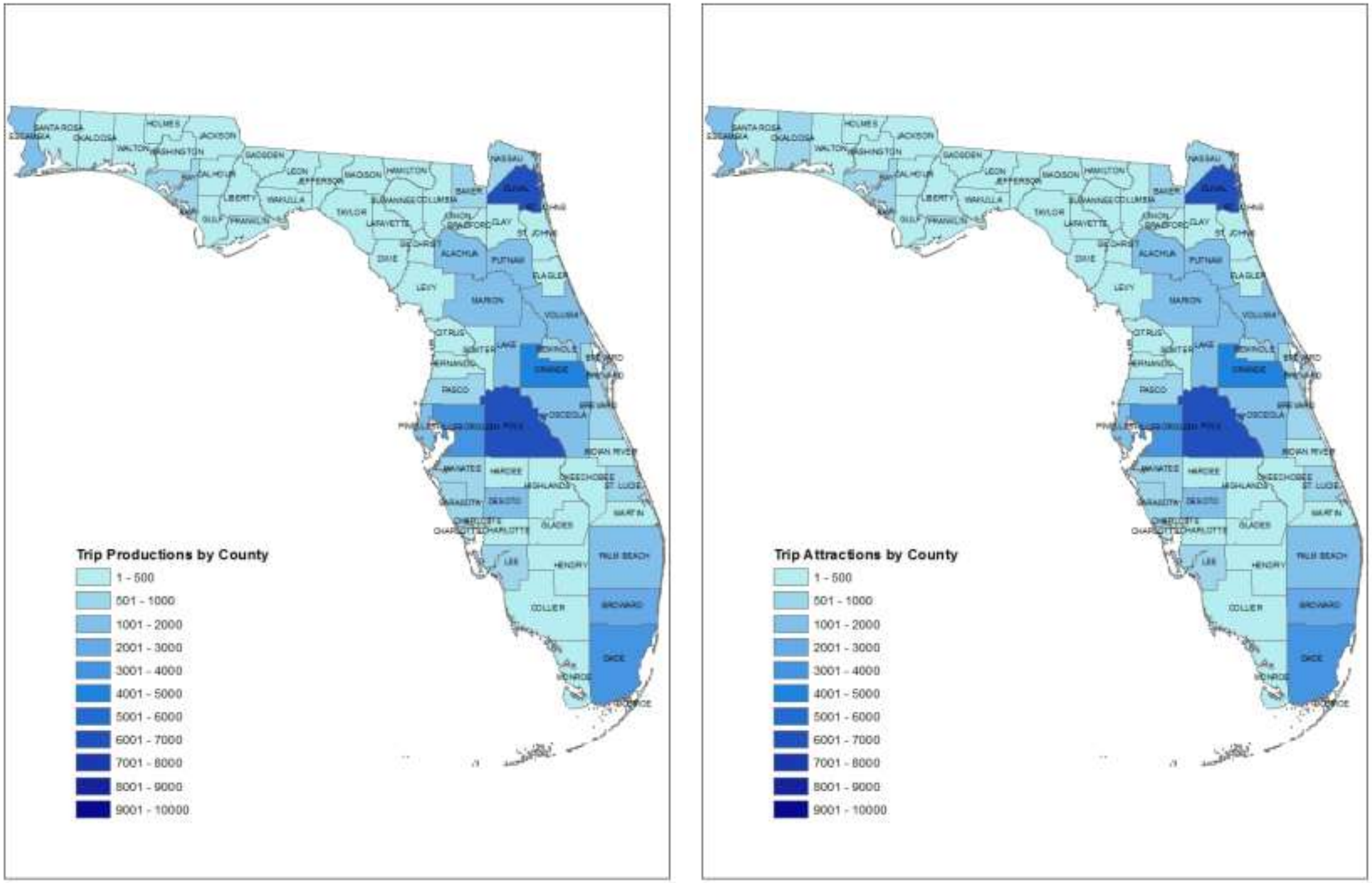


Figure 5.5 County-Level Trip Productions and Attractions in the ATRI Data (4 Months of Data Factored to One Day)

Figure 5.5 shows the trip generations aggregated to a county-level. According to the ATRI data, Duval, Polk, Orange, Miami-Dade, and Hillsborough counties, in that order, had the highest truck trip generation. It was expected that counties with major metropolitan areas have the highest heavy truck trip generation. Further, Polk County was expected to have a high truck trip generation due to the presence of several freight distribution centers in the county. However, it was interesting that the truck trip generation in Polk County was higher than that in Hillsborough (Tampa), Orange (Orlando) and Miami-Dade counties. Further, the truck trip generation in southeast Florida (Miami-Dade, Broward and Palm Beach counties) appeared to be smaller than that in Polk County. These trends were not expected and were likely to be a manifestation of spatial biases in the data. To address such spatial biases, Chapter 6 combines the truck trip flows derived from the ATRI data with observed heavy truck traffic volumes at different locations in the state.

Figure 5.6 presents the percentage of heavy truck traffic covered by ATRI data at different locations. This information is similar to what was presented in Figure 5.3. However, for clarity and ease in interpretation, the percentage covered is presented only for those locations with annual average daily heavy truck traffic greater than 1,000 trucks per day. It can be observed that at most locations, at least five percent of the heavy truck traffic was captured in the ATRI data. Also, it can be observed that the coverage in the southern part of Florida (within Miami) and the southern stretch of I-75 was slightly lower compared to the coverage in the northern and central Florida regions.

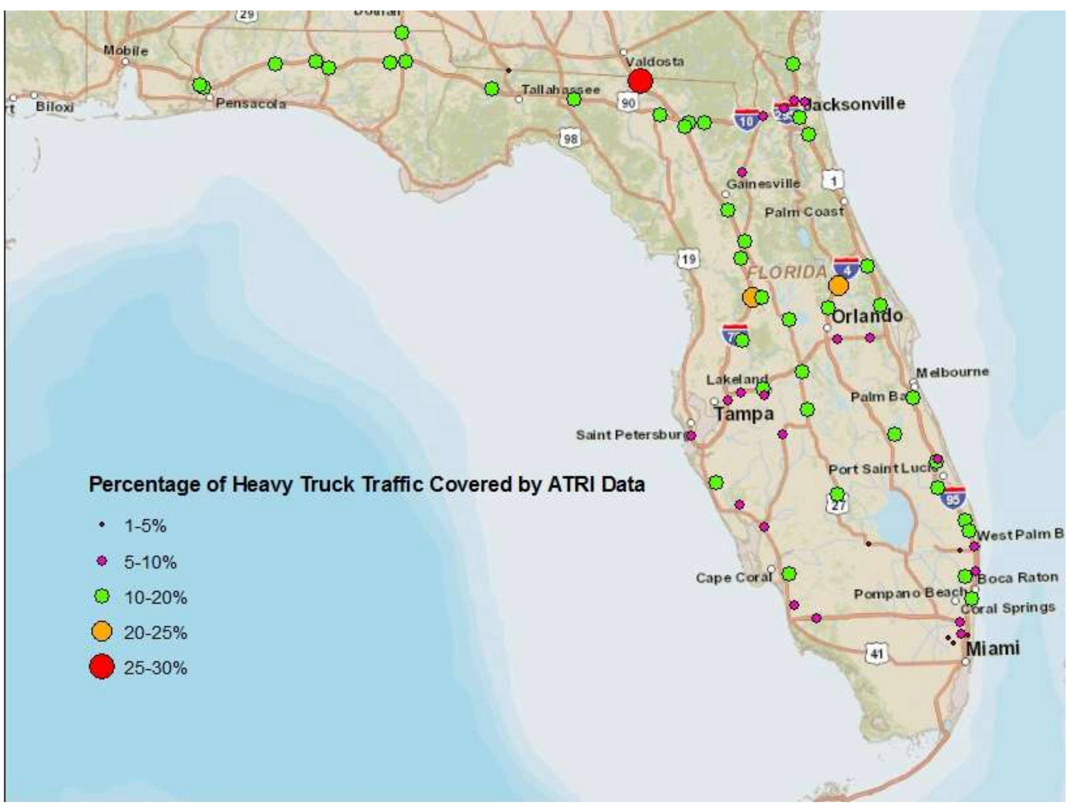


Figure 5.6 Percentage of Observed Heavy Truck (Classes 8-13) Volumes Represented by ATRI Data at Telemetric Traffic Monitoring Sites in Florida during May 9–15, 2010

CHAPTER 6 : ESTIMATION OF STATEWIDE ORIGIN-DESTINATION TRUCK FLOWS

6.1 Introduction

The freight truck trips derived from ATRI's truck GPS data can be used to derive statewide origin-destination tables (or OD flow tables or OD matrices) of freight truck flows between various traffic analysis zones. However, it was important to note that whereas the trips derived from the ATRI data were substantial, they represented only a sample and not a census of all freight truck flows within, to, and from the state. In addition, while it was known that the ATRI data comprised predominantly tractor-trailer trucks that fall under classes 8–13 of FHWA vehicle type classification (i.e., heavy trucks), it was not certain if the data represented a random sample of heavy truck flows in the state. Therefore, additional information and procedures must be employed to *factor* the *sample* of trips derived from the ATRI data to represent the *population* of heavy truck flows within, to, and from the state. The weighting process was required not only for inflating the sample of ATRI truck flows to the population truck flows but also for ensuring that the spatial distribution of the resulting truck flows was representative of the actual truck flows in the state. One approach to do this was Origin-Destination Matrix Estimation (ODME), which involved combining the *sample* OD truck flows derived from the ATRI data with other sources of information on truck flows observed at various links of the highway network to estimate a full OD flow matrix representing the *population* of truck flows in the state. This chapter describes the ODME approach used in this project, along with the results and findings. Section 6.2 describes the mathematical procedure of the ODME approach used in this study, Section 6.3 describes the inputs and assumptions in the ODME procedure, Section 6.4 presents the results, and Section 6.5 provides some suggestions to improve the ODME procedure and results.

6.2 Origin-Destination Matrix Estimation (ODME)

ODME is a class of mathematical procedures used to update an existing matrix of OD trip flows (i.e., number of trips between each origin-destination pair in a study area) using information on traffic flows at various locations in the transportation network. In the current project, the sample OD truck flows (also called the sample OD matrix or the seed matrix) extracted from ATRI's truck GPS data can be updated using external information on truck traffic flows (or traffic counts or traffic volumes) observed on various links in the highway network within and outside Florida. Very broadly, the ODME procedures factor the ATRI data-derived truck trip flows in such a way that the trips in the resulting estimated OD flow matrix, when assigned to the highway network, closely match the observed heavy truck counts at various locations on the network.

The mathematical procedure used for ODME in this project was based on the ODME procedure embedded in Cube Analyst Drive software from Citilabs. The procedure essentially is an optimization problem that tries to minimize a function of the difference between observed traffic counts and estimated traffic counts (from the estimated OD matrix) and the difference between the seed matrix and the estimated OD matrix, as below:

$$\begin{aligned} &\underset{X}{\arg\min} \quad J(X) = F(AX - b) + G(X - X_0) \\ &\text{subject to} \quad X \geq 0 \ \text{ and } \ X_{lower} \leq X \leq X_{upper} \end{aligned} \tag{1}$$

In this general optimization problem, X is the OD matrix to be estimated, X_0 is the initial (seed) OD matrix, G is a function measuring the distance between the estimated OD matrix and the initial matrix, b is a vector of observed counts at different locations in the study area, A is the route choice probability matrix obtained from the assignment of the OD flows in X on to the network (AX represents the estimated traffic counts at the same locations with available observed counts), and F is a function measuring the difference between estimated and observed traffic counts at different locations in the study area. As can be observed, the ODME procedure attempts to arrive at an OD flow matrix X in such a way that the resulting traffic volumes at different locations (AX) match closely with the observed traffic flows (b). At the same time, the procedure avoids overfitting to the observed traffic flows by including the term $G(X - X_0)$ so that the estimated matrix is not too far from the seed matrix. X_{lower} and X_{upper} are boundaries (lower and upper bounds) within which the estimated matrix should fall. The analyst has an option to use these boundary constraints to set lower and upper bounds on the estimated matrix, relative to the seed matrix.

Figure 6.1 shows a schematic of the ODME procedure used in the project. The primary inputs to the procedure were the seed matrix for freight truck trips (derived from the ATRI data), a highway transportation network for the study area and information on the travel times and capacity of each link in the network (extracted from the FLWSM), and observed heavy truck traffic volumes (or counts) at different locations added to corresponding links in the network. In addition to these, OD flow matrices corresponding to travel other than freight truck flows—an OD matrix for non-freight truck trips and an OD matrix for passenger travel (both extracted from the FLSWM)—were required as inputs to generate realistic travel conditions in the network.

In the first step of the ODME procedure, the seed matrix of truck trips derived from the ATRI data (assumed to represent a sample of freight truck trips) and other OD matrices representing passenger travel and non-freight truck travel were loaded on to the highway network using user-equilibrium-based traffic assignment procedures. The freight truck traffic volumes estimated from the traffic assignment procedure were then used in conjunction with the heavy truck traffic volumes observed at different locations in the network (along with the seed and estimated OD matrices for freight trucks, which were same in the first iteration) to compute the ODME objective function to be minimized. The seed matrix for freight truck trips was then updated toward minimizing the objective function while considering the lower and upper bounds on the matrix. This updated matrix was then used in conjunction with other OD matrices for passenger and non-freight travel (which were not updated in the procedure) as the seed matrix for the next iteration of the ODME procedure, which begins with highway traffic assignment and follows with the computation of the ODME objective function. This process was repeated until the ODME objective function reached its minimum, when the estimated freight truck traffic volumes were close enough to observed volumes and the estimated OD matrix was not too far from the initial seed matrix derived from the ATRI data.

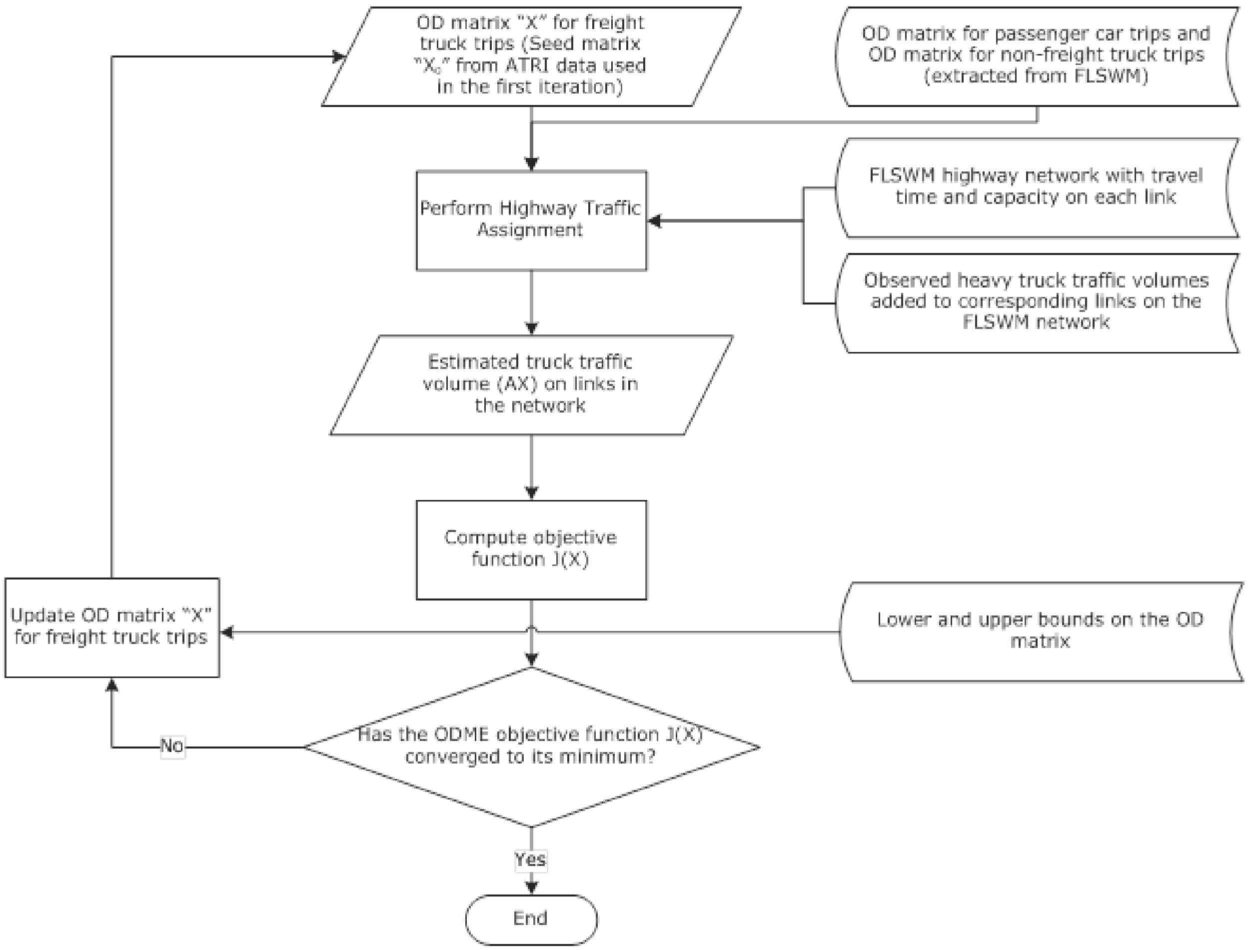


Figure 6.1 Schematic of the ODME Procedure Used in This Project

The estimated OD matrix of freight truck trips can be evaluated using different evaluation metrics and procedures. One approach to evaluate the estimated OD matrix is based on comparison of estimated heavy truck traffic volumes and observed heavy truck traffic volumes at different locations within and outside Florida. Specifically, one can evaluate a root mean square error (RMSE) measure as below:

$$RMSE = \frac{\sqrt{\dfrac{\sum_{i=1}^{N} (V_i - C_i)^2}{N}}}{C_{avg}} \tag{2}$$

where, V_i is the estimated heavy truck traffic volume corresponding to location *i*, C_i is the observed heavy truck traffic volume corresponding to location *i*, C_{avg} is the average heavy truck traffic count value of the entire set of observations, and N is the total number of truck counting locations in the set. A single RMSE value can be computed for the entire set of traffic counting locations and also separately for locations in Florida and for locations elsewhere. Similarly, the RMSE values can be computed separately for different ranges of observed heavy truck counts.

In addition to comparing the observed and estimated traffic volumes, it was important to assess the reasonableness of the estimated OD matrix in different ways. Aggregating the OD matrix to a coarser spatial resolution and examining the spatial distribution of flows, examining the total trips originating from (or trip productions) and total trips destined to (or trip attractions) each aggregate spatial zone, and examining the trip length distribution of the estimation OD matrix in comparison to the seed OD matrix were different ways of assessing the reasonableness of the estimated OD matrix.

6.3 Inputs and Assumptions for the ODME Procedure

6.3.1 The Seed Matrix

The seed matrix is essentially the matrix of OD truck trip flows derived from ATRI's truck GPS data. Specifically, the truck trips derived from the GPS data were assigned to the TAZ system used in the FLSWM to form the seed matrix. In FLSWM, Florida and the rest of the United States (and Canada) are divided into 6,242 TAZs; 5,403 of these zones are in Florida and the remaining zones are outside Florida. Therefore, the seed matrix is a matrix of size 6242 × 6242, with each cell in it representing the number of trips extracted between the corresponding origin-destination (OD) pair.

In this project, the seed matrix was derived from four months of truck GPS data—March, April, May, and June 2010. As described in an earlier chapter, whereas the total number of trips derived from four months of data was more than 2.7 million, for the purpose of OD matrix estimation, only those trips deemed to be made by heavy trucks that haul freight (i.e., FHWA classes 8–13 trucks, which are tractor-trailers) were considered here. This is because most freight in the U.S. is carried by tractor-trailer trucks of five axles or more[10] (i.e., class 9 or above), and some on tractor-trailer units of fewer than five axles (i.e., class 8 trucks). From discussions with ATRI, whereas most of the ATRI data comprise tractor-trailer trucks, it is known that a small share of trucks in the data do not necessarily haul freight over long distances. However, the raw data did not provide information on the classification of each truck. Therefore, some heuristics were developed to filter out trucks of class 7 or below. The heuristics used are discussed next.

Since the raw GPS data for each truck were available for at least two weeks (up to one month, in most cases), trucks that did not make at least one trip of 100-mile length in a two-week period were removed from the data. In this step, 88,869 trips made by 7,018 unique truck IDs were removed. The median length of such removed trips was 20 miles, suggesting the short-haul nature of these trucks. Subsequently, trucks that made more than five trips per day were removed, assuming that these trucks are not freight carrying, tractor-trailer combination trucks. In this step, 275,224 trips made by 918 unique truck IDs were removed. The median length of these trips was 16 miles. The remaining trucks in the data were considered to be tractor-trailer combination trucks that tend to make long-haul, freight carrying trips of interest to the FLSWM. Among the trips made by these tractor-trailer combination trucks, the following three scenarios were considered:

[10] http://www.fhwa.dot.gov/policy/vius97.pdf.

1) Only trips of greater than 10 miles made by tractor-trailer combination trucks,
2) Only trips of greater than 5 miles made by tractor-trailer combination trucks, and
3) All trips made by tractor-trailer combination trucks.

After the above discussed procedures, the OD matrix of truck trips derived from 4 months of data comprised 2.07 million trips. Since this was derived from 4 months of data (122 days), the OD matrix was scaled down to one day by dividing all the cells in the OD matrix by 122. The resulting OD matrix then represents one day of trips extracted from the ATRI data. We call this the one-day seed matrix. However, as discussed in Chapter 4, the research team found that at an aggregate level, the trucks flows in the ATRI data represent 10 percent of the heavy truck flows in Florida. Therefore, the one-day seed matrix was inflated by multiplying all the cells in the matrix by 10. We call this the weighted one-day seed matrix (or seed matrix). This weighted one-day seed matrix was the input as a seed matrix for the ODME process.

6.3.1.1 Geographical Coverage of the Seed Matrix

The spatial structure of the seed matrix is now examined, focusing on its geographical coverage. To do so, the seed matrix was aggregated to county level within Florida and state level outside Florida. The aggregation enabled meaningful analysis of the spatial coverage of the seed matrix.

Within the state of Florida, there are 67×67 = 4,489 county-to-county OD pairs. Of these, the seed matrix derived from the ATRI data contained trips for 3,564 OD pairs (i.e., 79.4% coverage). The remaining 925 (20.6%) of the county-to-county OD pairs in Florida did not have trips in the seed matrix. From this, it can be concluded that the heavy truck trips derived from the ATRI data covered close to 80 percent of the OD pairs in Florida. To examine the remaining 20 percent of OD pairs for which the seed matrix did not contain any trips, Table 6.1 separates those OD pairs by county of origin (in the second column) and county of destination (in the third column). For example, it can be observed from the row for the Baker County that 9 counties in Florida did not have trips coming from the county and 7 counties did not have trips going into the county. That is, the seed matrix contained trips coming from all other 58 (= 67 - 9) counties to Baker and trips going from Baker to 60 (= 67 - 7) counties in Florida. A close examination of this table suggested that counties associated with major urban regions (Miami-Dade, Hillsborough, Orange, and Duval) and other counties with large freight activity (e.g., Polk) had a small number of counties to or from which there were no trips in the seed matrix. Counties in northwest Florida such as Franklin, Gulf, Calhoun, Holmes, Lafayette, Jefferson, and Hamilton and some rural counties in the south such as Glades, Hardee, and Monroe had higher number of zero trip flows coming into and going out of other counties in Florida.

Table 6.1 County-to-County OD Pairs in Florida with No Trips in the Seed OD Flow Matrix Derived from ATRI's Truck GPS Data

County	No. of Counties to which There are No Trips in Seed Matrix	No. of Counties from which There are No Trips in Seed Matrix
Alachua	0	1
Baker	9	7
Bay	10	4
Bradford	11	10
Brevard	8	9
Broward	5	4
Calhoun	33	37
Charlotte	19	17
Citrus	16	15
Clay	9	8
Collier	14	18
Columbia	5	5
De Soto	11	8
Dixie	18	14
Duval	0	2
Escambia	13	11
Flagler	18	20
Franklin	**45**	**43**
Gadsden	8	8
Gilchrist	19	20
Glades	**30**	**32**
Gulf	**36**	**39**
Hamilton	**24**	**22**
Hardee	**27**	**26**
Hendry	13	20
Hernando	9	8
Highlands	15	15
Hillsborough	1	2
Holmes	**30**	**33**
Indian River	19	24
Jackson	6	10
Jefferson	**33**	**35**
Lafayette	**35**	**34**
Lake	3	3
Lee	7	8
Leon	4	7
Levy	19	13
Liberty	21	7
Madison	8	5
Manatee	5	7
Marion	4	3
Martin	16	16

Table 6.1 (cont.)

County	No. of Counties to which There are No Trips in Seed Matrix	No. of Counties from which There are No Trips in Seed Matrix
Miami-Dade	3	3
Monroe	**31**	**38**
Nassau	6	2
Okaloosa	19	10
Okeechobee	20	24
Orange	2	1
Osceola	2	5
Palm Beach	6	7
Pasco	5	9
Pinellas	5	7
Polk	1	0
Putnam	4	4
Santa Rosa	23	20
Sarasota	9	14
Seminole	8	16
St. Johns	11	13
St. Lucie	7	8
Sumter	4	8
Suwannee	9	8
Taylor	12	12
Union	20	19
Volusia	6	4
Wakulla	22	23
Walton	24	25
Washington	**30**	**15**
Total	**925**	**925**

For OD pairs with at least one end in Florida, Table 6.2 presents the number of OD pairs with no trips for each origin and destination county in Florida. Specifically, the second column shows the number of states outside Florida to which no single trip was extracted, and the third column shows the number of states from which no single trip was extracted. For example, it can be observed from the row for the Alachua County that 11 states outside Florida did not have trips coming from the county and 10 states did not have trips going into the county. Similar to the county-to-county flows, counties in the northwest such as Franklin, Gulf, Calhoun, Hamilton, Walton, Holmes, Lafayette, and Jefferson and rural counties in the south such as Glades and Monroe had no trips coming into or going out of other states.

Table 6.2 Florida County to Non-Florida State OD Pairs with No Trips in the Seed OD Flow Matrix Derived from ATRI's Truck GPS Data

County	**No. of Counties to which There are No Trips in Seed Matrix**	**No. of Counties from which There are No Trips in Seed Matrix**
Alachua	11	10
Baker	20	11
Bay	9	11
Bradford	22	23
Brevard	15	11
Broward	8	5
Calhoun	**41**	**37**
Charlotte	26	21
Citrus	26	24
Clay	20	13
Collier	21	20
Columbia	22	19
De Soto	19	10
Dixie	26	34
Duval	4	2
Escambia	11	12
Flagler	25	23
Franklin	**42**	**41**
Gadsden	16	20
Gilchrist	23	28
Glades	**33**	**33**
Gulf	**38**	**39**
Hamilton	**35**	**36**
Hardee	26	27
Hendry	13	25
Hernando	17	18
Highlands	18	23
Hillsborough	4	4
Holmes	**36**	**32**
Indian River	18	24
Jackson	21	23
Jefferson	**34**	**34**
Lafayette	**39**	**38**
Lake	4	5
Lee	23	20
Leon	25	20
Levy	23	26
Liberty	25	32
Madison	23	19
Manatee	7	14
Marion	13	9
Martin	21	28

Table 6.2 (cont.)

County	No. of Counties <u>to</u> which There are No Trips in Seed Matrix	No. of Counties <u>from</u> which There are No Trips in Seed Matrix
Miami Dade	5	2
Monroe	**36**	**37**
Nassau	16	18
Okaloosa	18	18
Okeechobee	24	26
Orange	4	3
Osceola	12	10
Palm Beach	10	9
Pasco	17	14
Pinellas	6	10
Polk	3	2
Putnam	8	12
Santa Rosa	22	20
Sarasota	22	17
Seminole	12	13
St. Johns	18	17
St. Lucie	18	15
Sumter	16	17
Suwannee	21	26
Taylor	24	29
Union	28	34
Volusia	8	12
Wakulla	25	27
Walton	**32**	**32**
Washington	26	29
Total	**1,334**	**1,353**

Overall, it can be concluded that the ATRI data provided a sound geographic coverage of trip flows within, to, and from Florida. Whereas several counties in northwest Florida and a few rural counties in south Florida (e.g., Glades and Monroe) showed no trips to and from several other counties and states, it is likely because these counties may not actually have truck flows to/from a large number of locations. Considering that the seed matrix was derived from four months of raw GPS data (which is a large amount of data), if some OD pairs at a county-level resolution did not have any trip exchanges, it is reasonable to expect that those OD pairs may not have truck flows, in reality. On the other hand, for OD pairs with both ends outside the state of Florida, 350 of the 2,500 (=50×50) state-to-state OD pairs did not have any trips in the seed matrix. Since the data were Florida-centric, it was likely that the seed matrix was not necessarily a good representation of OD flows outside Florida.

6.3.1.2 Zero Cells in the Seed Matrix

When the seed OD matrix was examined at its actual spatial resolution (i.e., the FLSWM TAZ level), only 0.41 million of the 39 million TAZ-to-TAZ OD pairs had trips. That is, the 2 million heavy truck trips extracted from ATRI's truck GPS data could fill only 0.41 million OD pairs.

The remaining 38.5 million OD pairs had no trips. This is relevant because most ODME methods used in practice operate only with OD pairs that have non-zero trips in the seed matrix. Consequently, the final OD matrix output from ODME methods will have zero trips for OD pairs that began with zero in the seed matrix. To address this issue, a common practice is to introduce a small positive number (e.g., 0.01) for zero-cells (i.e., OD pairs with zero trips) in the seed matrix that the analyst believes should have trip flows. The question, then, becomes which OD pairs with zero trips can be expected to have trip flows in reality. The earlier discussion on the spatial coverage of the seed matrix, albeit at an aggregate spatial resolution of counties and states, sheds light on this issue. Recall from the earlier discussion that the OD pairs with at least one end in Florida had sufficient coverage at the county level in Florida and at the state level outside Florida. While there may be gaps at the disaggregate TAZ level, it was considered unnecessary to alter zero cells for such OD pairs. For OD pairs outside Florida, it may be reasonable to explore altering the zero-cells to include a small number (0.01) and examine if the ODME procedure provides better results.

The following scenarios were considered for altering the zero cells in the seed matrix:

1) None of the zero cells were altered (assuming the zero cells in the seed matrix are truly representative of zero truck flows),
2) Only the zero-cells for OD pairs outside Florida were altered to 0.01 to allow for the possibility of truck flows between those OD pairs. This scenario assumes that zero cells for OD pairs within, to, and from Florida are truly representative of zero truck flows, and
3) All zero-cells were altered to 0.01. This scenario—that all OD pairs will have truck flows—is very unlikely in reality. Nevertheless, it was considered to be sure.

6.3.2 Truck Traffic Counts

Observed volumes of truck traffic at different locations on the network was an important input into the ODME process. For the current study, data on heavy truck traffic counts were gathered for several locations within and outside Florida. Since the OD matrix to be estimated included truck traffic flows going into (out of) Florida from (to) other states, it was considered important to include truck traffic counts outside Florida as well.

6.3.2.1 Truck Traffic Counts in Florida

Data on truck traffic counts in Florida were obtained from FDOT's Telemetered Traffic Monitoring Sites (TTMS) traffic counting program. FDOT collects daily data on traffic volumes (by direction), speed, vehicle type, and weight from more than 250 TTMS locations on Florida's highway network. From such TTMS data for the year 2010, the daily traffic volume information for different vehicle classes was extracted for the months of March, April, May, and June 2010 (the same months for which the seed matrix is available). The vehicle classifications range from 1 to 15, with classes 8–13 representing heavy trucks (i.e., tractor-trailer combinations) and class 15 representing "Unknown". For each TTMS location, the average daily traffic (ADT) was computed for heavy trucks along with the number of days for which the traffic count data were available. Subsequently, the data were examined for any anomalies as discussed below.

First, 241 locations whose coordinates fell on the FLSWM highway network locations were selected. The other TTMS locations that were on highway links not in the FLSWM network were removed from consideration. For 237 of these locations, the TTMS traffic count data were available for both directions (141 sites with traffic counts in north–south directions and 96 sites in east–west directions); the remaining 4 sites had counts for one direction. Thus, 478 TTMS traffic counts were distinguished by location and direction. Of these, only 460 locations with TTMS data for more than 30 days of the 4 months were considered. Subsequently, sites with the following types of anomalies were removed: those with abnormally high percentage of traffic counts, those with abnormally high difference in directional counts, and those with a high percentage of unclassified trucks (i.e., class 15). After all these screening procedures, TTMS heavy truck counts (i.e., ADT for heavy trucks) for 413 different locations were retained for use in the ODME process. Figure 6.2 shows the spatial distribution of those locations in Florida (percentages in parentheses show the distribution of heavy truck ADT at these 413 locations). It is worth noting that 22.5 percent of these locations were on freeways and expressways, 36 percent were on divided arterials, 30 percent were on undivided arterials, 6.5 percent were on toll facilities, and the remaining were on collector roads, ramps, one-way facilities, and centroid connectors. Of the 413 heavy truck counts at different locations in Florida, data from 365 locations were used in the ODME process, and data from the remaining 48 locations were kept aside for validation purposes.

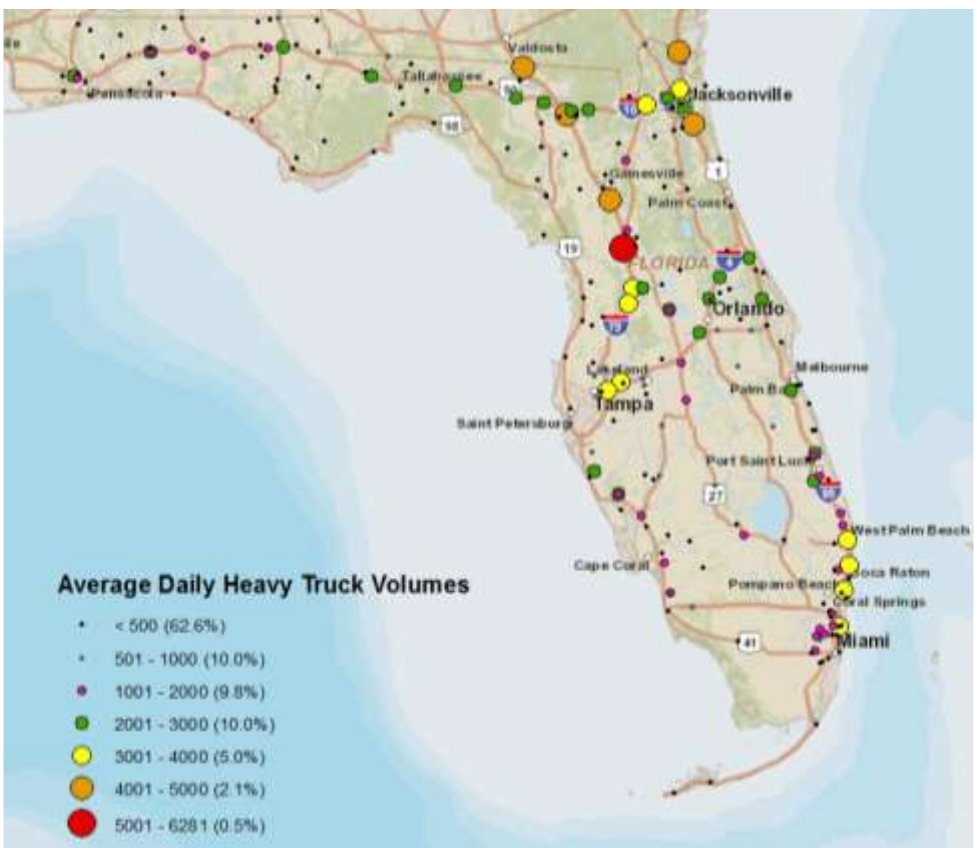


Figure 6.2 Spatial Distribution of Telemetered Traffic Monitoring Sites (TTMS) in Florida Used for ODME

6.3.2.2 Truck Traffic Counts outside Florida

FHWA's Vehicle Travel Information System (VTRIS) database was used to obtain truck traffic counts on highway network locations in all states other than Florida and Georgia. For Georgia, truck traffic counts from Georgia Automated Traffic Recorder (ATR) locations were obtained from Georgia Department of Transportation (GDOT). Whereas the VTRIS database provided traffic count data for a large number of locations outside Florida and the Georgia ATR data provided so similar data in Georgia, only 635 of these locations fell on the FLSWM highway network links outside Florida. This is because the FLSWM network outside Florida is not very detailed. Figure 6.3 shows the locations of all 635 counting sites along with the 413 counting sites in Florida. As can be observed, Florida and Georgia had good coverage of traffic counting stations, but other states in the southeast, such as Alabama, Mississippi, Louisiana, and South Carolina, had very few traffic counting locations. Tennessee, Kentucky, and North Carolina did not have any traffic counting locations. This will likely have a bearing on ODME results. In the future, the ODME results potentially can be improved by increasing the spatial coverage of the traffic counting stations in the southeastern states. Finally, of the 635 different heavy truck counts at different locations outside Florida, data from 598 locations were used in the ODME process and data from the remaining 37 locations were kept aside for validation purposes.

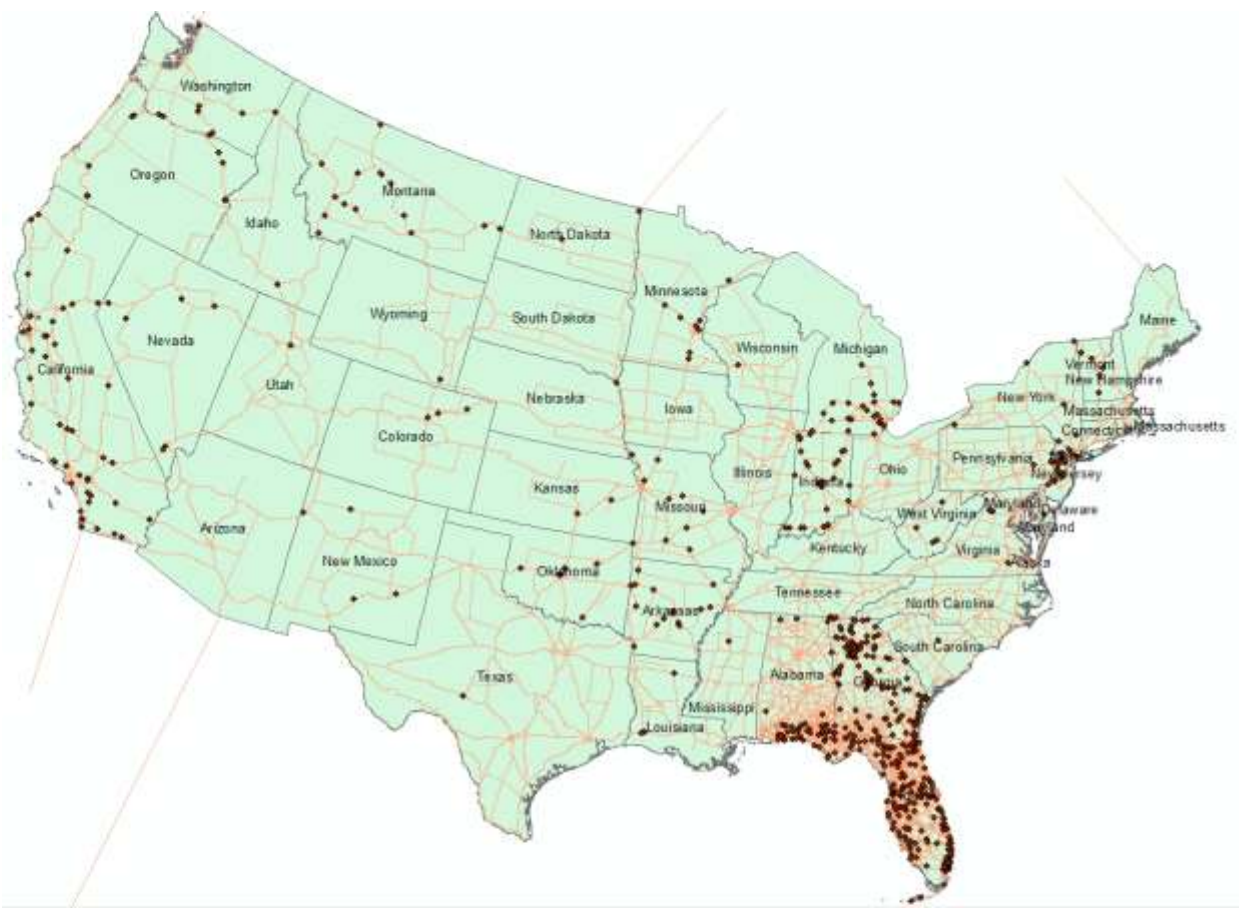


Figure 6.3 Spatial Distribution of Traffic Counting Stations in U.S. Used for ODME

6.3.3 Network

The highway network from the FLSWM was used as an input for traffic assignment purposes in ODME. The network is detailed within Florida and just outside the border of Florida and less detailed as it extends into other states farther from Florida. As can be observed from figure 6.3, the network extends into Canada and Mexico as well. The inputs associated with the network included the following:

a) Free flow speed, travel time (including any delays due to toll plazas), and capacity of each link in the network, and
b) Observed average daily heavy truck counts by direction on over 200 links obtained from TTMS data in Florida and VTRIS data in other states (figures 6.2 and 6.3 show these traffic counting locations of those traffic counting locations).

6.4 Results from the ODME Procedure

6.4.1 Evaluation of Different Assumptions

The ODME procedure in CUBE's Analyst Drive was run several times to evaluate different assumptions on the OD matrix. These assumptions include assumptions (or constraints) of lower and upper bounds on the seed matrix, assumptions on zero cells in the seed matrix, and assumptions on the minimum trip length to be considered in the seed matrix.

Assumptions on the bounds for trips between different OD pairs in the seed matrix include:

1) Lower bound equal to the seed matrix; i.e., none of the estimated number of trips between any OD pairs should be less than those in the seed matrix,
2) No lower bound on the seed matrix; i.e., the estimated matrix can have zero trips between OD pairs even if there were trip flows observed in the seed matrix,
3) Lower bound equal to 0.7 of the seed matrix; i.e., none of the estimated trips between any OD pair should be less than 0.7 times those in the seed matrix,
4) Upper bound of 50 times the seed matrix; i.e., none of the estimated trips between any OD pair should be more than 50 times those in the seed matrix,
5) Upper bound of 100 times the seed matrix; i.e., none of the estimated trips between any OD pair should be more than 100 times those in the seed matrix, and
6) No upper bound on the seed matrix.

It is worth noting here that Cube's Analyst Drive software does not allow the bounds to be different across different cells in the matrix. The bounds have to be uniform across all cells.

Assumptions on zero cells in the seed matrix include the following:

1) Assume OD pairs with zero cells in the seed matrix do not have truck flows in reality (i.e., all zero-cells were retained as zeroes),
2) Alter only the zero cells for OD pairs outside Florida to 0.01 to allow the possibility of truck flows between those OD pairs, and

3) Alter all zero cells to 0.01, assuming that each zero-cell in the seed matrix is likely to have truck trips in reality.

Assumptions on minimum trip length in the seed matrix include:

1) Minimum trip length of 10 miles,
2) Minimum trip length of 5 miles, and
3) Minimum trip length of 1 mile.

Among the assumptions on lower/upper bounds on the OD matrix, the extent of upper bound did not influence the results (i.e., the estimated OD matrix) as long as the bound was large enough. Therefore, the upper bound on the OD matrix was removed. The extent of lower bounds had a significant influence on the estimated OD matrix. When lower bounds were removed on all cells in the OD matrix, the estimated truck traffic volumes matched better than the scenarios that imposed lower bounds on the OD matrix. This can be observed from Table 6.3. Specifically, the RMSE values between estimated and observed truck traffic volumes were smallest when no lower bounds were imposed on the OD matrix. However, in this scenario, the trip length distribution of the estimated OD matrix was changing considerably toward a greater share of shorter trips than those in the seed matrix. There were two possible reasons for such a change in the trip length distribution from the seed matrix to the estimated OD matrix: one was that the seed matrix was biased toward long-distance trips and that combining the seed matrix with the observed traffic counts helped reduce the bias by estimating more short-length trips, and the other was that the estimated OD matrix from the ODME procedure was over-fitting to the observed traffic counts without necessarily correcting for biases in the seed matrix. To investigate this further, any possible anomalies in the estimated OD matrix were closely examined.

Table 6.3 RMSE Values between Estimated and Observed Heavy Truck Traffic Volumes at Different Locations in Florida for Different Assumptions in ODME Procedure

	No Lower Bounds Assumed on OD Matrix		**Lower Bound Equal to No. of Trips in Seed Matrix**		**Lower Bound Equal to 0.7 Times No. of Trips in Seed Matrix**	
Observed Daily Heavy Truck Counts	***RMSE for Input Stations***	***RMSE for Validation Stations***	***RMSE for Input Stations***	***RMSE for Validation Stations***	***RMSE for Input Stations***	***RMSE for Validation Stations***
20–100	8%	92%	83%	104%	70%	105%
100–500	6%	91%	77%	93%	47%	93%
500–1000	2%	38%	46%	47%	33%	49%
1000–7000	2%	25%	37%	40%	11%	24%
All	**4%**	**37%**	**59%**	**60%**	**20%**	**38%**

When closely examined, the estimated OD matrix (when the lower bounds were removed) had zero trips between many OD pairs that originally had some observed trips in the seed matrix from the ATRI data. While this was not necessarily a problem in itself, the estimated OD matrix had zero trips between Florida and some southeastern states that had no observed traffic counts from the VTRIS data (recall that no observed truck traffic counts from Tennessee and North Carolina could be used). For example, no OD pair between North Carolina and Florida and between Tennessee and Florida had any trips in the estimated OD matrix, although at least 100 trips were observed between those states and Florida in the ATRI data. This suggested that the estimated OD matrix was an artifact of over-fitting to the observed traffic volumes rather than a realistic representation of OD flows within, to, and from Florida. A closer examination of the RMSE values for this scenario also suggested that the ODME procedure in this scenario was over-fitting to the observed traffic counts. Specifically, the RMSE value between the estimated and observed heavy truck volumes for input stations (i.e., the TTMS locations from which the data were used for ODME procedure) was only 4 percent. Such an excellent fit to the observed data did not translate to the validation data; i.e., the RMSE between estimated and observed heavy truck volumes was 37 percent for TTMS locations from which the truck traffic count data was kept aside for validation. Therefore, the research team believes that the estimated OD matrix in this scenario was an artifact of over-fitting to the observed truck traffic volumes. In future work, this issue can be resolved by obtaining better observed truck traffic count information from all southeastern states, especially those that do not have any or very few traffic counts in the inputs used in the project.

When the lower bound was set to be equal to the seed matrix, the estimated OD matrix was very close in its trip length distribution to the seed matrix. However, the heavy truck traffic volumes implied by the estimated OD matrix (obtained from traffic assignment) were not close enough to the observed heavy truck traffic counts. The root mean squared value between the estimated traffic volumes and the observed traffic volumes was close to 60 percent.

As a middle ground between the above two scenarios, a scenario was explored in which the lower bounds were set to be 0.7 times the seed matrix (i.e., none of the estimated trips between any OD pairs should be less than 0.7 times those in the seed matrix). Note that the seed matrix used as input for the ODME procedure was a 10-fold inflated version of the one-day seed matrix extracted from the ATRI data. This was done to recognize that the ATRI data represented about 10 percent of the observed heavy truck flows in the state (at an aggregate level). However, it is not necessary that the data represents 10 percent of heavy truck flows at every location. In some locations, the data might represent more or less than 10 percent of the observed heavy truck flows. Therefore, setting a lower bound of 0.7 allows for the possibility that the actual heavy truck trip flows might be less than the 10-fold inflated number of heavy truck trips in the ATRI data. This scenario provided reasonable results, with RMSE value of 20 percent for input stations and 38 percent validation stations while also allowing trips from (and to) all states to (and from) Florida.

Among the assumptions on zero cells, keeping the zero cells as is provided better results both in terms of validation measures against observed heavy truck counts as well as reasonableness of the spatial distribution of truck flows. For instance, altering all zero cells to 0.01 provided high RMSE values results unless the lower bounds were removed on all cells. However, removing the lower bounds on all cells, as discussed earlier, was leading to over-fitting of the estimated heavy truck traffic volumes to observed truck traffic volumes. Since there was no easy mechanism in Cube's Analyst Drive software to incorporate different bounds for different OD pairs, lower bounds could not be imposed on only non-zero cells in the OD matrix and allow the altered zero cells to become zero. Besides, since the seed matrix was derived using a large database from four months of ATRI data, zero cells can be reasonably assumed to represent no truck flows between the corresponding OD pairs. Recall from the discussion in Section 6.3.1.1 that when the seed matrix was aggregated to the county level, few OD pairs in the state had zero trips.

Assumptions on minimum trip length in the seed matrix did not significantly alter the estimated OD matrix except that assumptions with smaller trip length cutoffs led to a higher share of intra-county trips. Since the purpose of this effort was toward statewide freight truck flow modeling, we retained the assumption that valid pickup/delivery trips of heavy trucks should be of at least 10-mile length.

6.4.2 ODME Results for One Set of Assumptions

This section presents and discusses results from the following set of assumptions in the ODME procedure: (1) no upper bounds, but a lower bound of 0.7 times the seed matrix on the estimated OD matrix; (2) trips of at least 10-mile length; and (3) zero cells in the seed matrix assumed to truly represent zero truck flows. The results based on these assumptions were considered to be the final results in the project. However, there is scope for improving the results, which is discussed toward the end of this chapter.

Table 6.4 presents a summary of the truck trips in the seed matrix and those in the estimated OD matrix. As mentioned previously, the seed matrix had trips between nearly 0.41 million OD pairs. Of these, close to 0.3 million OD pairs had at least one end in Florida, and 0.18 million OD pairs had both ends in Florida. As can be observed from the table, the same OD pairs had trips in the estimated OD matrix. The seed matrix contained a total of 69,025 trips that started and/or ended in Florida, and the estimated OD matrix contained a total of 104,587 trips. Close to 70 percent (73,202) of the estimated trips with at least one end in Florida were within Florida. The daily mileage of estimated trips with at least one end in Florida was more than 27 million miles. A total of 26.6 percent of these miles (more than 7 million miles) was due to trips within Florida.

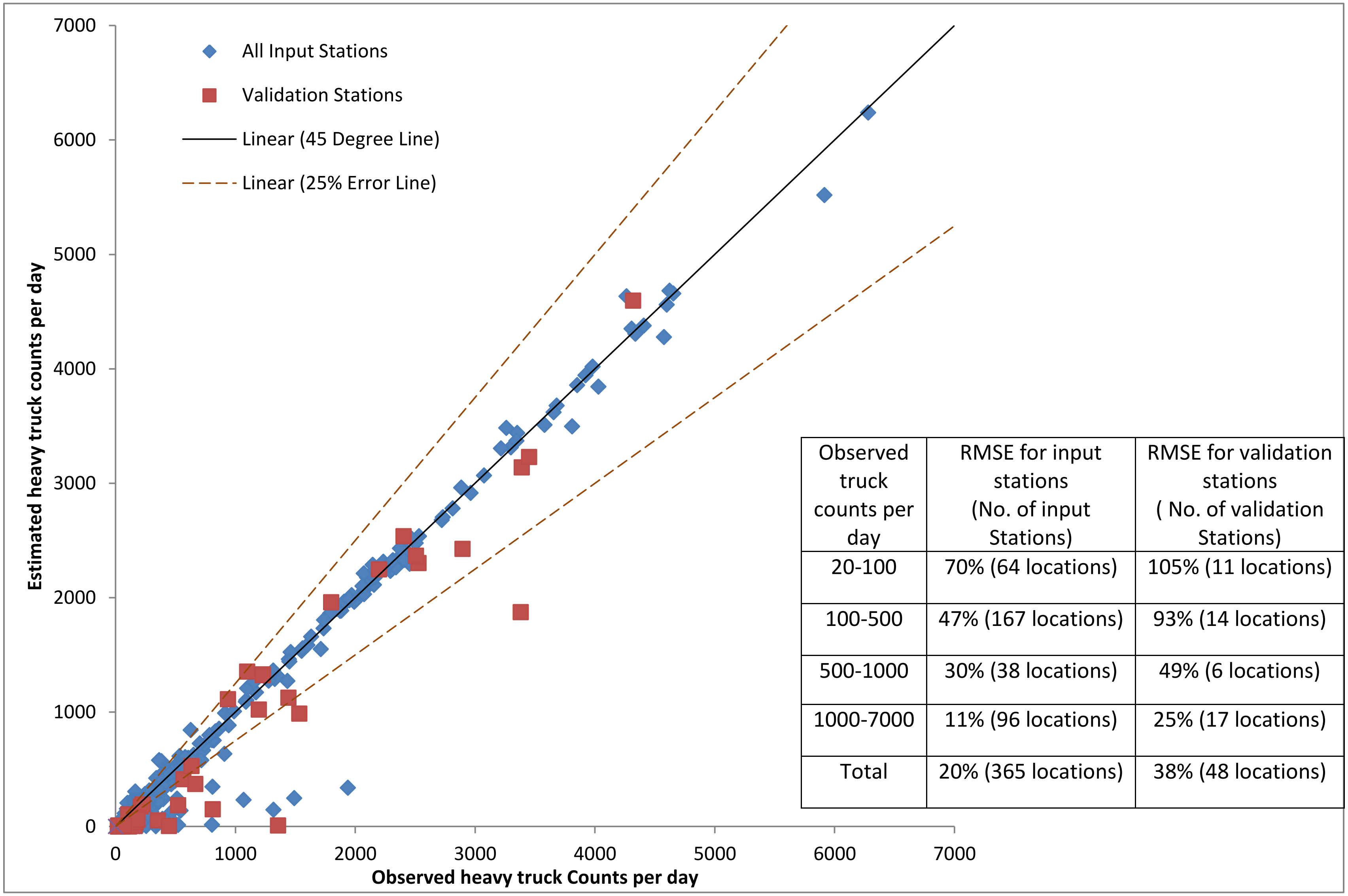
Table 6.4 Summary of Truck Trips in Seed and Estimated OD Matrices

	Seed OD Matrix	Estimated OD Matrix
Trips between All OD pairs within and outside Florida		
No. of OD pairs with trips	410,559	410,559
No. of trips per day	169,859	343,071
Miles traveled per day	54,642,638	206,760,073
Trips with at Least One End in Florida		
No. of OD pairs with trips	304,730	304,730
No. of trips per day	69,025	104,587
Miles traveled per day	18,877,950	27,207,442
Trips with Both Ends in Florida		
No. of OD pairs with trips	183,050	183,050
No. of trips per day	42,434	73,202
Miles traveled per day	4,662,039	7,246,461

Figure 6.4 shows a comparison of estimated truck traffic volumes (using the estimated OD matrix) and observed truck traffic volumes in the TTMS data. The blue dots in the figure are for TTMS stations from which the observed traffic volume data was used on the ODME process, and the red dots are for TTMS stations from which the observed traffic volume data were kept aside for validation. The solid straight line is the 45-degree line. All dots that fall on this line indicate a perfect fit between the estimated truck volume and the observed truck volume. The dots that fall between the two dotted lines correspond to those locations at which the estimated truck traffic volumes are within 25 percent deviation from the observed truck traffic volumes. A table embedded within the figure shows the aggregate RMSE values for different ranges of observed truck traffic volumes. It can be observed that the estimated truck traffic volumes were matching reasonably well with the observed volumes, especially at locations with truck volumes higher than 1,000 trucks per day.

Figure 6.5 shows the trip length distributions of the trips in the seed and estimated OD matrices (the trip lengths are based on TAZ-to-TAZ distances in the FLSWM). The top graph in the figure shows the distribution for trips with at least one end in Florida (this include trips between other states and Florida), and the bottom graph shows the distribution for trips with both ends in Florida. It can be observed that the distribution of the trips in the estimated OD matrix was closely following those from the seed matrix derived from the ATRI data, albeit the estimated OD matrix had a slightly greater proportion of shorter length trips than the seed matrix. Notice from the top graph that the estimated trips showed a spike in the trips of length greater than 2,000 miles when compared to those in the seed matrix. These likely were trips between Florida and states from the northwestern U.S., including California.

Figures 6.6 and 6.7 show the county-level trip productions and attractions, respectively, for both the seed and estimated OD matrices. As discussed in Chapter 4, the seed matrix showed lower than expected trip generation in the south Florida region (especially in and around Miami) and the southern stretch of I-75 beginning from the Tampa region (when compared to those in the Polk County). These trends were observed in discussions related to the coverage of heavy truck flows in Florida by the ATRI data. The estimated OD matrix, due to its use of additional information on the observed heavy truck traffic flows, addressed this issue to a certain extent. This can be observed in Figures 6.6 and 6.7, where counties in southeast Florida and Hillsborough County had higher trip generation in the estimated OD matrix than in the seed OD matrix. Also note that the trip generation in the Duval County has increased as well. This was perhaps due to a high volume of heavy truck traffic in the Jacksonville region.



Observed truck counts per day	RMSE for input stations (No. of input Stations)	RMSE for validation stations (No. of validation Stations)
20-100	70% (64 locations)	105% (11 locations)
100-500	47% (167 locations)	93% (14 locations)
500-1000	30% (38 locations)	49% (6 locations)
1000-7000	11% (96 locations)	25% (17 locations)
Total	20% (365 locations)	38% (48 locations)

Figure 6.4 Observed vs. Estimated Heavy Truck Counts per Day at Different Locations in Florida

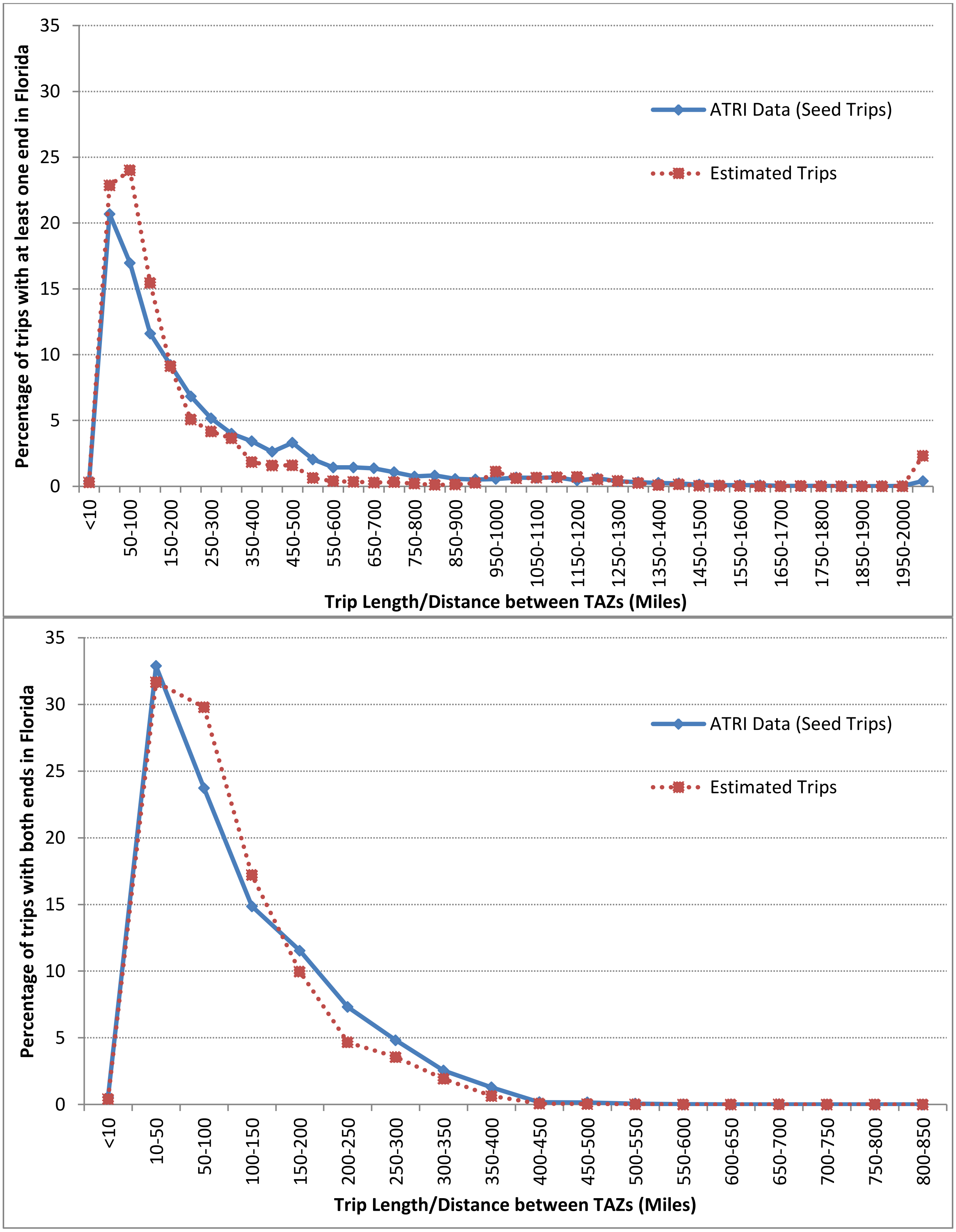


Figure 6.5 Trip Length Distributions of Trips in Estimated and Seed OD Matrices

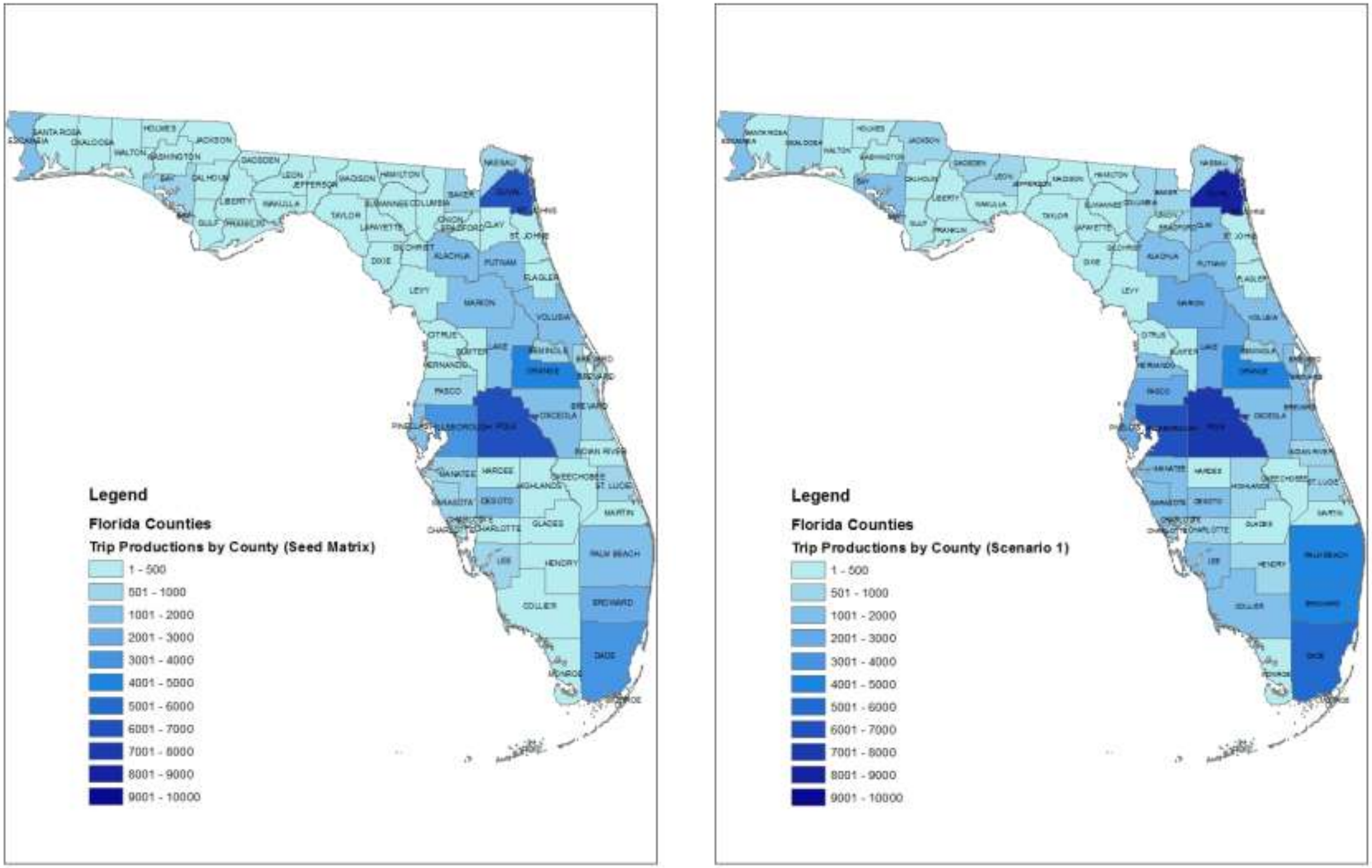


Figure 6.6 Comparison of Trip Productions by County between Seed OD Matrix and Estimated OD Matrix

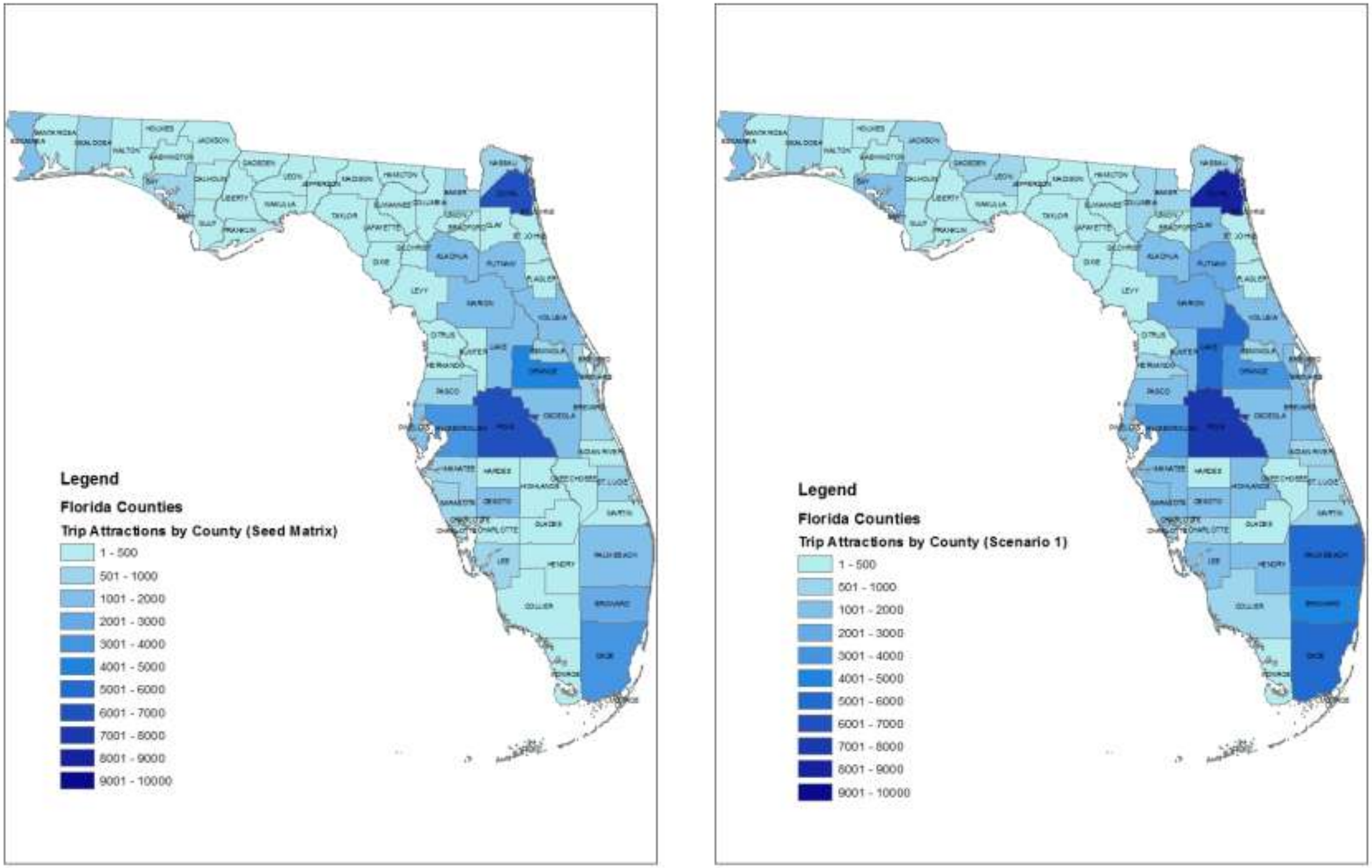


Figure 6.7 Comparison of Trip Attractions by County between Seed OD Matrix and Estimated OD Matrix

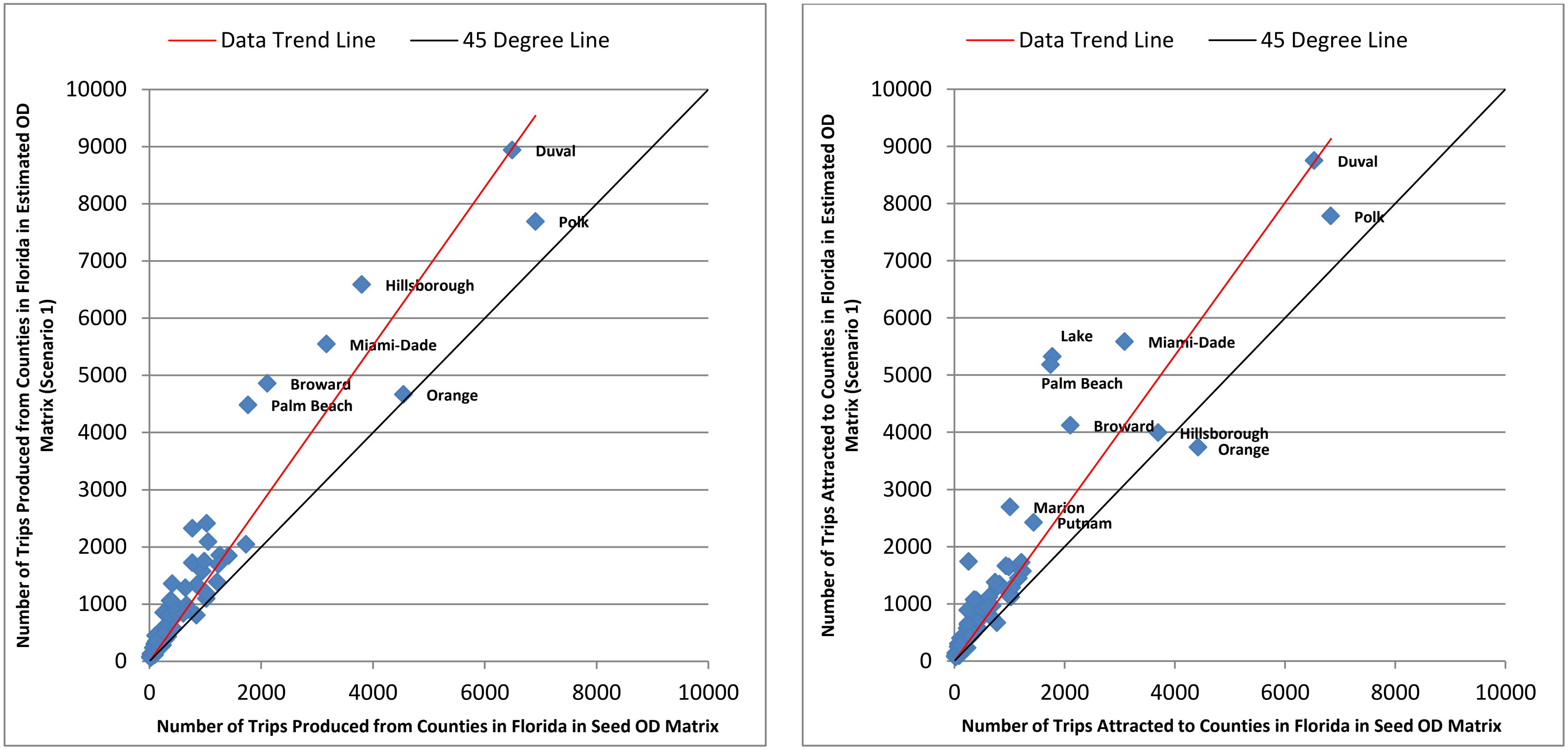


Figure 6.8 Comparison of Truck Trip Productions and Attractions between Seed and Estimated OD Matrices

Tables 6.5 and 6.6 show the state-to-state trip flows in the seed and estimated OD matrices for a selected set of states. Specifically, Table 6.5 shows the distribution of the trips starting in Florida, and Table 6.6 shows the distribution of trips ending in Florida. The seed matrix showed that around 75 percent of the trips staring (ending) in Florida stay within (are from within) Florida, and the estimated matrix adjusted this distribution to contain about 82 percent of those trips within Florida. The next top destinations (origins) for trips starting (ending) in Florida include Georgia, Alabama, and California. It is interesting that California was one of the top destinations (origins) for trips starting in Florida. The reasons for this are not clear and need further investigation. One possibility is that such heightened flows between California and Florida may be artifacts of the ODME procedure given the observed heavy truck traffic volumes in the two states.

Tables 6.7 and 6.8 show the county-to-county trip flows in the seed and estimated OD matrices for counties with the highest truck trip productions and attractions in the data. In both the tables, cells with greater than 10 percent value are shaded in red and those with 5–10 percent value are shaded in brown. Table 6.7 shows the destinations of heavy truck flows from counties with highest trip production in Florida, and Table 6.8 shows the origins of heavy truck flows to counties with highest trip attraction. Several observations can be made from these tables. First, as expected, a good proportion of trips to/from each county were from/to within the county. Second, the seed matrix showed Polk County as one of the major origins/destinations for trips from/to other counties. The estimated OD matrix made adjustments to this trend for Miami-Dade, Palm Beach, and Broward counties; specifically, the estimated OD matrix showed greater flows between these three counties. Third, the estimated OD matrix showed smaller proportion of flows between Hillsborough and Miami-Dade counties than that in the seed OD matrix. While one would expect greater amount of flows between these two counties, the observed heavy truck traffic volumes on major highways between these two counties were not high enough to support this notion.

Finally, Figure 6.9 shows a comparison of the truck trip flows between seed and estimated OD matrices. It can be observed that only those OD pairs with less than 100 trips in the seed matrix have been modified in the estimated seed matrix.

6.5 Scope for Improvements to ODME Results

Some improvements can be implemented in the ODME procedure to obtain a better OD matrix of truck flows within, to, and from the state. Observed heavy truck volumes at different locations within and outside Florida comprise an important input to the ODME process. The research team made several efforts to obtain heavy truck counts for several states outside Florida, but for several states in the Southeast, the team could not obtain the data for a large number of locations. Therefore, the ODME results potentially can be improved by increasing the spatial coverage of observed traffic volume data in the southeastern states (Alabama, Louisiana, South Carolina, North Carolina, Mississippi, and Tennessee). This will help capture the heavy truck flows more accurately, especially the flows between other states and Florida.

Cube’s Analyst Drive software does not allow the lower and upper bounds on the OD matrix to be different across different cells in the matrix (i.e., the bounds have to be uniform across all cells). Allowing different boundary conditions on different types of OD pairs (e.g., separate boundary conditions for OD pairs within Florida and for those outside Florida) may help improve the ODME results. Further, closely examining the accuracy of observed truck traffic counts and specifying confidence levels on this data at different locations may help address issues related to the inaccuracy of the observed truck traffic count data.

Table 6.5 Heavy Truck Trip Flows from Florida to Other States (Greater than 0.5 % in Estimated Matrix)

Destination State	AL	CA	FL	GA	IL	MI	NJ	Other	Total
Seed OD Matrix from ATRI Data	4.6%	0.1%	75.8%	10.3%	0.3%	0.2%	0.3%	8.4%	100.0%
Estimated OD Matrix	2.8%	1.2%	82.1%	9.3%	1.0%	0.9%	1.1%	1.6%	100.0%

Table 6.6 Heavy Truck Trip Flows from Other States to Florida (Greater than 0.5 % in Estimated Matrix)

Origin State	Seed OD Matrix from ATRI Data	Estimated OD Matrix
AL	3.9%	2.8%
CA	0.1%	1.4%
FL	76.4%	82.6%
GA	9.4%	8.4%
IL	0.3%	1.1%
MI	0.1%	0.6%
NJ	0.3%	0.8%
Other	9.5%	2.3%
Total	100%	100%

Table 6.7 Destinations of Heavy Truck Trip Flows from Selected Counties in Florida

Destination / Origin	Broward	Duval	Hillsborough	Miami-Dade	Orange	Palm Beach	Polk	…	…	
Broward (Seed Matrix)	13.6%	5.4%	1.9%	18.5%	3.8%	10.4%	8.5%	…	…	100%
(Estimated Matrix)	16.9%	2.0%	0.3%	28.0%	0.3%	29.0%	2.2%	…	…	100%
Duval (Seed Matrix)	2.2%	16.0%	2.5%	2.7%	4.5%	1.5%	3.7%	…	…	100%
(Estimated Matrix)	2.6%	16.5%	1.4%	2.9%	3.6%	1.4%	2.5%	…	…	100%
Hillsborough (Seed Matrix)	0.8%	5.6%	14.4%	2.2%	6.4%	0.7%	15.5%	…	…	100%
(Estimated Matrix)	0.4%	1.6%	11.1%	0.8%	3.6%	0.6%	15.9%	…	…	100%
Miami-Dade (Seed Matrix)	10.9%	6.2%	3.0%	15.4%	4.7%	7.5%	7.5%	…	…	100%
(Estimated Matrix)	16.4%	0.8%	0.9%	13.4%	0.5%	30.4%	1.2%	…	…	100%
Orange (Seed Matrix)	1.8%	9.1%	5.2%	3.1%	10.4%	2.1%	15.1%	…	…	100%
(Estimated Matrix)	1.0%	8.3%	4.1%	2.6%	10.7%	1.4%	15.7%	…	…	100%
Palm Beach (Seed Matrix)	10.6%	7.7%	1.9%	10.2%	6.2%	10.9%	7.8%	…	…	100%
(Estimated Matrix)	10.7%	13.0%	0.4%	12.8%	0.4%	15.8%	2.4%	…	…	100%
Polk (Seed Matrix)	2.7%	4.3%	8.5%	3.1%	8.2%	2.0%	16.7%	…	…	100%
(Estimated Matrix)	1.8%	2.3%	9.1%	1.8%	6.8%	2.0%	18.1%	…	…	100%

Table 6.8 Origins of Heavy Truck Trip Flows to Selected Counties in Florida

Origin \ Destination	Broward	Duval	Hillsborough	Lake	Miami-Dade	Orange	Palm Beach	Polk
Broward (Seed Matrix)	13.6%	1.7%	1.1%	1.6%	12.6%	1.8%	12.5%	2.6%
(Estimated Matrix)	19.9%	1.1%	0.3%	0.3%	24.3%	0.3%	27.2%	1.4%
Duval (Seed Matrix)	6.7%	15.9%	4.4%	1.8%	5.7%	6.5%	5.5%	3.5%
(Estimated Matrix)	5.7%	16.8%	3.2%	1.3%	4.7%	8.6%	2.4%	2.8%
Hillsborough (Seed	1.5%	3.2%	14.8%	4.7%	2.7%	5.5%	1.6%	8.6%
(Estimated Matrix)	0.6%	1.2%	18.4%	14.8%	1.0%	6.3%	0.8%	13.5%
Miami-Dade (Seed	16.4%	3.0%	2.6%	4.2%	15.8%	3.4%	13.5%	3.5%
(Estimated Matrix)	22.0%	0.5%	1.3%	0.5%	13.3%	0.7%	32.5%	0.9%
Orange (Seed Matrix)	3.8%	6.3%	6.4%	13.7%	4.5%	10.7%	5.6%	10.1%
(Estimated Matrix)	1.1%	4.4%	4.8%	3.6%	2.2%	13.3%	1.2%	9.4%
Palm Beach (Seed	8.9%	2.1%	0.9%	1.1%	5.8%	2.5%	11.0%	2.0%
(Estimated Matrix)	11.6%	6.6%	0.4%	0.1%	10.2%	0.5%	13.7%	1.4%
Polk (Seed Matrix)	8.8%	4.5%	16.0%	19.7%	6.9%	12.8%	7.7%	16.9%
(Estimated Matrix)	3.4%	2.0%	17.4%	5.9%	2.4%	13.9%	3.0%	17.9%
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
Total (Seed Matrix)	100%	100%	100%	100%	100%	100%	100%	100%
Total (Estimated Matrix)	100%	100%	100%	100%	100%	100%	100%	100%

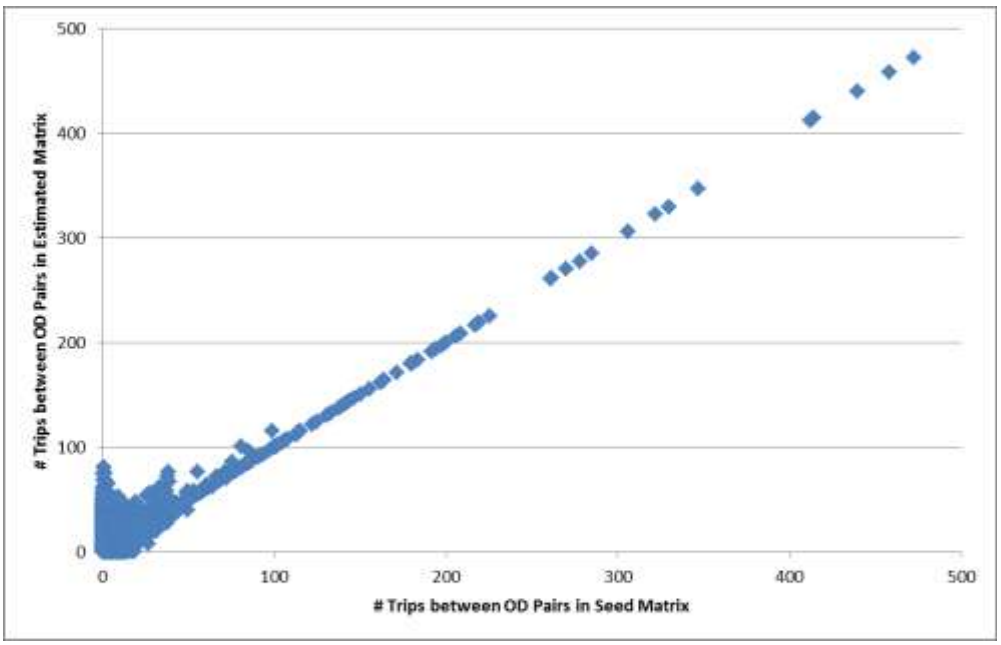


Figure 6.9 Comparison of Truck Trip flows between Each OD Pair in Seed and Estimated OD Matrices

CHAPTER 7 : SUMMARY AND CONCLUSIONS

7.1 Summary

Freight is gaining increasing importance in transportation planning and decision making at all levels of the government, particularly MPOs, states, and at the federal level. An accelerated growth in the volume of freight shipped on American highways has led to a significant increase in truck traffic. This has put enormous pressure on national highways, which impacts traffic operations, safety, highway infrastructure, port operations, and distribution center operations. Traffic congestion, in turn, impedes the speed and reliability of freight movement on the highway system and leads to direct economic costs for producers and consumers, passenger traffic congestion, safety issues, and environmental impacts.

As freight movement continues to grow within and between urban areas, appropriate planning and decision making processes are necessary to mitigate the above-mentioned impacts. However, a main challenge in establishing these processes is the lack of adequate data on freight movements such as detailed origin-destination (OD) data, truck travel times, freight tonnage distribution by OD pairs, transported commodity by OD pairs, and details about truck trip stops and paths. As traditional data sources on freight movement are either inadequate or no longer available, new sources of data must be investigated.

A recently-available source of data on nationwide freight flows is based on a joint venture by American Transportation Research Institute (ATRI) and Federal Highway Administration (FHWA) to develop and test a national system for monitoring freight performance measures (FPM) on key corridors in the nation. These data are obtained from trucking companies who use GPS-based technologies to remotely monitor their trucks. ATRI's truck GPS database contains GPS traces of a large number of trucks as they traveled through the national highway system. This provides unprecedented amounts of data on freight truck movements throughout the nation (and Florida). Such truck GPS data potentially can be used to support planning, operation, and management processes associated with freight movements. Further, the data can be put to better use when used in conjunction with other freight data obtained from other sources.

The overarching goal of this project was to investigate the use of ATRI's truck GPS data for statewide freight performance measurement, statewide freight truck flow analysis, and other freight planning and modeling applications in the state. The specific objectives of the project were to:

1) Derive freight performance measures for Florida's Strategic Intermodal System (SIS) highways,
2) Develop algorithms to convert large streams of ATRI's truck GPS data into a more useable truck trip format,
3) Analyze truck trip characteristics in Florida using ATRI's truck GPS data,
4) Assess ATRI's truck GPS data in terms of its coverage of truck traffic flows in Florida,

5) Develop OD tables of statewide freight truck flows within, into, and out of Florida for different geographic resolutions, including the Florida Statewide Model (FLSWM) traffic analysis zones (TAZs), and
6) Explore the use of ATRI's GPS data for other applications of interest to Florida, including the analysis of truck flows out of two sea ports, the re-routing patterns of trucks after a major highway incident, and the routing patterns of trucks traveling between Jacksonville and Ocala.

7.2 Project Outcomes and Findings

This section summarizes the outcomes, findings and benefits from the project.

7.2.1 Freight Performance Measures on Florida's SIS Highway Network

The project resulted in the development of average truck speed data for each (and every) mile of the SIS highway network for different time periods in the day—AM peak, PM peak, mid-day, and off peak—using 3 months of ATRI's truck GPS data in the year 2010. In doing so, it was found that the existing shape files of the SIS network available with FDOT were either not accurate enough or they lacked the details (for example, separate links by direction for divided highways) to derive performance measures using geospatial data. Therefore, a highly-accurate network was developed to represent highways on the SIS network.

The SIS highway network shape file and the data on average truck speeds by time-of-day were submitted in a GIS shape file that can be used in an ArcGIS environment to identify the major freight bottlenecks on Florida's SIS highway network. In addition to the development of average speed measures, the project developed example applications of ATRI's truck GPS data for measuring truck speed reliability and for highway freight bottleneck analysis.

7.2.2 Algorithms to Convert ATRI's Raw GPS Data Streams into a Database of Truck Trips

The raw GPS data streams from ATRI need to be converted into a truck trip format to realize the full potential of the data for freight planning applications. The project resulted in algorithms to convert the raw GPS data into a data base of truck trips. The results from the algorithms were subject to different validations to confirm that the algorithms can be used to extract accurate trip information from the raw GPS data provided by ATRI.

These algorithms were then applied to four months of raw GPS data from ATRI, comprising a total of 145 million raw GPS data records, to develop a large database of truck trips traveling within, into, and out of the state. The resulting database comprises more than 1.2 million truck trips traveling within, into, and out of the state. This database of truck trips can be used for a variety of purposes, including the development of truck travel characteristics and OD truck flow patterns for different geographical regions in Florida. The database can be used to calibrate and validate the next-generation statewide freight travel demand model being developed by Florida Department of Transportation (FDOT). In future work, this database potentially can be used to develop data on truck trip-chaining and logistics patterns in the state.

7.2.3 Analysis of Truck Travel Characteristics in Florida

The truck trip database developed from four months of ATRI's truck GPS data was used to analyze a variety of truck travel characteristics in the state of Florida. The truck travel characteristics analyzed included trip duration, trip length, trip speed, time-of-day profiles, and origin-destination flows. Each of these characteristics was derived at a statewide level as well as for different regions in the state—Jacksonville, Tampa Bay, Orlando, Miami, and rest of Florida—defined based on the freight analysis framework (FAF) zoning system. The time-of-day profiles of truck trips in all urban regions of Florida show a single peak during the late morning period as opposed to a bi-modal peak typically observed for passenger travel during morning and evening peak periods.

In addition, the truck trips were used in conjunction with the GPS data to derive distributions of OD travel distances, travel times, and travel speeds between over 1,200 TAZ-to-TAZ OD pairs in the FLSWM. The distributions for each OD pair are reported in the form of average values and minimum, 5th percentile, 15th percentile, 50th percentile, 85th percentile, and maximum values. Comparing the minimum truck travel times measured using GPS data for the 1,200 OD pairs with free-flow travel times used as inputs to FLSWM indicated that the FLSWM travel times systematically underestimate the truck travel times. A similar comparison with the travel times extracted from Google Maps also suggested that the Google Maps travel times underestimate (albeit not as much the FLSWM travel times) the truck travel times. This is most likely because the travel times used as inputs for the FLSWM and those reported by Google Maps are predominantly geared toward passenger cars that tend to have higher travel speeds and better acceleration characteristics. ATRI's truck GPS data, on the other hand, provide an opportunity to accurately measure travel times exclusively for trucks (and for different times of the day).

In addition to the measurement of OD truck travel distances, travel times, and speeds, the project team performed an exploratory analysis of truck travel routes for more than 1,600 trips between 10 OD pairs in FLSWM. A preliminary exploratory analysis suggested that a majority of trips between any OD pair tend to travel largely by similar routes (i.e., the variability in route choice is not high for the 10 OD pairs examined in this study). Specifically, considerable overlap was observed among the routes across a large number of trips between an OD pair. Upon further examination of truck travel routes for a few randomly-sampled OD pairs, it was noticed that truck travel routes tend to exhibit higher variability for travel over shorter distances within urban areas than for travel over longer distances. These observations have interesting implications for future research on understanding and modeling truck route choice. While this study did not delve further into understanding the route choice patterns of long-haul trucks, this is an important area for future research using the truck GPS data from ATRI.

7.2.4 Assessment of ATRI's Truck GPS Data and Its Coverage of Truck Traffic in Florida

This project resulted in a better understanding of ATRI's truck GPS data in terms of their coverage of truck traffic in the state of Florida. This includes deriving insights on (a) the types of trucks (e.g., heavy trucks and medium trucks) present in the data, and (b) the geographical coverage of the data in Florida, and (c) the proportion of the truck traffic flows in the state covered by the data.

Based on discussions with ATRI and anecdotal evidence, it is known that the major sources of ATRI data are freight shipping companies that own large trucking fleets, which typically comprise tractor-trailer combinations (or FHWA vehicle type classes 8–13). However, a close observation of the data, from following the trucks on Google Earth and examining travel characteristics of individual trucks, suggested that the data included a small proportion of trucks that are likely to be smaller trucks that do not necessarily haul freight over long distances. The project used simple rules to divide the data into two categories: (1) long-haul trucks or heavy trucks (considered to be FHWA vehicle classification 8–13), and (2) short-haul trucks or medium trucks. Specifically, trucks that did not make at least one trip of 100-mile length in a two-week period and those that made more than 5 trips per day were considered "short-haul" trucks. Of a total of 169,714 unique truck IDs in the data, about 4.6 percent were labeled as short-haul trucks (or medium trucks) and separated from the remaining long-haul trucks (or heavy trucks). In future work, it will be useful to derive better definitions of heavy trucks and medium trucks. Whereas heavy trucks are of primary interest to FLSWM (assuming these are the long-haul freight carrying trucks), medium trucks are also of potential use for updating the non-freight truck models. Further, extracting sufficient data on medium trucks potentially can help understand truck movement within urban regions as well (because a considerable proportion of truck traffic in urban areas tends to comprise medium trucks).

ATRI's truck GPS data represented a large sample of truck flows within, coming into, and going out of Florida. However, the sample was not a census of all trucks traveling in the state, and it was unknown what proportion of heavy truck flows in the state is represented by these data. To address this question, truck traffic flows implied by one week of ATRI's truck GPS data were compared with truck counts data from more than 200 Telemetered Traffic Monitoring Sites (TTMS) in the state. The results from this analysis suggest that**,** at an aggregate level, the ATRI data provided 10.1 percent coverage of heavy truck flows observed in Florida. When the coverage was examined separately for different highway facilities (based on functional classification), the results suggest that the ATRI data provided a representative coverage of truck flows through different types of highway facilities in the state.

The coverage of ATRI data was examined for different geographical regions in the state by examining the spatial distribution of the number of truck trips generated at TAZ-level and at county-level geography. In addition, the percentage of heavy truck traffic covered by ATRI data at different locations was examined. All these examinations suggested potential geographical differences in the extent to which ATRI data represent heavy truck traffic volumes at different locations in the state. For instance, truck trips generated from the Polk County were much higher than those generated from Hillsborough and Miami-Dade counties. Further, the percentage of heavy truck traffic covered by ATRI data in the southern part of Florida (within Miami) and the southern stretch of I-75 is slightly lower compared to the coverage in the northern and central Florida regions. Such geographical differences (or spatial biases) potentially can be adjusted by combining ATRI's truck GPS data with observed data on truck traffic flows at different locations in the state (from FDOT's TTMS traffic counting program).

7.2.5 Origin-Destination (OD) Tables of Statewide Truck Flows

An important outcome of the project was to use ATRI's truck GPS data in combination with other available data to derive OD tables of freight truck flows within, into, and out of the state of Florida. The OD flow tables were derived at the following levels of geographic resolution:

a) TAZs of the FLSWM, with Florida and the rest of the country divided into about 6,000 TAZs,
b) County-level resolution, in which Florida is represented at a county-level resolution and the rest of the country is represented at a state-level resolution, and
c) State-level resolution, in which Florida and the rest of the country are represented at a state-level resolution.

As part of this task, first, the truck trip database developed from four months of ATRI's GPS data was converted into OD tables at the TAZ-level spatial resolution used in the FLSWM. Such an OD table derived only from the ATRI data, however, was not necessarily representative of the freight truck flows in the state. This was because the ATRI data did not comprise the *census* of trucks in the state. Although it was a large sample, it was not necessarily a random sample and was likely to have spatial biases in its representation of truck flows in the state. To address these issues, the OD tables derived from the ATRI data were combined with observed truck traffic volumes at different locations in the state (and outside the state) to derive a more robust OD table that was representative of the freight truck flows within, into, and out of the state. To achieve this, a mathematical procedure called origin-destination matrix estimation (ODME) method was employed to combine the OD flow table generated from the ATRI data with observed truck traffic volume information at different locations within and outside Florida. The OD flow table estimated from the ODME procedure was likely to better represent the heavy truck traffic volumes in the state, as it used the observed truck traffic volumes to weigh the ATRI data-derived truck OD flow tables.

The truck flow OD tables derived in the project can be used for a variety of different purposes:

1) To understand the spatial distribution of truck travel demand in the region,
2) To validate, calibrate, and update the heavy truck modeling components of FLSWM, and
3) Analysis of truck flows into and out of selected locations in Florida.

7.2.6 Explorations of the Use of ATRI's Truck GPS Data for Other Applications

In addition to the above, this project conducted preliminary explorations of the use of ATRI's truck GPS data for the following applications:

a) Analysis of truck flows out of two ports in Florida—Port Blount Island in Jacksonville and Port Everglades in Fort Lauderdale,
b) Analysis of routing patterns of trucks that used the US 301 roadway to travel between I-95 around Jacksonville and I-75 around Ocala, and
c) Analysis of changes in truck routing patterns during the closure of a stretch of I-75 near Ocala due to a major multi-vehicle crash in January 2012.

These applications were only preliminary explorations conducted as proofs of concept. Future work can expand on these explorations to conduct full-scale applications.

7.3 Future Work

The work conducted in this project can be extended in several directions of interest to Florida, as discussed in this section.

7.3.1 Explore the Use of ATRI's Truck GPS Data for Understanding Urban Freight Movements and Statewide Non-freight Truck Flows

A significant part of the project was aimed at generating data useful for the FLSWM—for example, statewide truck OD flows. In future work, it will be useful to explore if ATRI's truck GPS data can be used to develop and understand truck flows within urban areas as well. As mentioned earlier, while the data predominantly comprise heavy trucks that tend to haul freight over long distances, a non-negligible portion of the data contains medium trucks that tend to serve local distribution and delivery. Extracting such trucks and analyzing their travel patterns to understand the extent to which the data covers urban truck flows is a fruitful avenue for future research. In addition, it will be useful to understand the gaps in these data in terms of what types of trucks and what industries are not represented in this data. This potentially can help in augmenting the data with other data sources for use in regional freight travel demand models.

It will be worth exploring the use of these data for generating non-freight truck travel patterns for FLSWM. Currently, the FLSWM uses Quick-Response Freight Manual (QRFM) techniques for modeling non-freight truck flows. While QRFM techniques are useful in the absence of data on non-freight truck flows, it is preferable to develop Florida-specific data to better model non-freight truck flows in the state.

7.3.2 Estimation of OD Truck Travel Times for FLSWM

This project resulted in measurements of truck travel times (and the distribution of travel times for different time periods of the day) for more than 1,200 OD pairs in FLSWM. However, FLSWM has more than 36 million OD pairs (since the model divides Florida and the rest of the country into more than 6,000 zones). It is not feasible to measure truck travel times using only the data. However, the travel times measured for 1,200 OD pairs potentially can be used to develop a travel time estimation model that can be used to estimate the truck travel times for other OD pairs in FLSWM. Such development of accurate truck travel times that can be input to the FLSWM is a fruitful avenue for future work.

7.3.3 Analysis of Truck Route Choice

The project explored the route choice patterns of trucks to a limited extent. The data provide a significant opportunity to better understand truck route choice and to develop truck route choice models based on accurate data. Combining the data with additional surveys on trucking companies' and drivers' route choice decisions potentially can lead to significant advances in truck route choice modeling. This can also help improve the truck traffic algorithms currently used in statewide models.

7.3.4 Improvements to ODME

The ODME performed in this study can be improved in different ways. First, the observed truck traffic volumes used in this study come from FDOT's telemetric traffic monitoring program (for more than 200 locations in Florida), Georgia Department of transportation (for several locations in Georgia), and FHWA's Vehicle Travel Information System (VTRIS) database (for locations outside Florida and Georgia). Within the timeframe of this study, the research team could not gather robust data on observed truck traffic volumes in several southeastern states. For example, there was little to no traffic count information for states such as Tennessee and a few other southeastern states. Providing robust truck traffic count data for southeastern states into the ODME procedure potentially can help in better estimating the truck flows into and out of the state. Second, the truck GPS data used to develop the seed OD flow table (an input into the ODME procedure) is Florida-centric. The data do not necessarily provide a reliable picture of the truck flows between origins and destinations outside Florida. Therefore, using more of ATRI's truck GPS data, at least for the southeastern states other than Florida, can potentially help improve the ODME results. Third, the ODME procedure itself can be improved in different ways: (a) by allowing different constraints that are specific to different OD pairs, (b) by exploring the different weighting schemes used to expand the seed matrix, and (c) by improving the traffic assignment procedure based on observed route choice patterns of trucks. In this context, analyzing the route choice behavior of trucks is an important avenue for future research both for improving existing procedures used for traffic assignment and for improving the ODME procedure for estimating truck OD flows.

7.3.5 Development of Truck Trip Chaining and Logistics Data

This project resulted in procedures for identifying truck stops and truck trips from raw GPS data. This work can be extended further to derive truck trip chaining and logistics patterns from the data. In doing so, adding detailed land-use information can help in characterizing the truck travel patterns.

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APPENDIX A: EXPLORATORY ANALYSES OF USING ATRI DATA FOR FREIGHT PLANNING APPLICATIONS IN FLORIDA

In this project, the research team was charged with using the ATRI data for different freight planning applications of interest to FDOT. Some of the applications, which were intended to be full-scale applications, are described in the main chapters of the report. Other applications, which were intended to be of exploratory nature and conducted as proofs-of-concept (not as full applications) are described in this appendix. The reader will note here that these analyses are intended to be of exploratory nature, conducted using samples of ATRI's truck GPS data. Given the ATRI data sample (and the sample drawn from it) are neither a census of all trucks in Florida nor a random sample, the results of these analyses must be interpreted with caution.

A.1 I-75 Incident Analysis

ATRI's truck GPS data can be used to study freight diversion in the event of a road closure or other significant event. This information is useful for helping to plan for disasters in the future and also for understanding the impacts of a specific event on a region's economic activities. As an example of such an incident, FDOT requested the research team to explore the influence of a multi-vehicle crash event that occurred on January 29, 2012, which forced the closure of I-75 near Ocala for more than 30 hours. Using ATRI truck GPS data, the research team quantified unique truck counts on major roadways near the incident area before and during the closure. The period from 3:00 a.m. on January 22, 2012, to 10:00 a.m. on January 23, 2012 (i.e., one week before the incident occurred) served as a benchmark to characterize normal traffic flows and relative volumes experienced on the study area roadways. The study period for the closure due to the incident extended from 3:00 a.m. on January 29, 2012, to 10:00 a.m. on January 30, 2012. In the Figure A.1, alternate paths used due to the closure are highlighted by comparing the number of unique truck counts for each roadway pre-closure to those during the closure. The section that was closed due to the incident is shown in red. In this example, a color scale depicts loss in unique truck counts due to diversion in shades of orange. Roadways that were used more frequently during the closure than pre-closure are shown using a color scale in shades of green. Such visualizations can be used to understand the truck re-routing patterns during the highway closure for further detailed analyses of the influence of the incident.

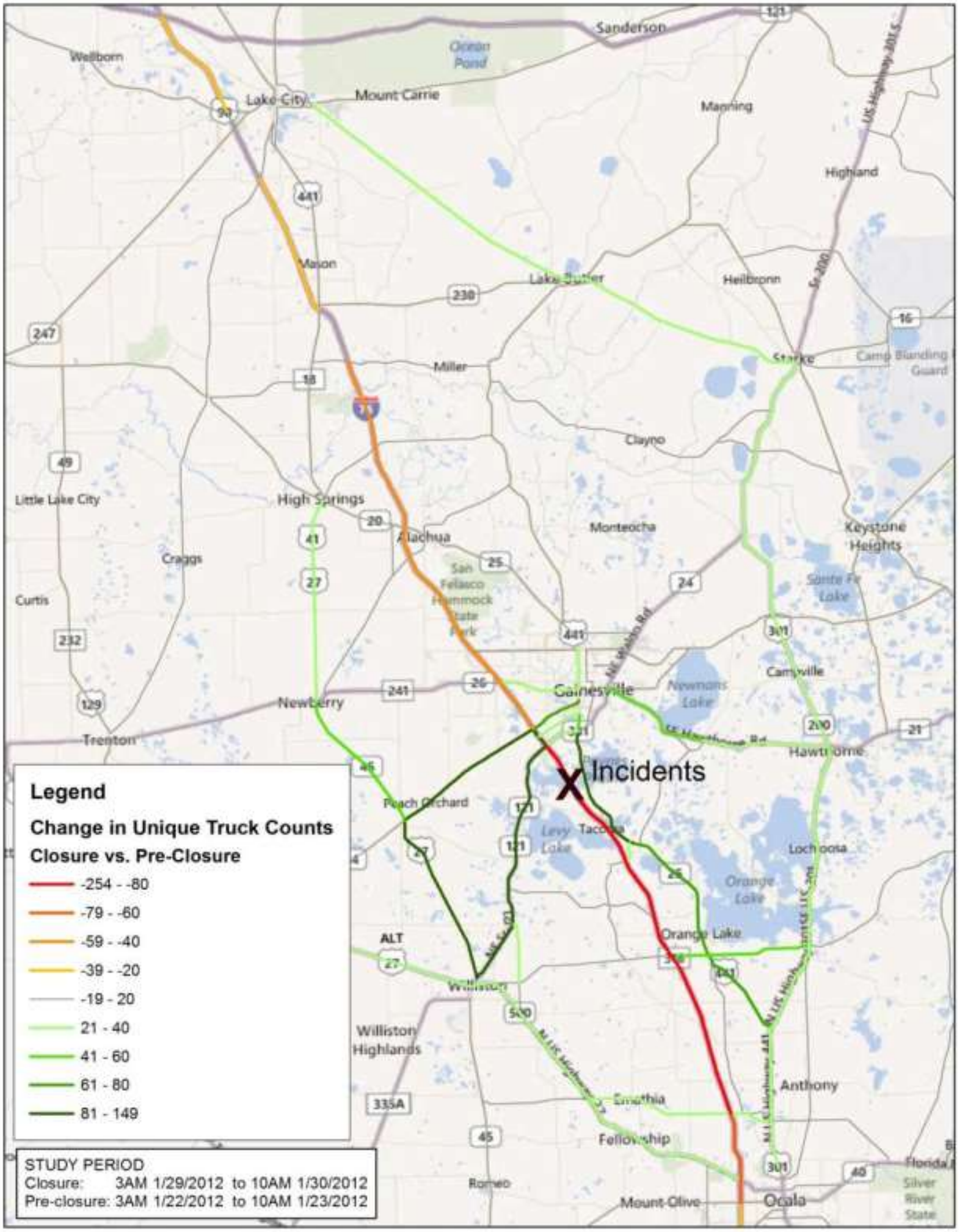


Figure A.1 Visualization of Truck Re-routing after Highway (I-75) Closure due to Multi-vehicle Crash

A.2 Trucks Flows from Ports

In another exploratory application, FDOT requested the research team to use the ATRI data to visualize the travel patterns of trucks leaving two ports in Florida: (1) Jacksonville's Blount Island Port and (2) Port Everglades in Fort Lauderdale.

A.2.1 Blount Island Analysis

For this application, ATRI took a sample of trucks that had a nexus with Blount Island in 2010 and followed them from when they left the island for a maximum of 11 hours. Each truck trip, beginning in Blount Island, was terminated after exhibiting little to no movement for longer than 2 hours. Figure A.2 displays the resulting truck flows from the analysis.

Figure A.2 Analysis of Truck Flows from Blount Island

Once the flows were established, ATRI determined the approximate distribution of route choices for trucks leaving the island. As Figure A.3 shows, more than 7,500 trips were identified in the analysis. Of all these trips, a considerable proportion (46.4%) was urban trips that did not have a destination beyond the I-295 perimeter highway, presumably because there are drayage trips. Investigating these urban trips further, ATRI discovered that a significant portion of trips were servicing intermodal facilities in the northern Jacksonville area. As Figure A.4 illustrates, the vast majority of urban trips (90–95%) did not travel south of I-10 or SR 10.

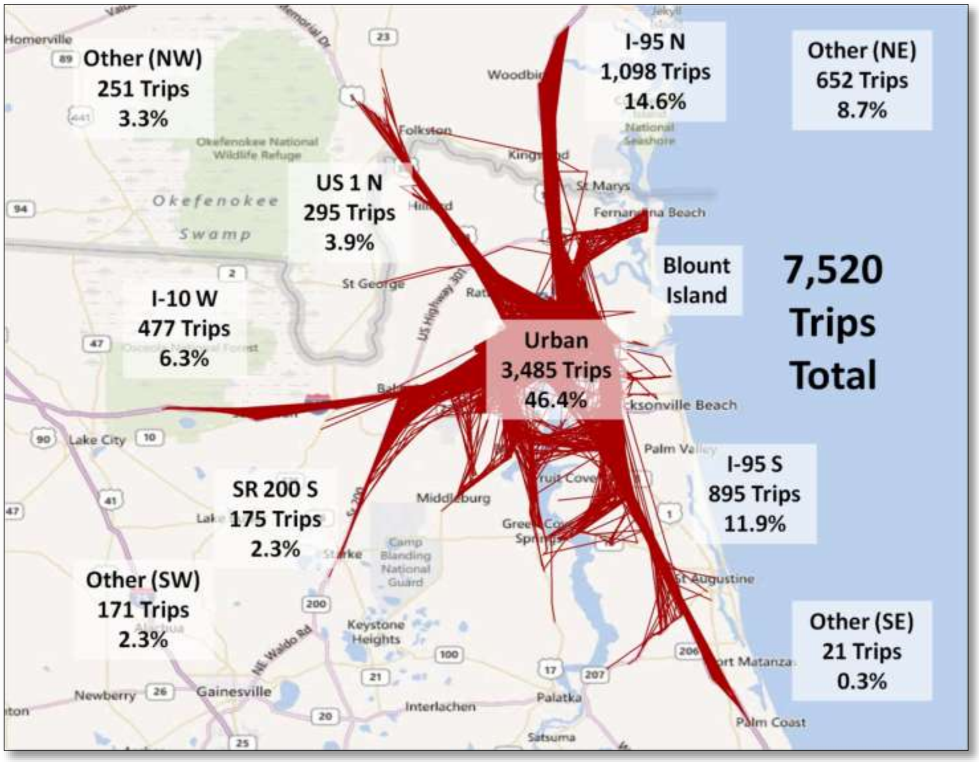


Figure A.3 Truck Trips within 1 Hour of Departing Blount Island

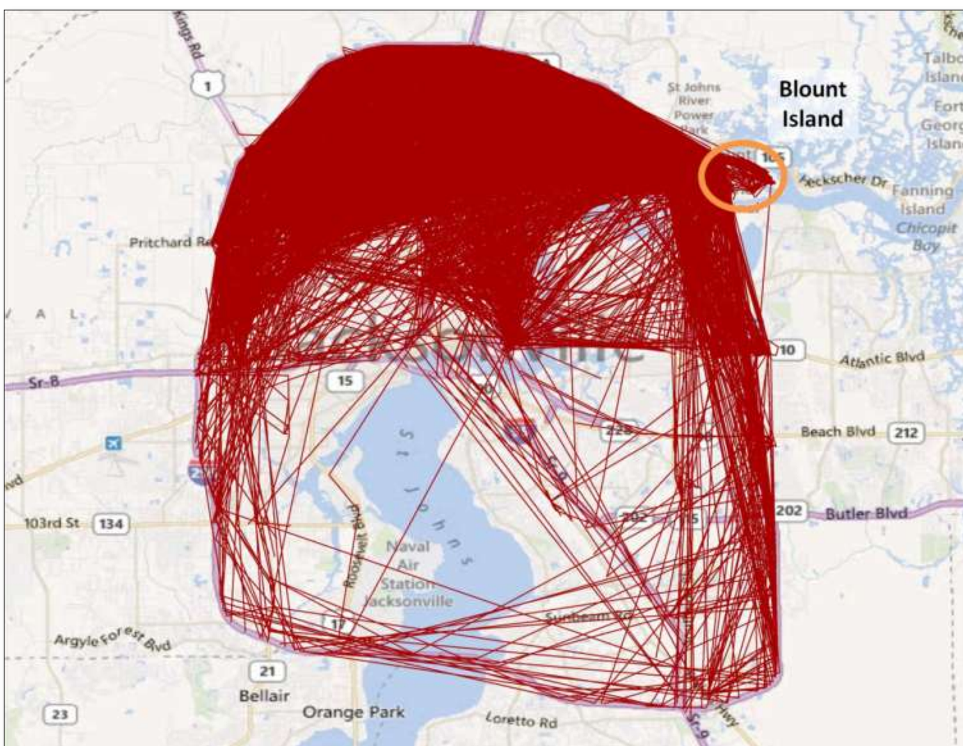


Figure A.4 Urban Truck Trips within 1 Hour of Departing Blount Island

A.2.2 Port Everglades Analysis

Similar to the Blount Island analysis, ATRI analyzed truck movements for vehicles servicing Port Everglades. This analysis isolated a sample of trucks that had a nexus with Port Everglades in 2010 and followed them from when they left the port area for a maximum of 11 hours. Each trip was terminated after exhibiting little to no movement for longer than 2 hours. Figure A.5 presents the resulting truck flows generated from the analysis.

Figure A.5 Analysis of Truck Flows from Port Everglades

Figure A.6 shows truck movement within the first hour of leaving Port Everglades. Urban trips are those that do not leave the Miami–Ft. Lauderdale area (defined by Sawgrass Expressway on the south, Florida Turnpike on the west, the intracoastal waterway on the east, and US 441 on the north). As would be expected for a facility so far to the south, the plurality of trips (49.3%) used I-95 northbound to exit the Miami region. Figure A.7 depicts the 1,341 “urban” trips. Approximately two-thirds of urban trips traveled south of I-595, and one-third traveled north of I-595.

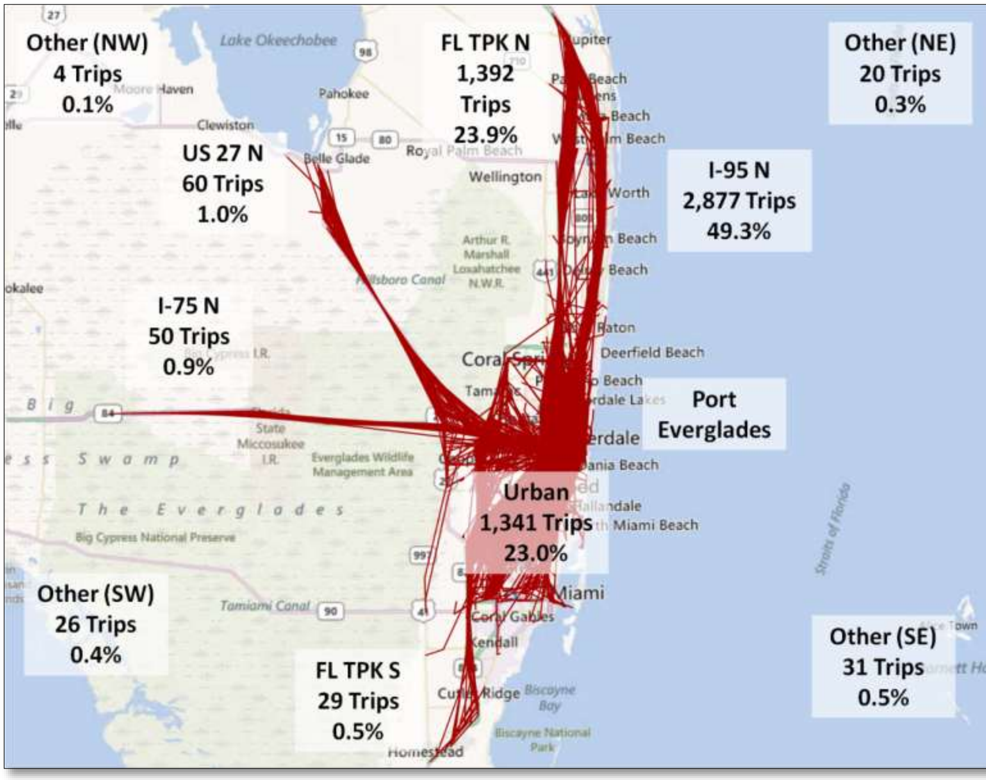


Figure A.6 Truck Trips within 1 Hour of Departing Port Everglades

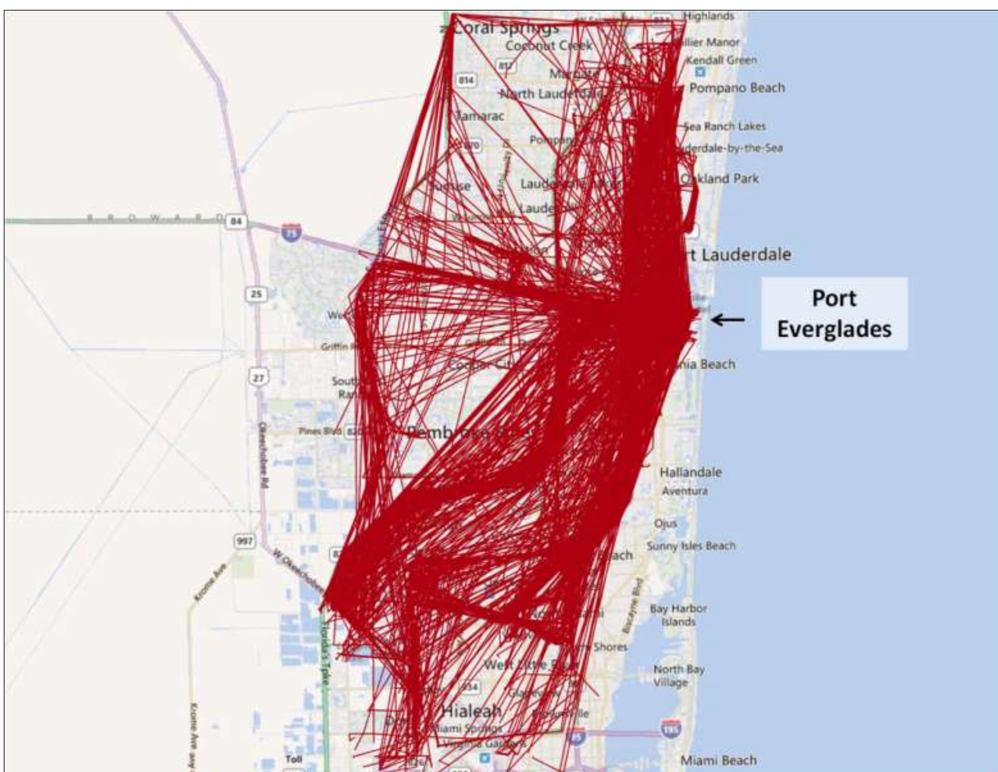


Figure A.7 Urban Truck Trips within 1 Hour of Departing Port Everglades

A.3 I-75 Ocala Analysis

For this task, the research team was requested to characterize truck movements before and after crossing a traffic counting station on I-75 near Ocala, specifically focusing on the trucks using US 301. Such analysis can be used to understand the need for a future corridor connecting I-95 in Jacksonville to I-75 at Ocala. ATRI analyzed one week of truck GPS data (April 26–May 2, 2010) to determine the routes that trucks used before and after crossing the counting station. The resulting truck flow data were aggregated to determine the share of trips that used specific routes (Figure A.8). Specifically, Figure A.8 shows where trucks came from before passing Ocala on I-75. For example, 32.9 percent of the trucks that were on I-75 north of I-10 passed Ocala on I-75 (see northern part of Figure A.8), but only 2.8 percent of the trucks that traveled on I-75 south of Naples passed Ocala on I-75 (see southern part of Figure A.8).

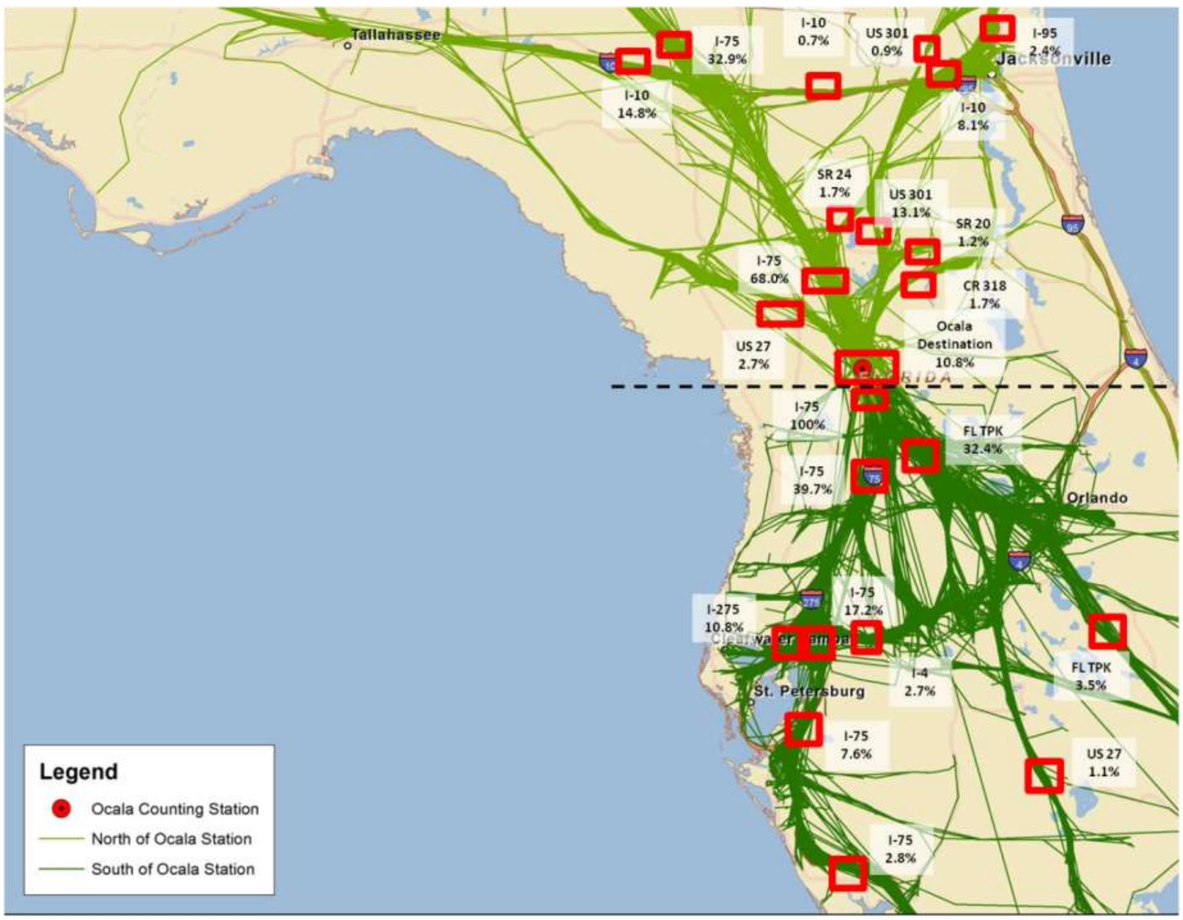


Figure A.8 Travel Routes of Trucks Crossing the Traffic Counting Station on I-75 at Ocala

FDOT was interested in specifically understanding the degree to which trucks were using US 301 to travel between I-95 and I-75. To answer this question, ATRI analyzed only trips that used part of US 301 (Figures A.9 and A.10). For example, in Figure A.9, 13.1 percent of southbound trips on I-75 (north of Jacksonville) traveled on US 301 to get to I-75 through Ocala.

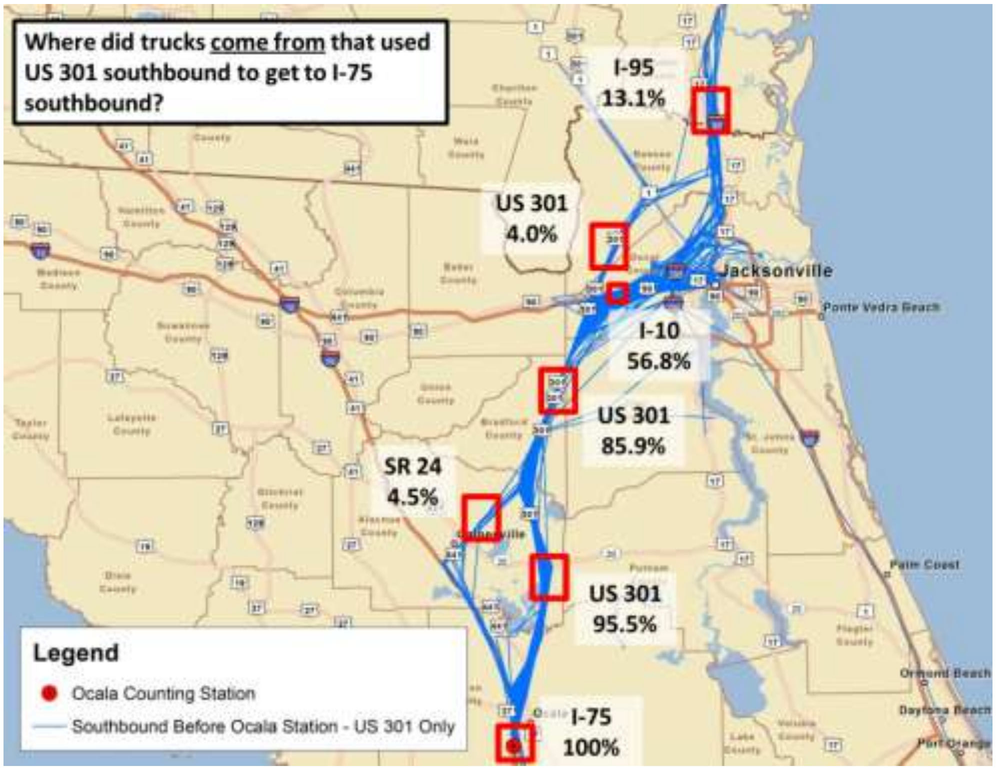


Figure A.9 Routing Patterns of Southbound Trucks Using US 301 in Florida

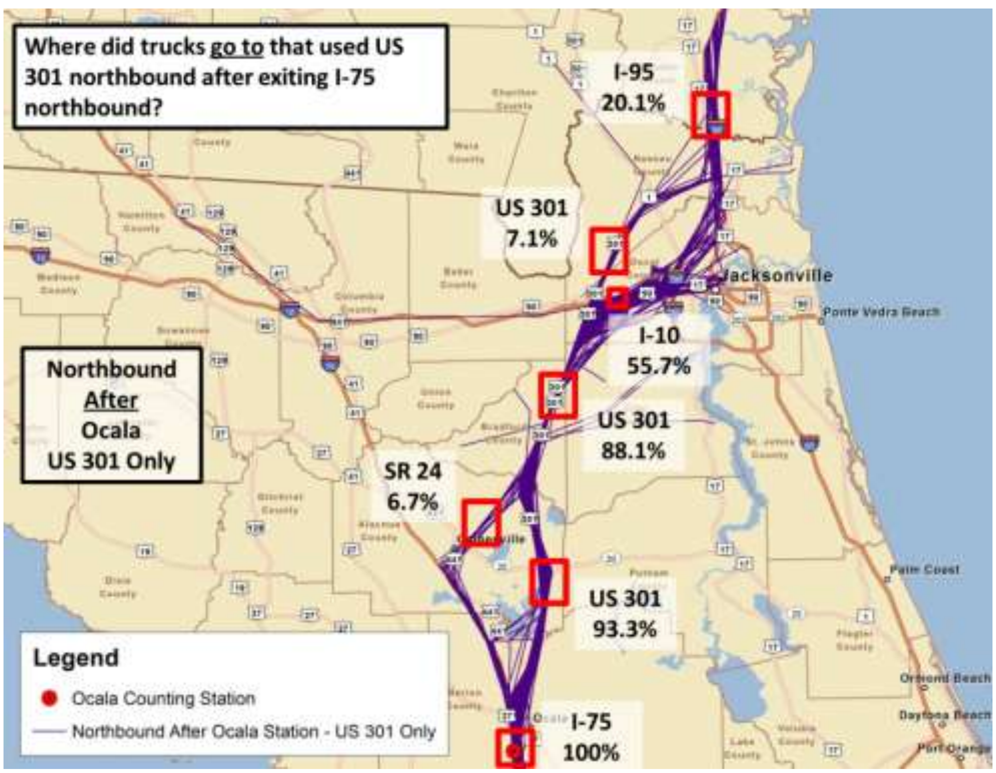


Figure A.10 Routing Patterns of Northbound Trucks Using US 301 in Florida

APPENDIX B: DISTRIBUTIONS OF TRIP LENGTH, TRIP DURATION, TRIP SPEED, AND TRIP TIME-OF-DAY FOR DIFFERENT SEGMENTS OF TRUCK TRIPS WITHIN, TO, AND FROM FLORIDA

This appendix provides the distributions of trip length, duration, speed, and time-of-day[11] profiles for different segments of the 2.7 million trips derived from four months of ATRI's truck GPS data. The different segments include trips starting and ending in different FAF zones in Florida—Jacksonville, Tampa, Orlando, and Miami. Following are the specific counties in each of these FAF zones:

- Jacksonville FAF zone: Baker, Clay, Duval, Nassau, St. Johns
- Miami FAF zone: Broward, Miami-Dade, Palm Beach
- Orlando FAF zone: Flagler, Lake, Orange, Sumter, Osceola, Seminole, Volusia
- Tampa FAF zone: Hernando, Hillsborough, Pasco, Pinellas

The distributions are provided separately for weekday and weekend trips. Such distributions potentially can be used for modeling heavy truck trip characteristics within the major regional models in the state. In addition to the above distributions, for each urbanized county in each of these FAF zones, the top 10 origins and destinations are provided at the state-level and county-level geography. In addition, the appendix provides truck trip characteristics for the following trip segments as well:

a) trips that start and end in Florida (Internal–Internal trips for Florida),
b) trips that start in Florida but end outside Florida (Internal–External trips), and
c) trips that start outside Florida and end in Florida (External–Internal trips).

[11] Note: Time-of-day of a trip is determined based on the hour in which the midpoint of the trip falls.

Characteristics of Truck Trips within the Tampa FAF Zone

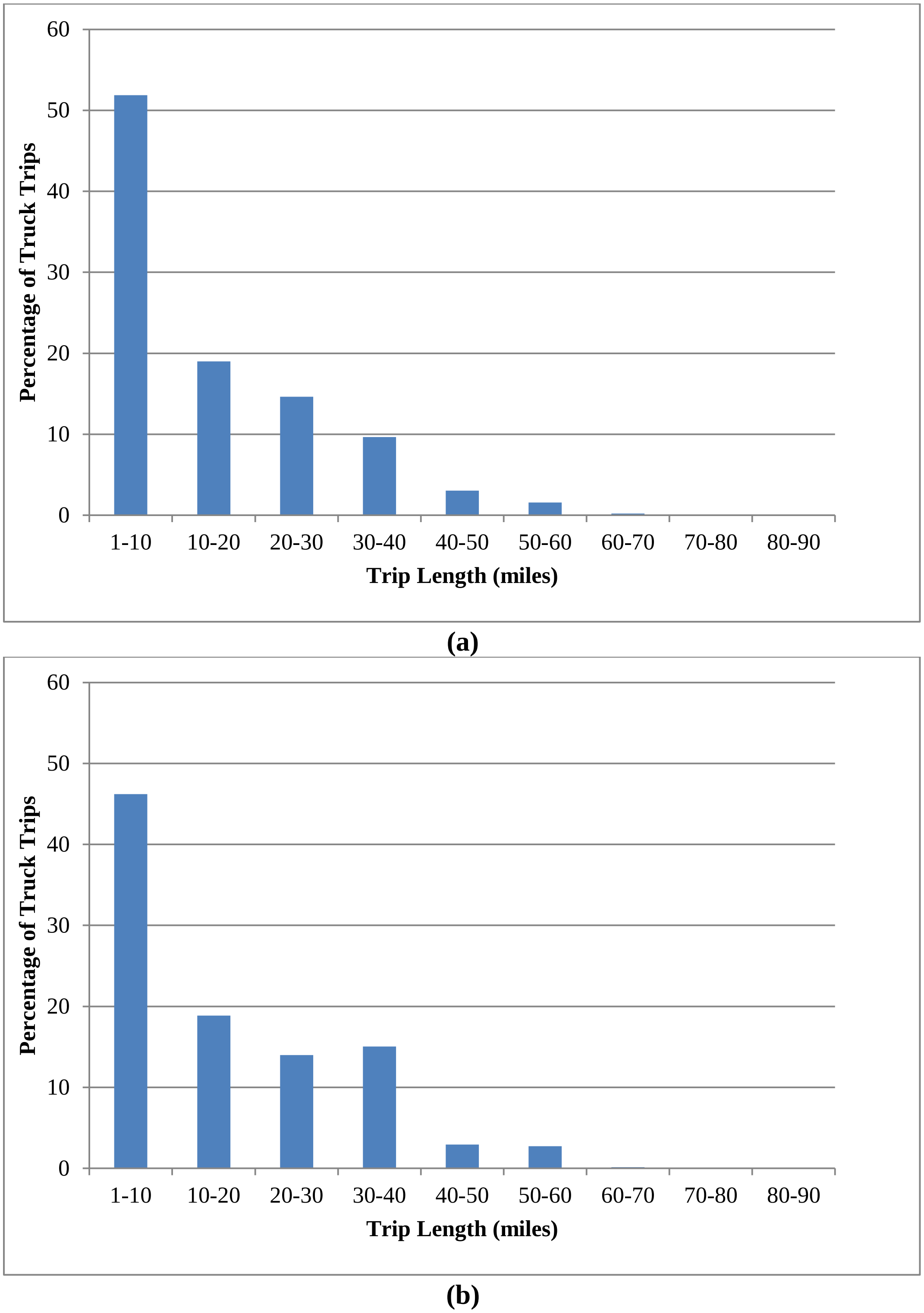
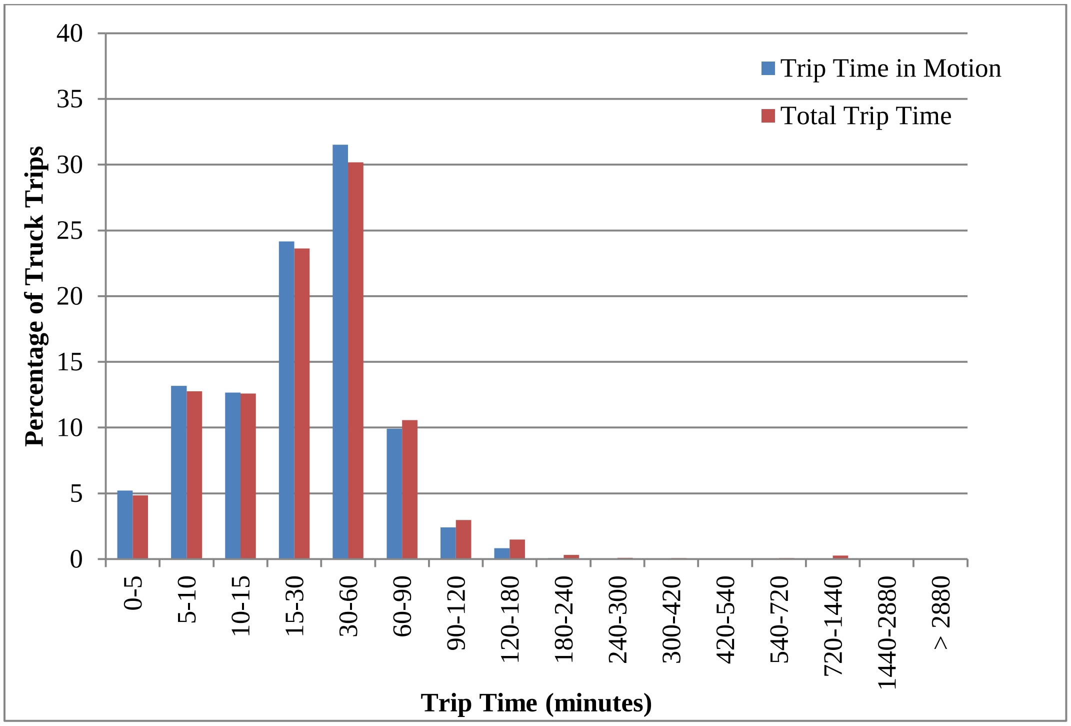
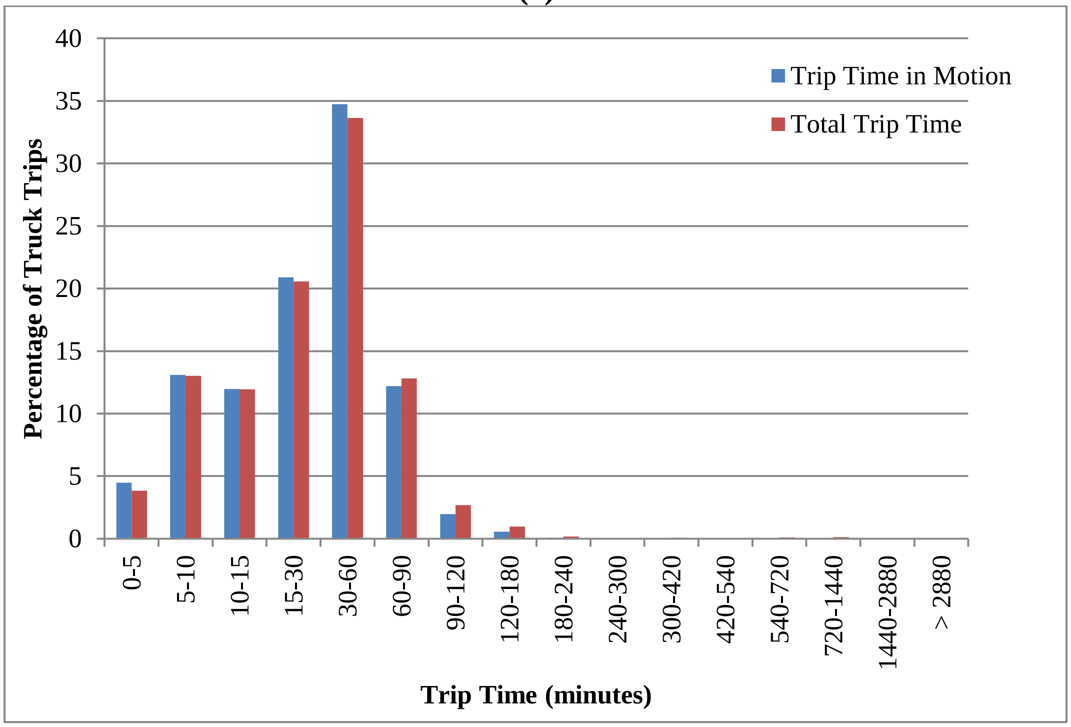


Figure B.1 Trip Length Distribution of Trips Starting and Ending in Tampa FAF Zone during (a) Weekdays (61,465 trips), and (b) Weekend (7,780 trips)

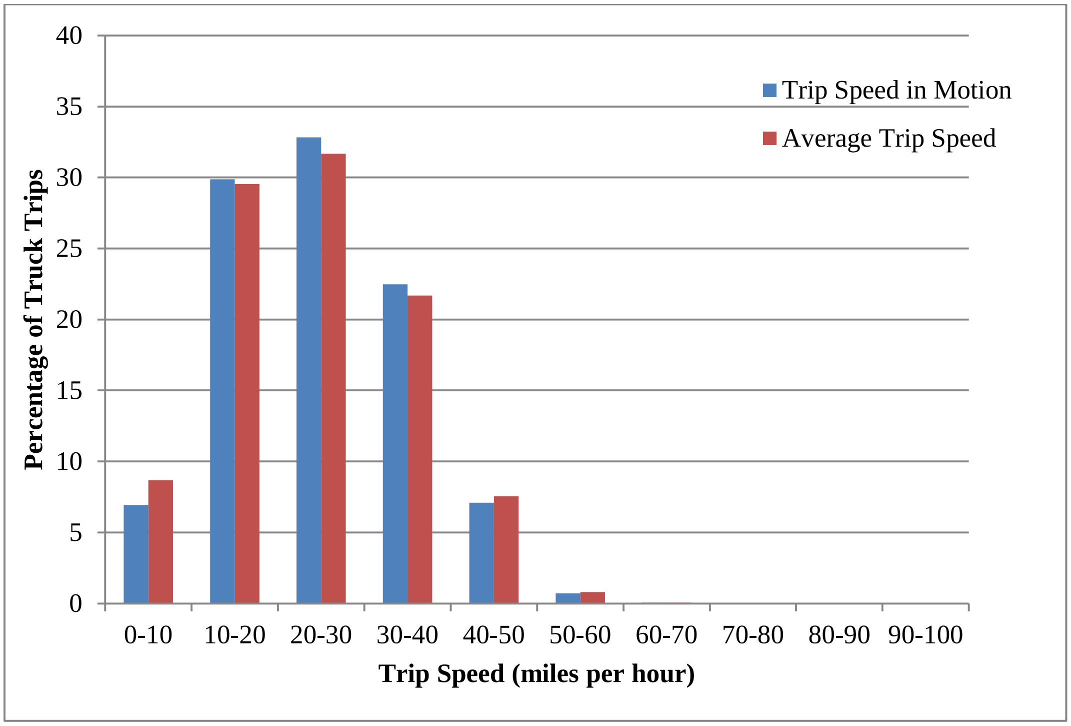


(a)

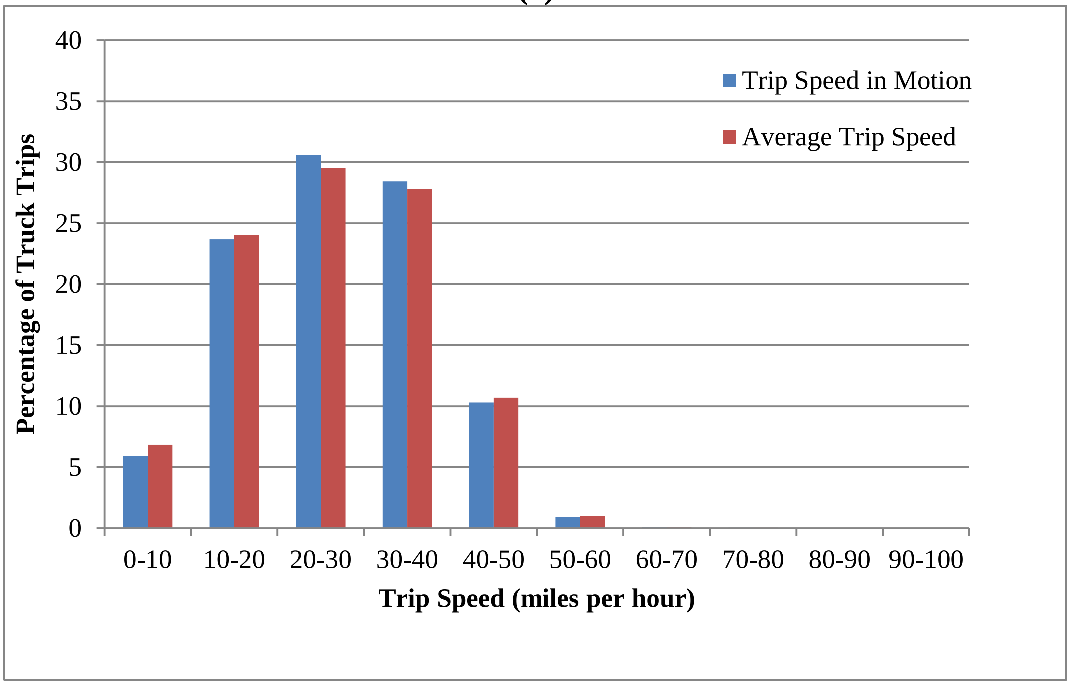


(b)

Figure B.2 Trip Time Distribution of Trips Starting and Ending in Tampa FAF Zone during (a) Weekdays (61,465 trips), and (b) Weekend (7,780 trips)

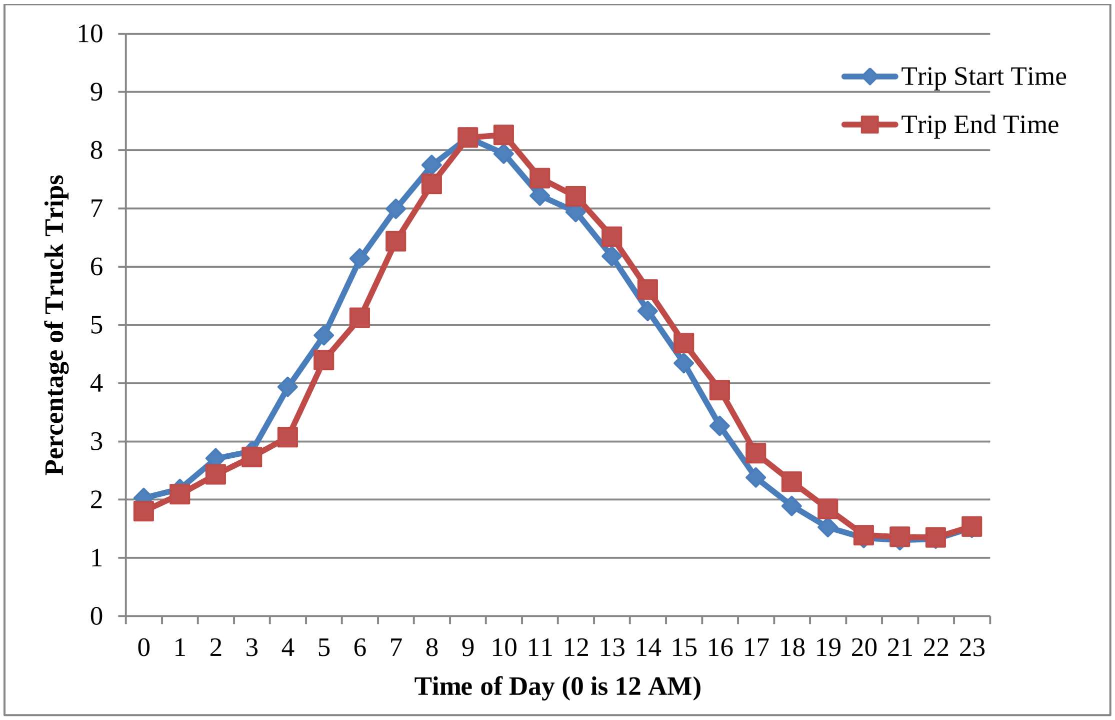


(a)

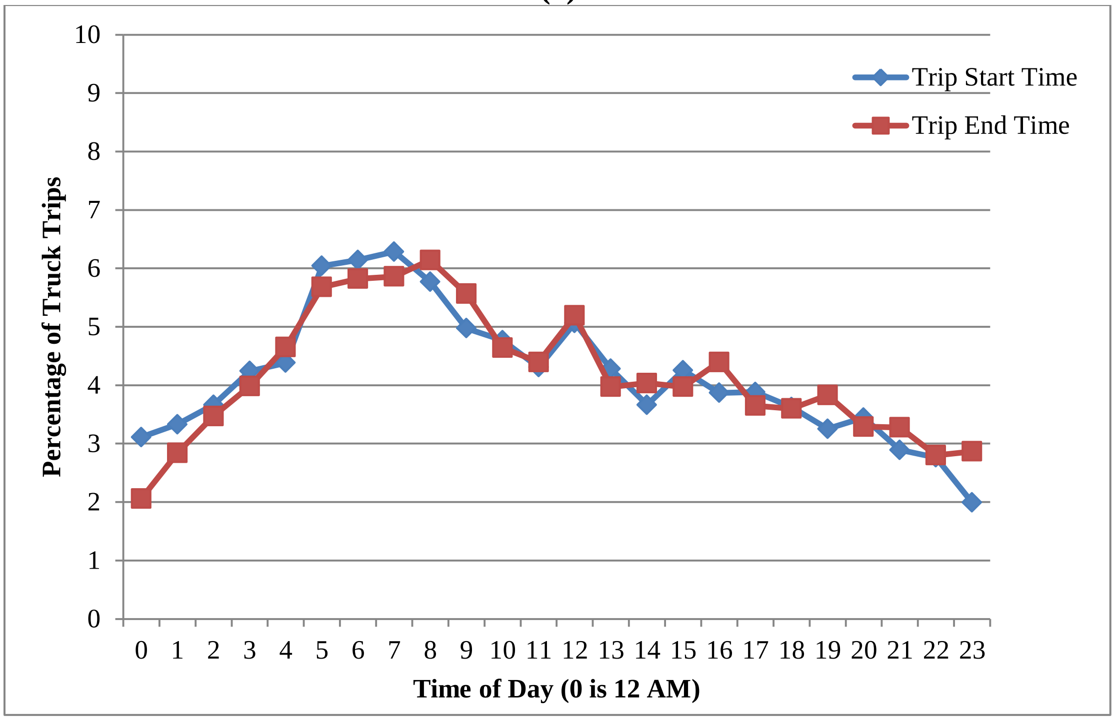


(b)

Figure B.3 Trip Speed Distribution of Trips Starting and Ending in Tampa FAF Zone during (a) Weekdays (61,465 trips), and (b) Weekend (7,780 trips)

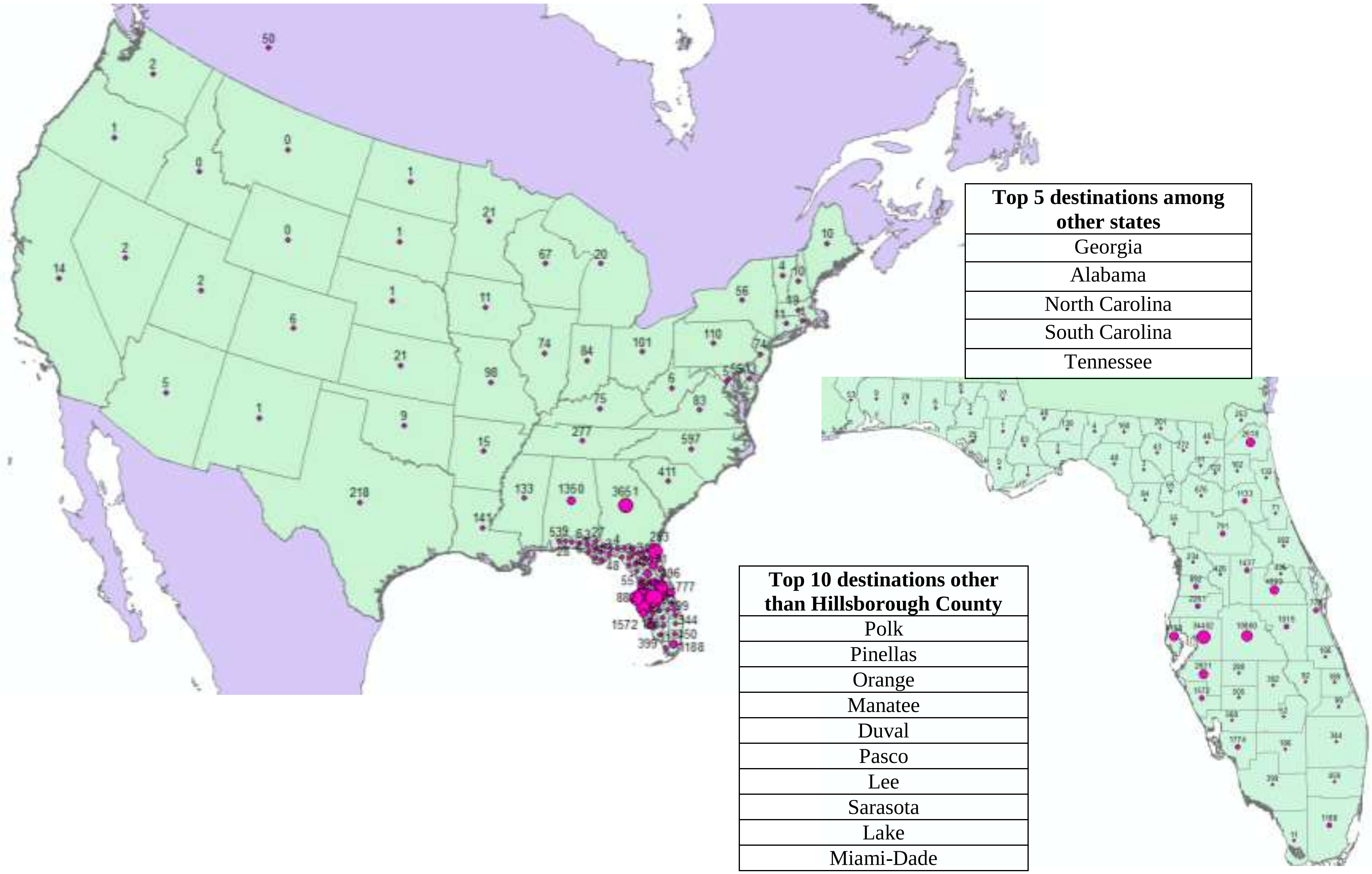


(a)



(b)

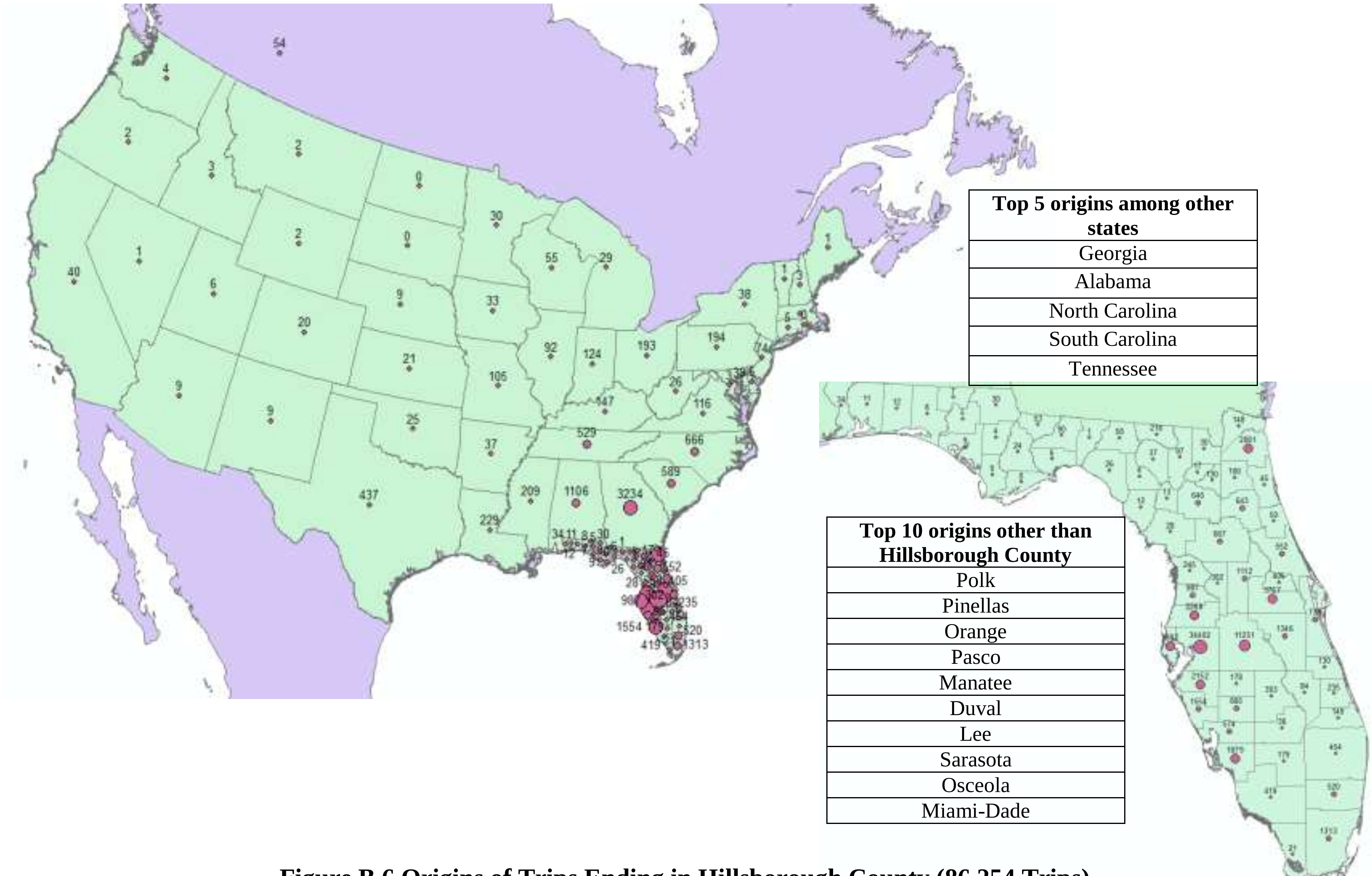
Figure B.4 Time-of-Day Profile of Trips Starting and Ending in Tampa FAF Zone during (a) Weekdays (61,465 trips), and (b) Weekend (7,780 trips)



Top 5 destinations among other states
Georgia
Alabama
North Carolina
South Carolina
Tennessee

Top 10 destinations other than Hillsborough County
Polk
Pinellas
Orange
Manatee
Duval
Pasco
Lee
Sarasota
Lake
Miami-Dade

Figure B.5 Destinations of Trips Starting in Hillsborough County (87,701 Trips)

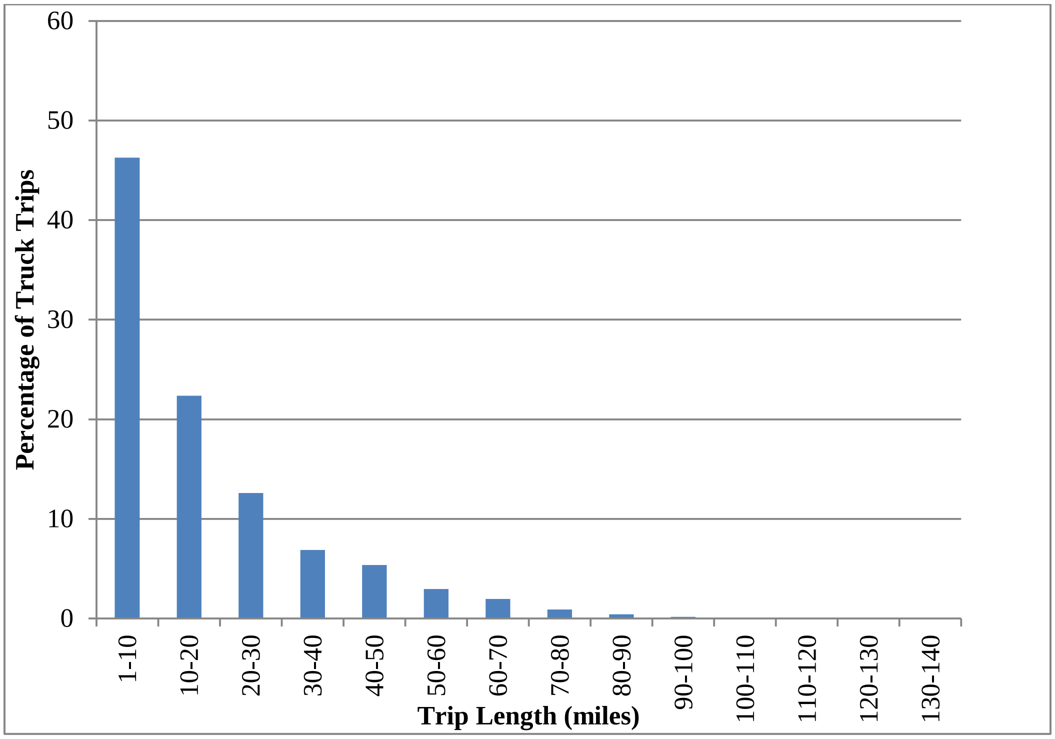


Top 5 origins among other states
Georgia
Alabama
North Carolina
South Carolina
Tennessee

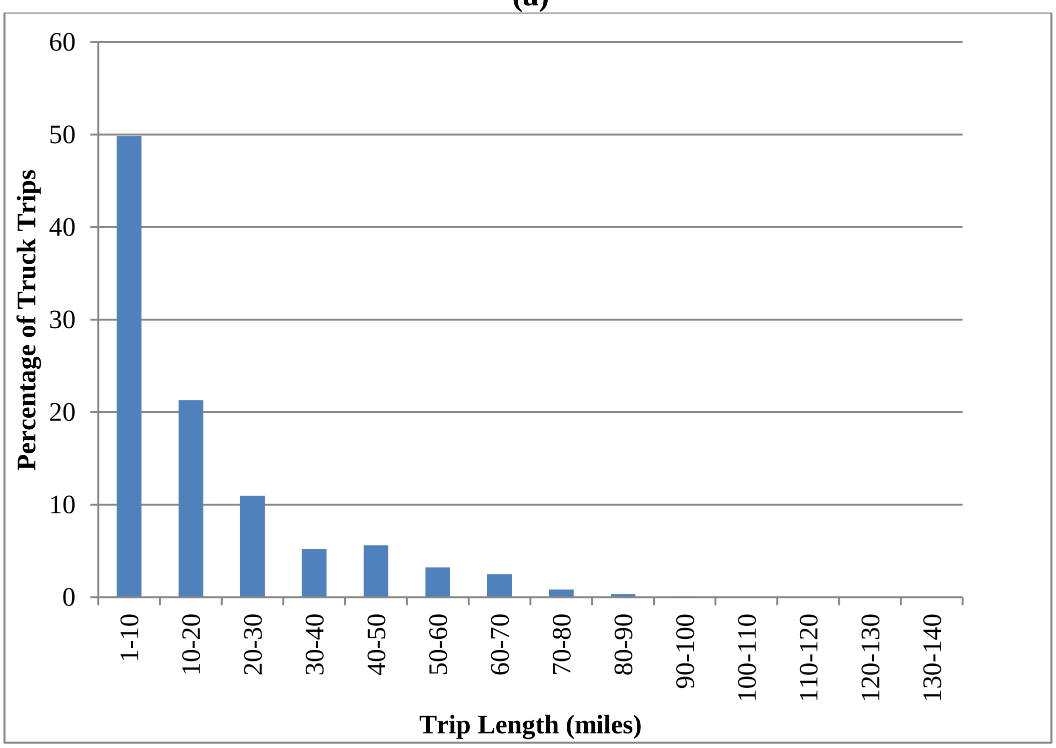
Top 10 origins other than Hillsborough County
Polk
Pinellas
Orange
Pasco
Manatee
Duval
Lee
Sarasota
Osceola
Miami-Dade

Figure B.6 Origins of Trips Ending in Hillsborough County (86,254 Trips)

Characteristics of Truck Trips within the Orlando FAF Zone

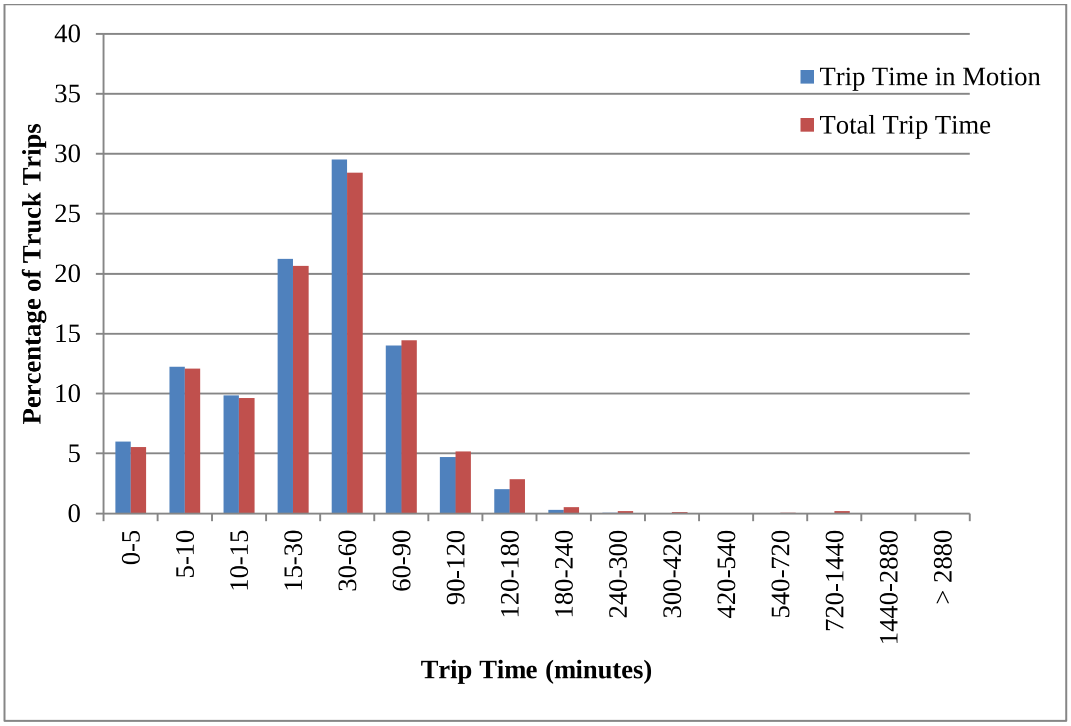


(a)

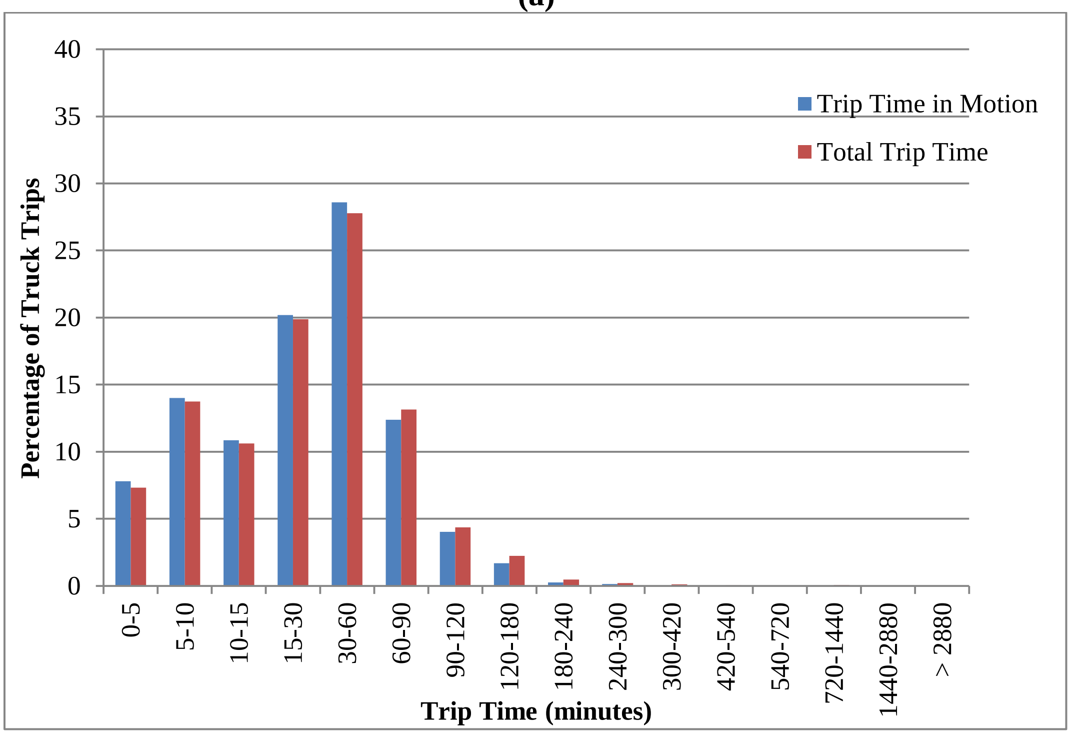


(b)

Figure B.7 Trip Length Distribution of Trips Starting and Ending in Orlando FAF Zone during (a) Weekdays (79,094 trips), and (b) Weekend (10,528 trips)

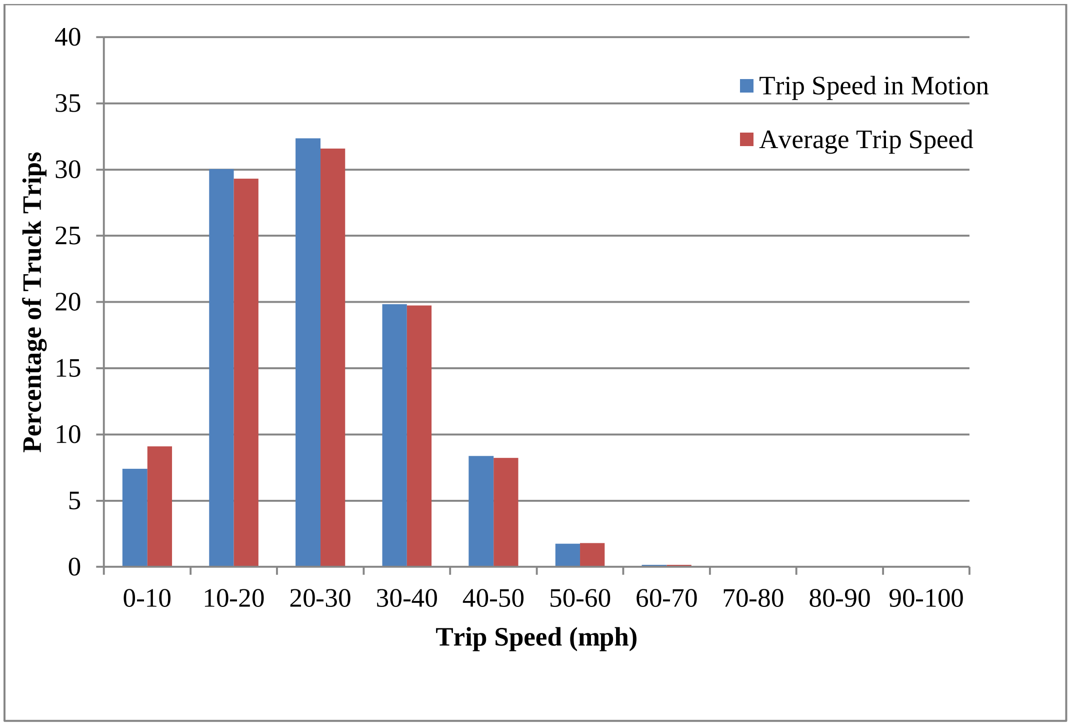


(a)

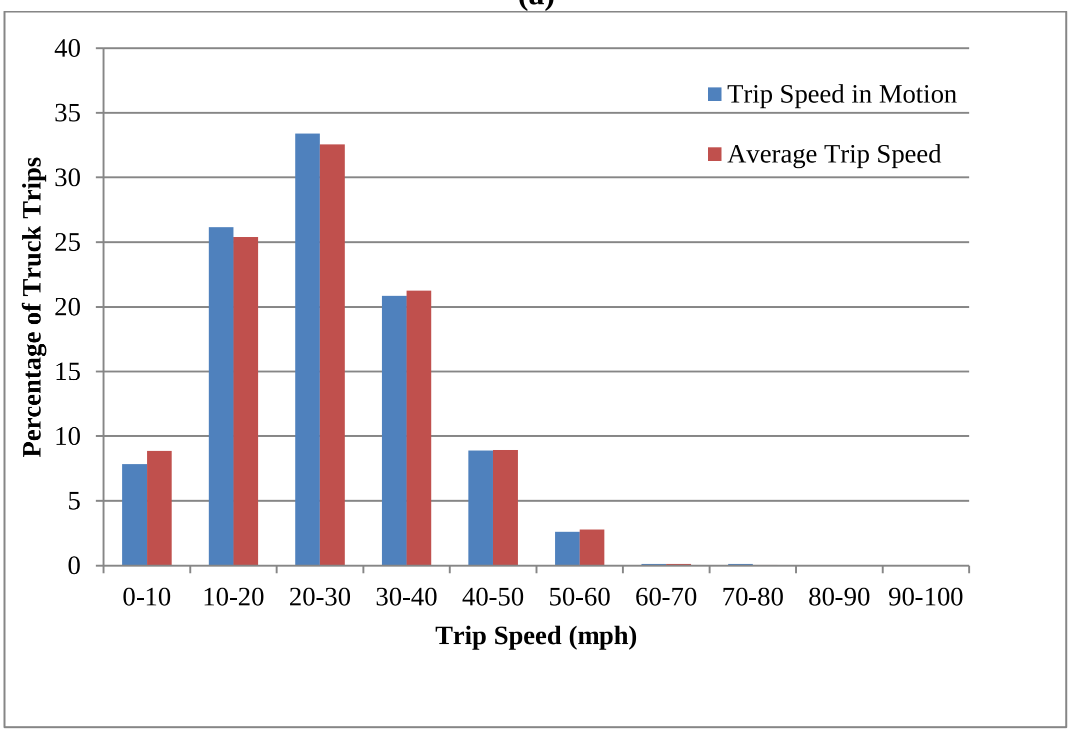


(b)

Figure B.8 Trip Time Distribution of Trips Starting and Ending in Orlando FAF Zone during (a) Weekdays (79,094 trips), and (b) Weekend (10,528 trips)

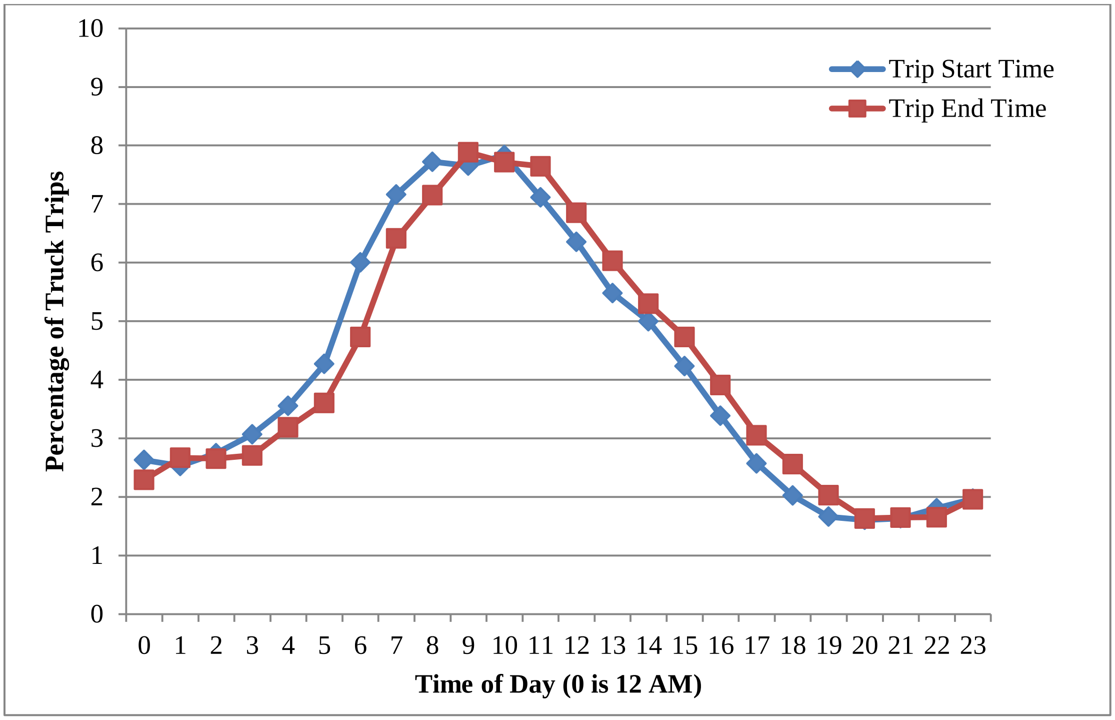


(a)

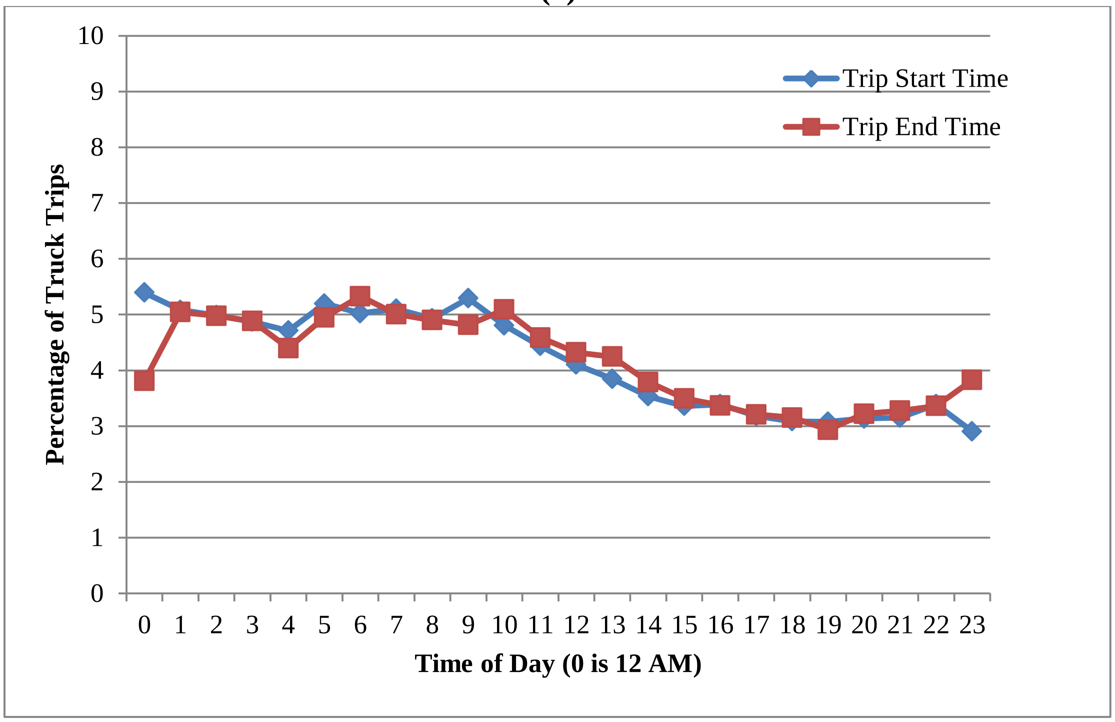


(b)

Figure B.9 Trip Speed Distribution of Trips Starting and Ending in Orlando FAF Zone during (a) Weekdays (79,094 trips), and (b) Weekend (10,528 trips)

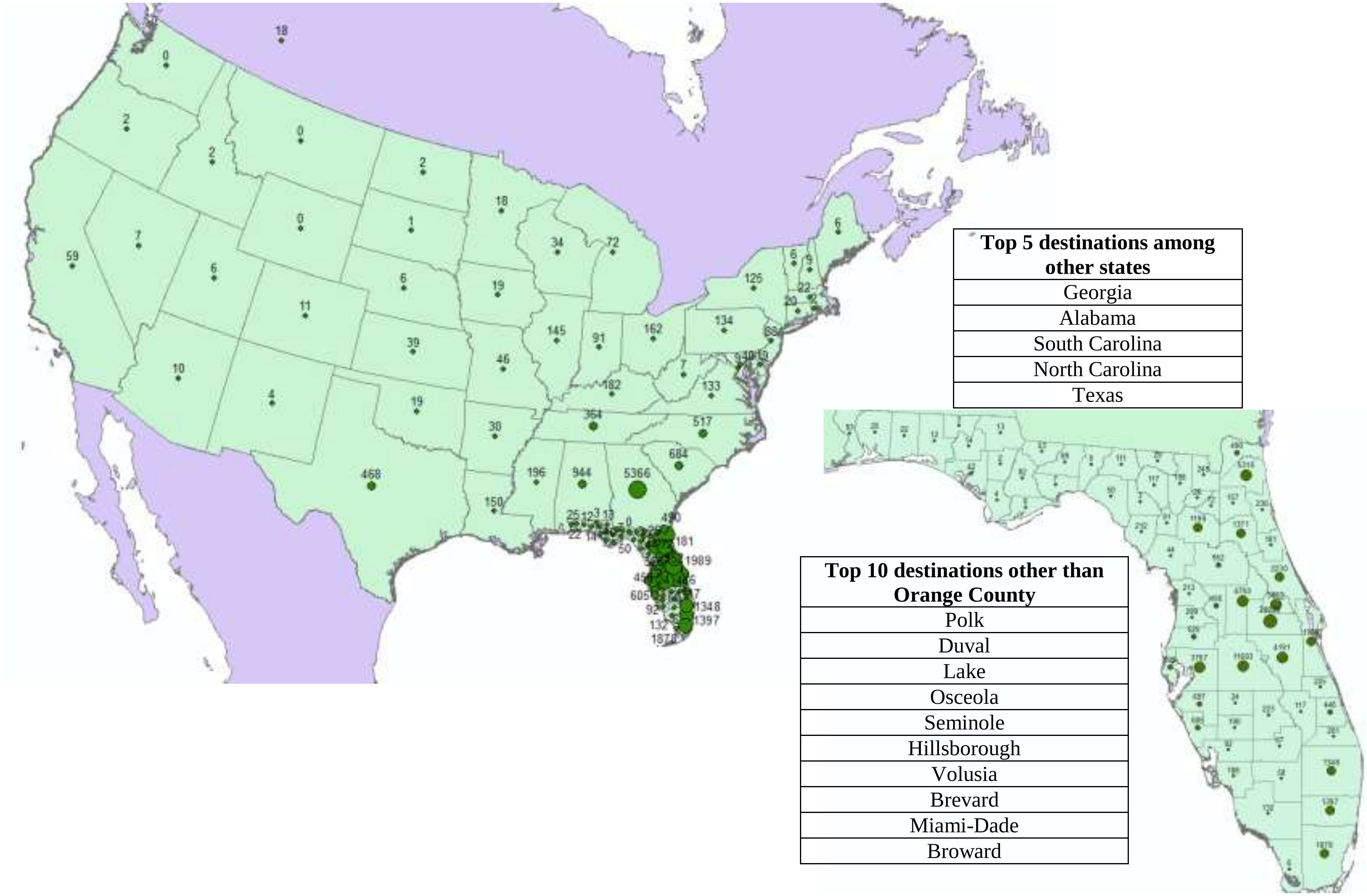


(a)



(b)

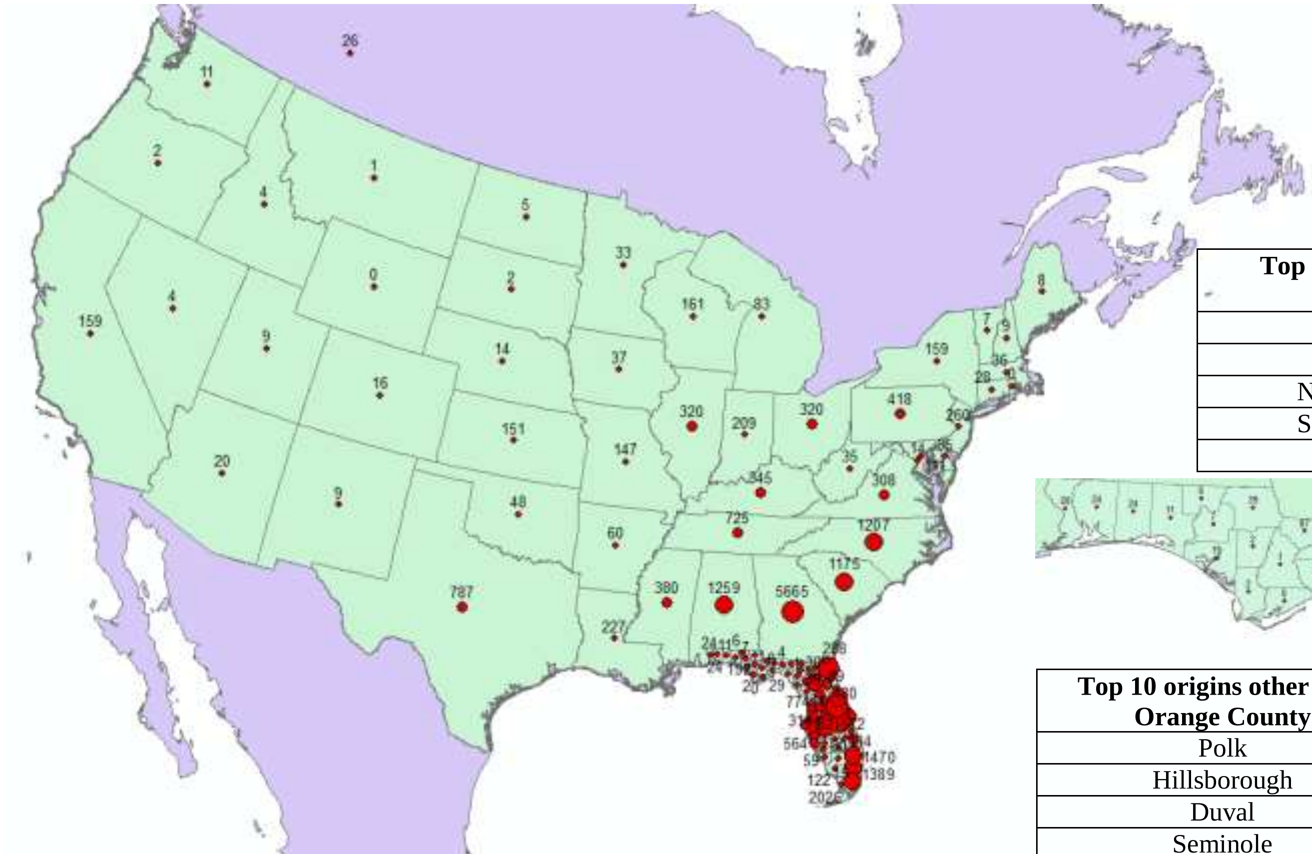
Figure B.10 Time-of-Day Profile of Trips Starting and Ending in Orlando FAF Zone during (a) Weekdays (79,094 trips), and (b) Weekend (10,528 trips)



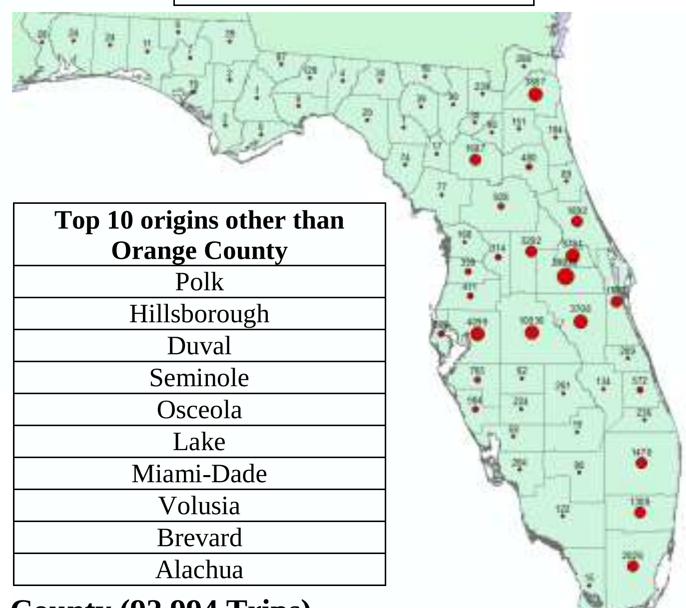
Top 5 destinations among other states
Georgia
Alabama
South Carolina
North Carolina
Texas

Top 10 destinations other than Orange County
Polk
Duval
Lake
Osceola
Seminole
Hillsborough
Volusia
Brevard
Miami-Dade
Broward

Figure B.11 Destinations of Trips Starting in Orange County (94,575 Trips)



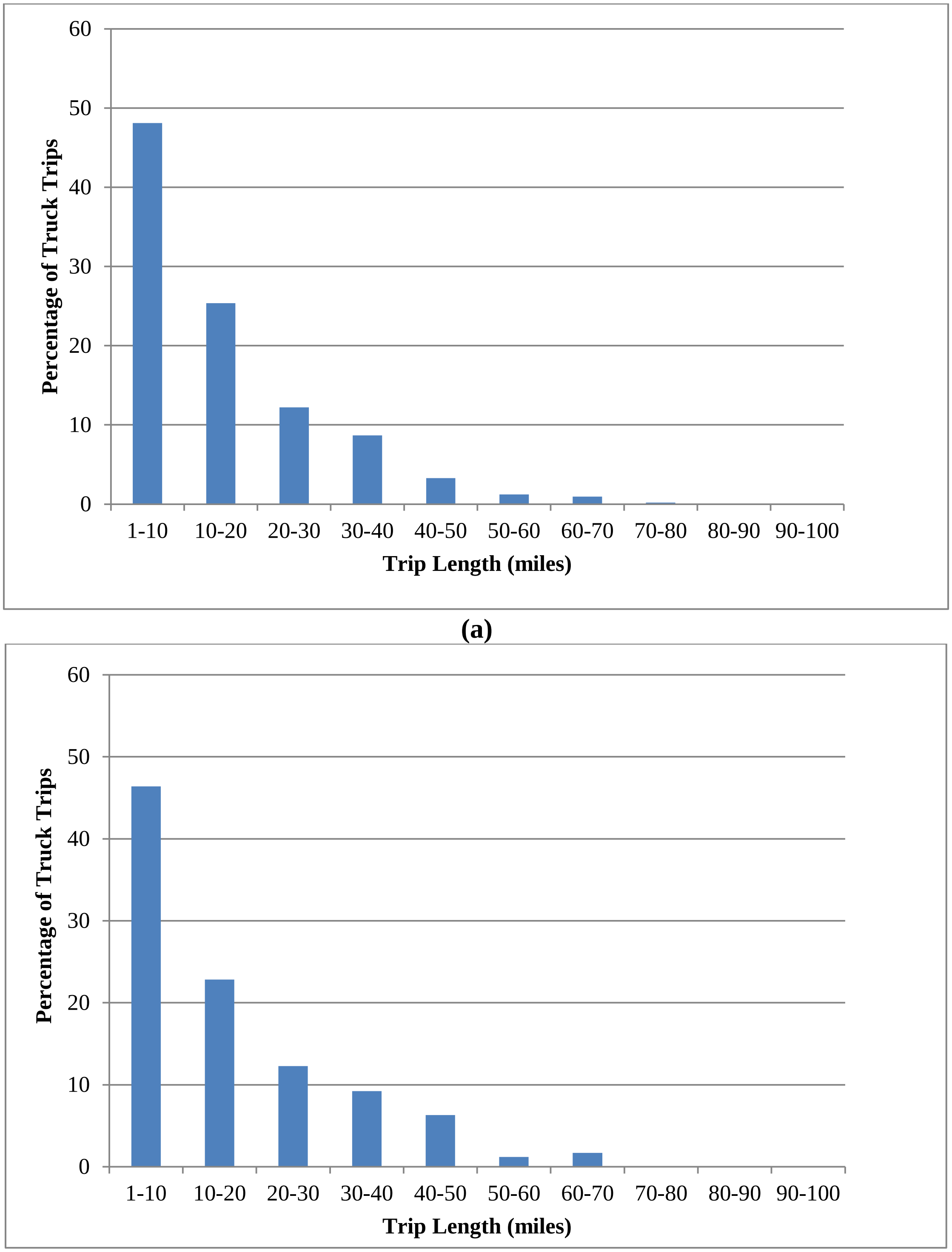
Top 5 origins among other states
Georgia
Alabama
North Carolina
South Carolina
Texas



Top 10 origins other than Orange County
Polk
Hillsborough
Duval
Seminole
Osceola
Lake
Miami-Dade
Volusia
Brevard
Alachua

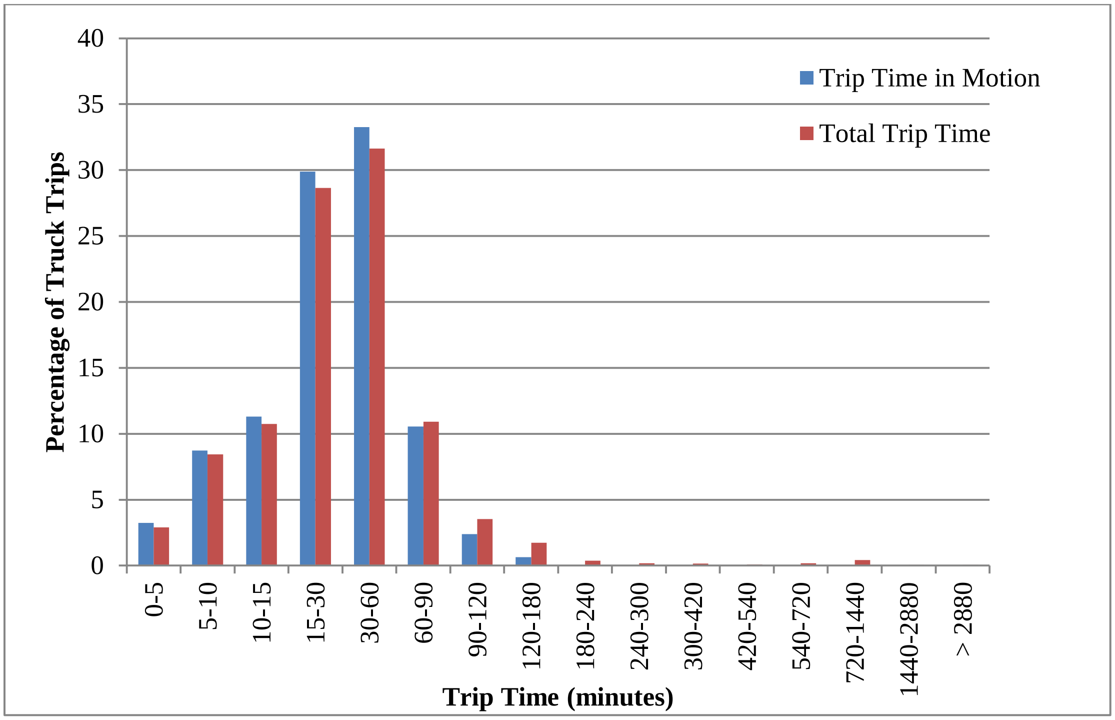
Figure B.12 Origins of Trips Ending in Orange County (92,994 Trips)

Characteristics of Truck Trips within the Jacksonville FAF Zone

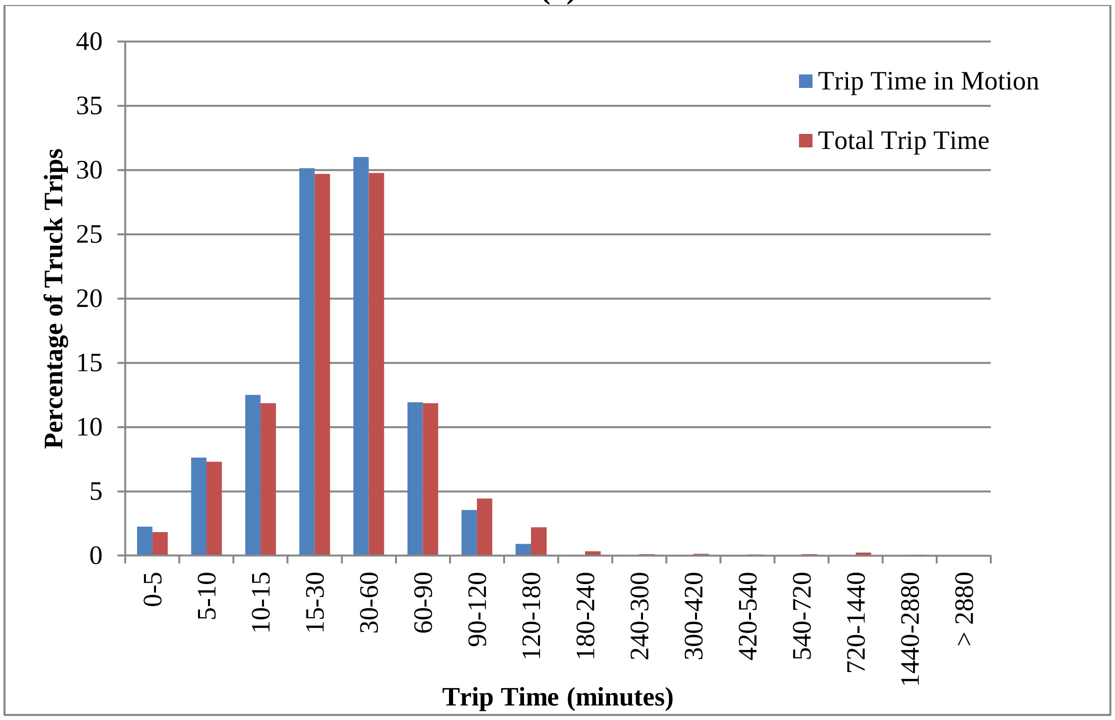


(b)

Figure B.13 Trip Length Distribution of Trips Starting and Ending in Jacksonville FAF Zone during (a) Weekdays (56,319 trips), and (b) Weekend (5,789 trips)

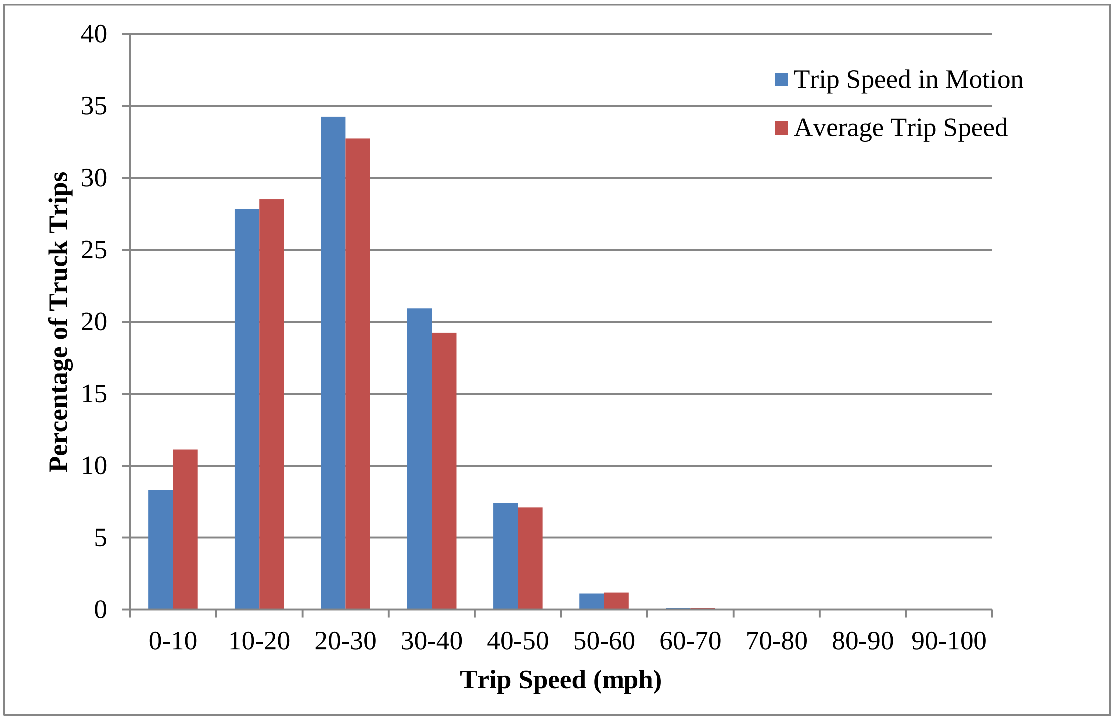


(a)

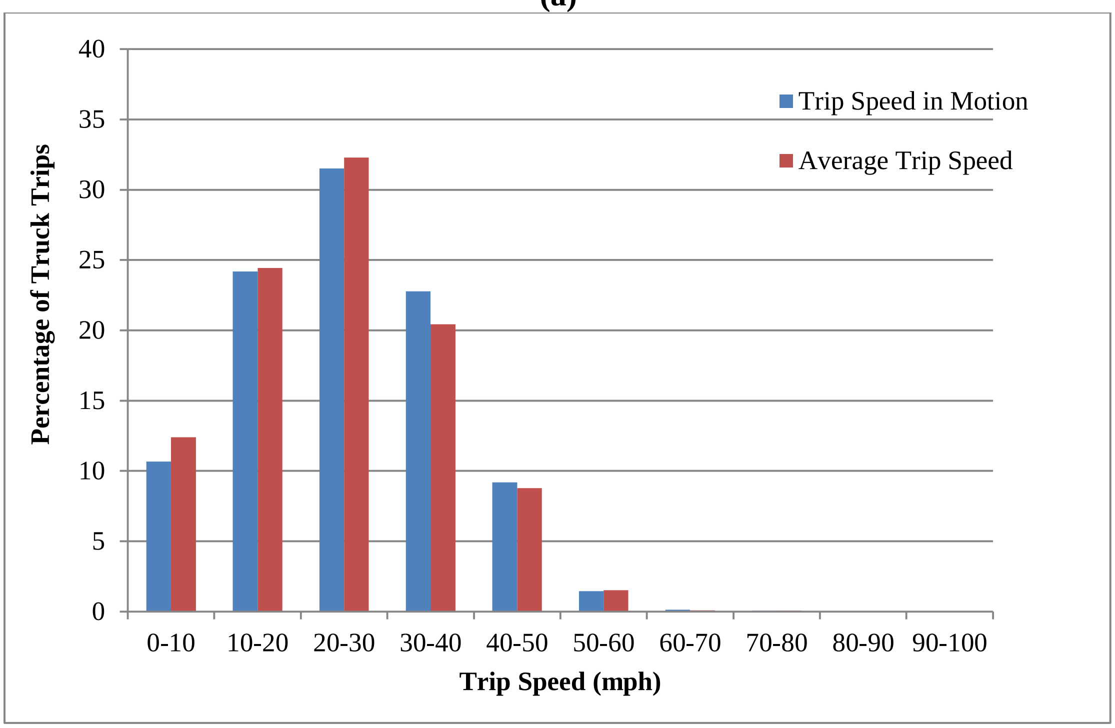


(b)

Figure B.14 Trip Time Distribution of Trips Starting and Ending in Jacksonville FAF Zone during (a) Weekdays (56,319 trips), and (b) Weekend (5,789 trips)

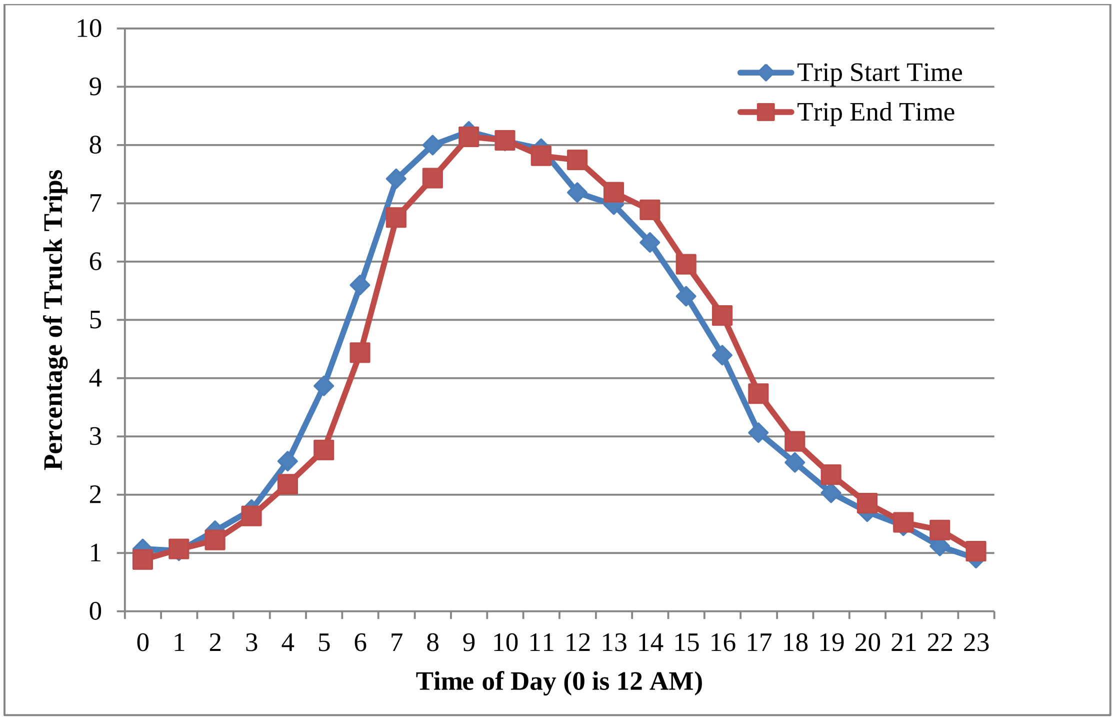


(a)

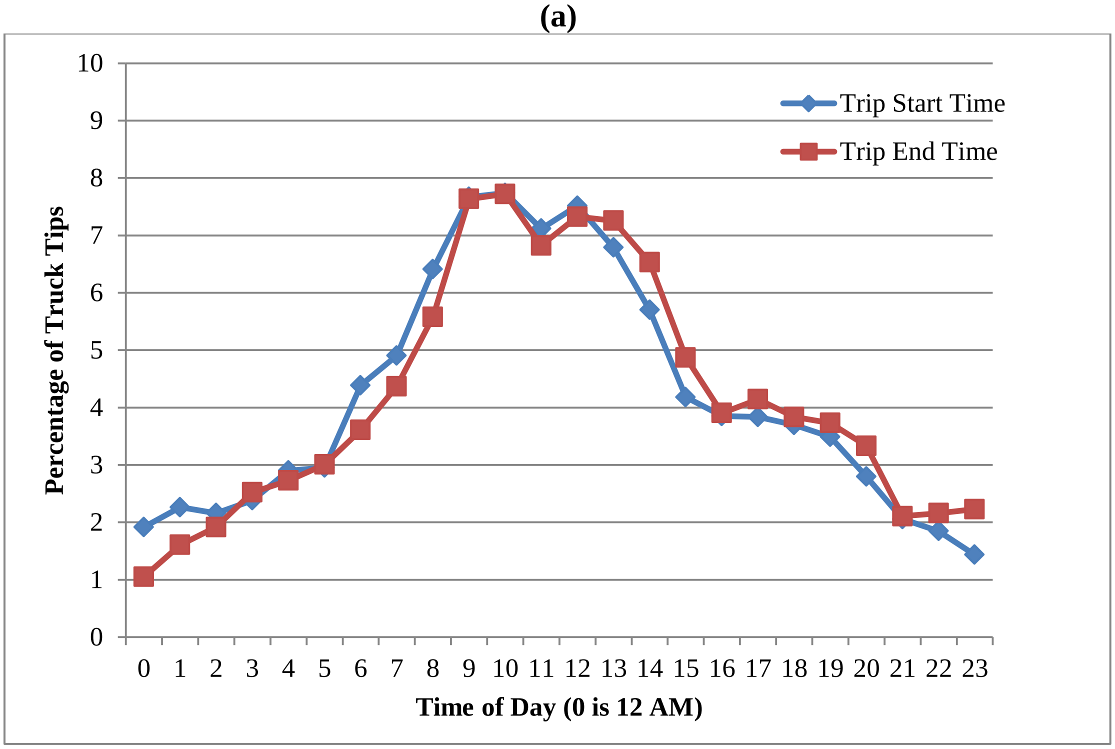


(b)

Figure B.15 Trip Speed Distribution of Trips Starting and Ending in Jacksonville FAF Zone during (a) Weekdays (56,319 trips), and (b) Weekend (5,789 trips)

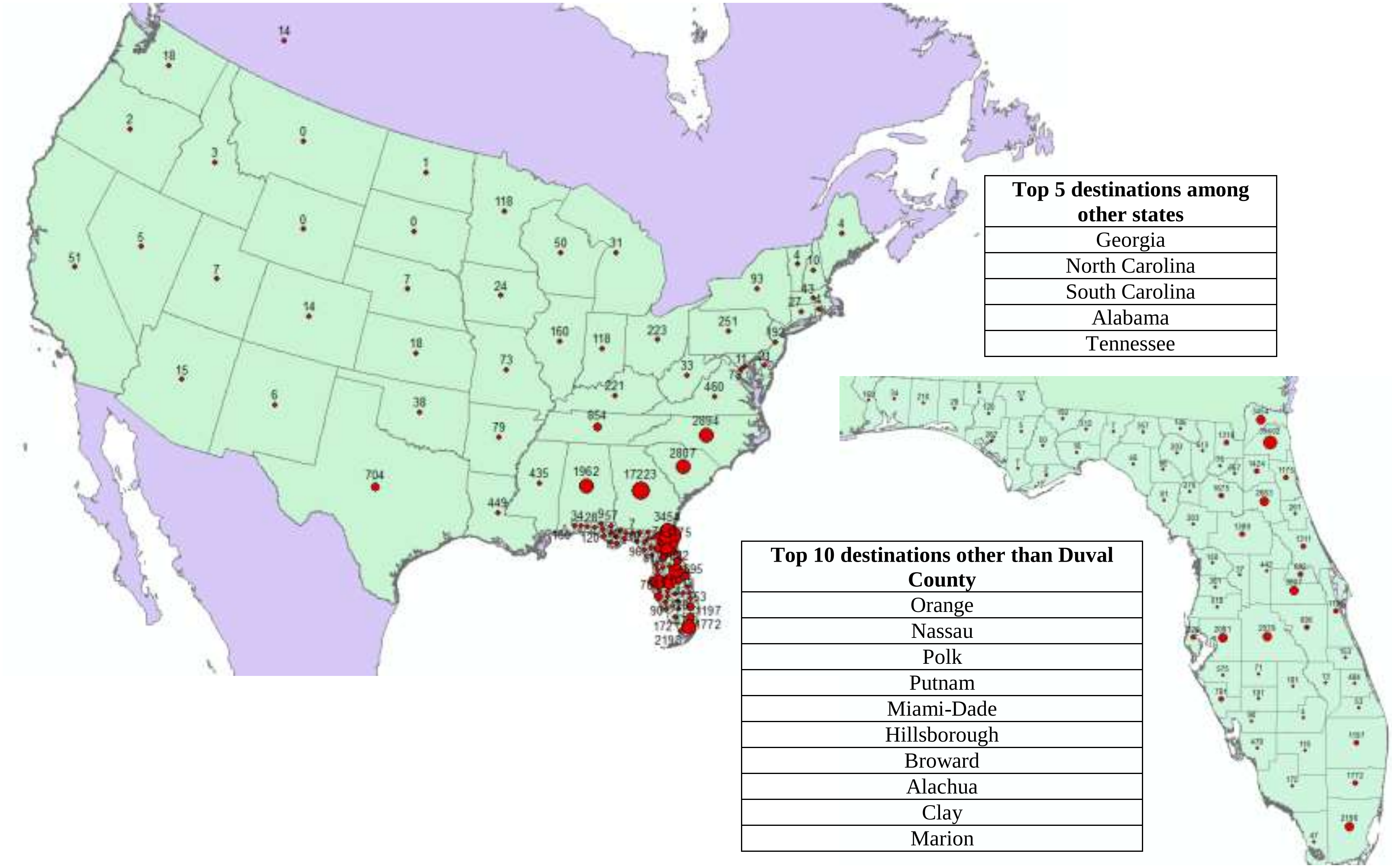


(a)



(b)

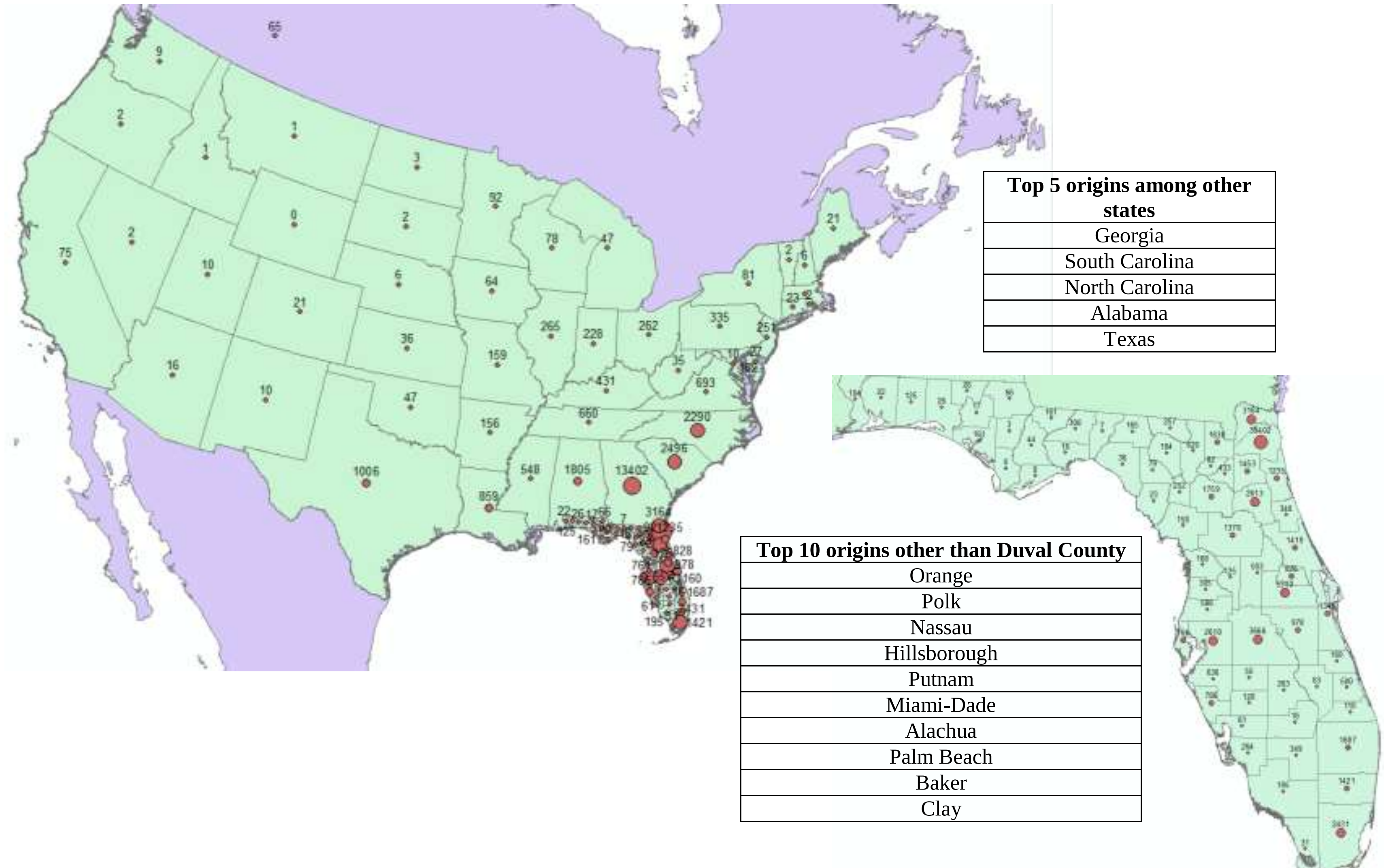
Figure B.16 Time-of-Day Profile of Trips Starting and Ending in Jacksonville FAF Zone during (a) Weekdays (56,319 trips), and (b) Weekend (5,789 trips)



Top 5 destinations among other states
Georgia
North Carolina
South Carolina
Alabama
Tennessee

Top 10 destinations other than Duval County
Orange
Nassau
Polk
Putnam
Miami-Dade
Hillsborough
Broward
Alachua
Clay
Marion

Figure B.17 Destinations of Trips Starting in Duval County (110,314 Trips)

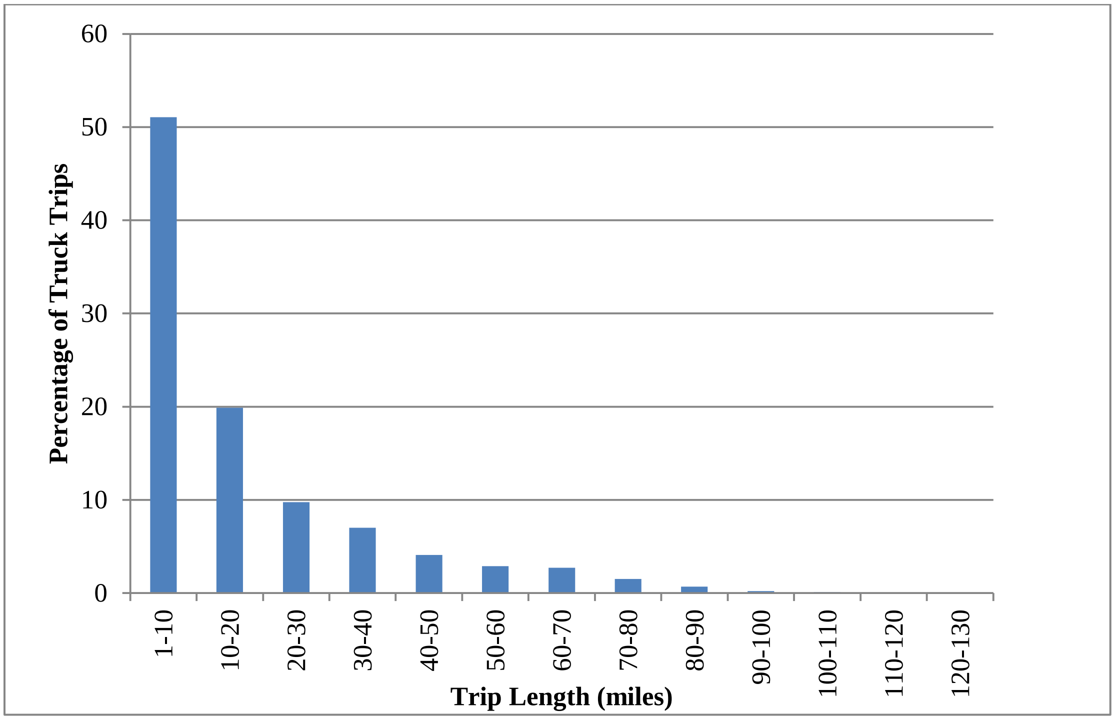


Top 5 origins among other states
Georgia
South Carolina
North Carolina
Alabama
Texas

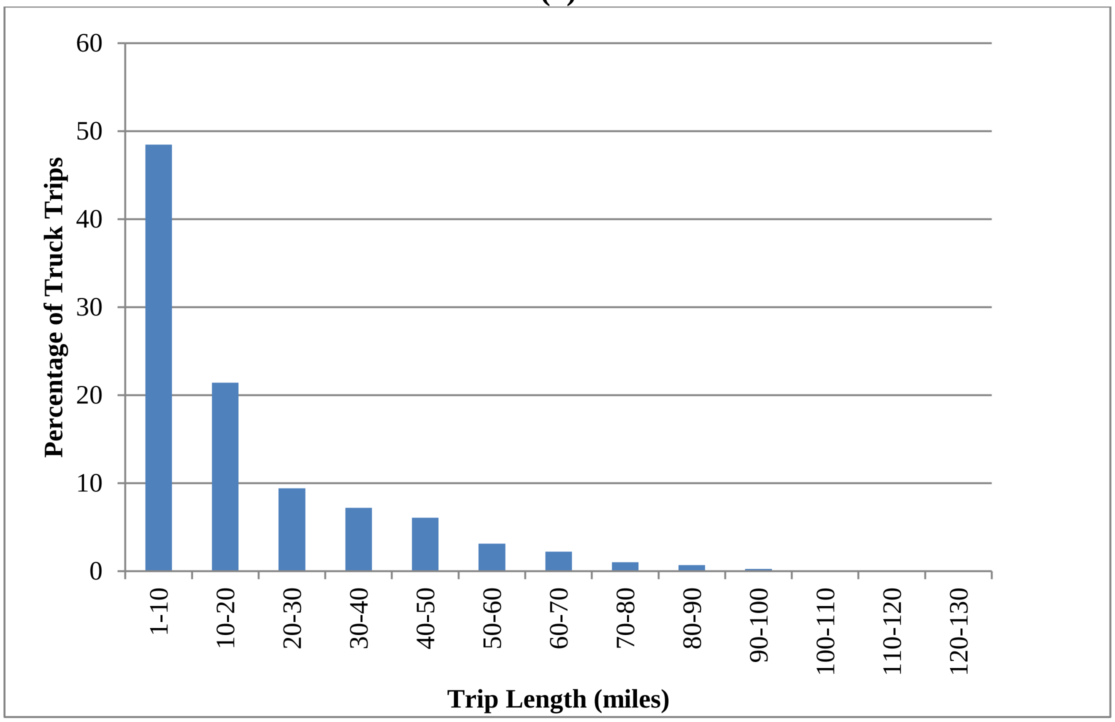
Top 10 origins other than Duval County
Orange
Polk
Nassau
Hillsborough
Putnam
Miami-Dade
Alachua
Palm Beach
Baker
Clay

Figure B.18 Origins of Trips Ending in Duval County (111,023 Trips)

Characteristics of Truck Trips within the Miami FAF Zone

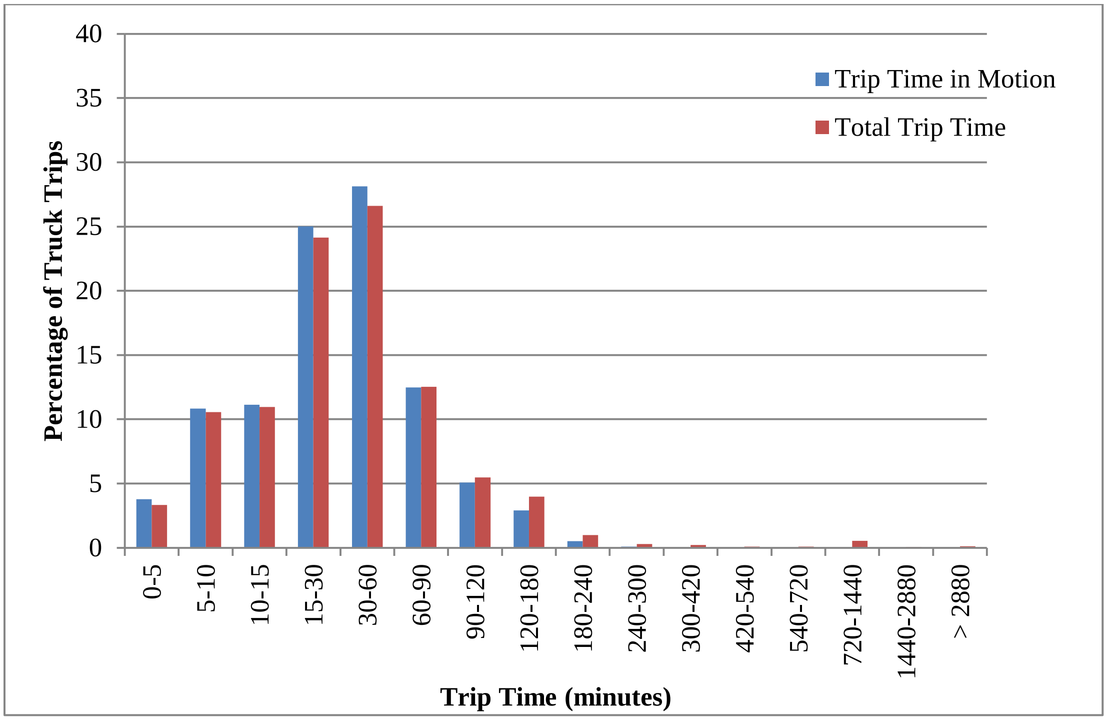


(a)

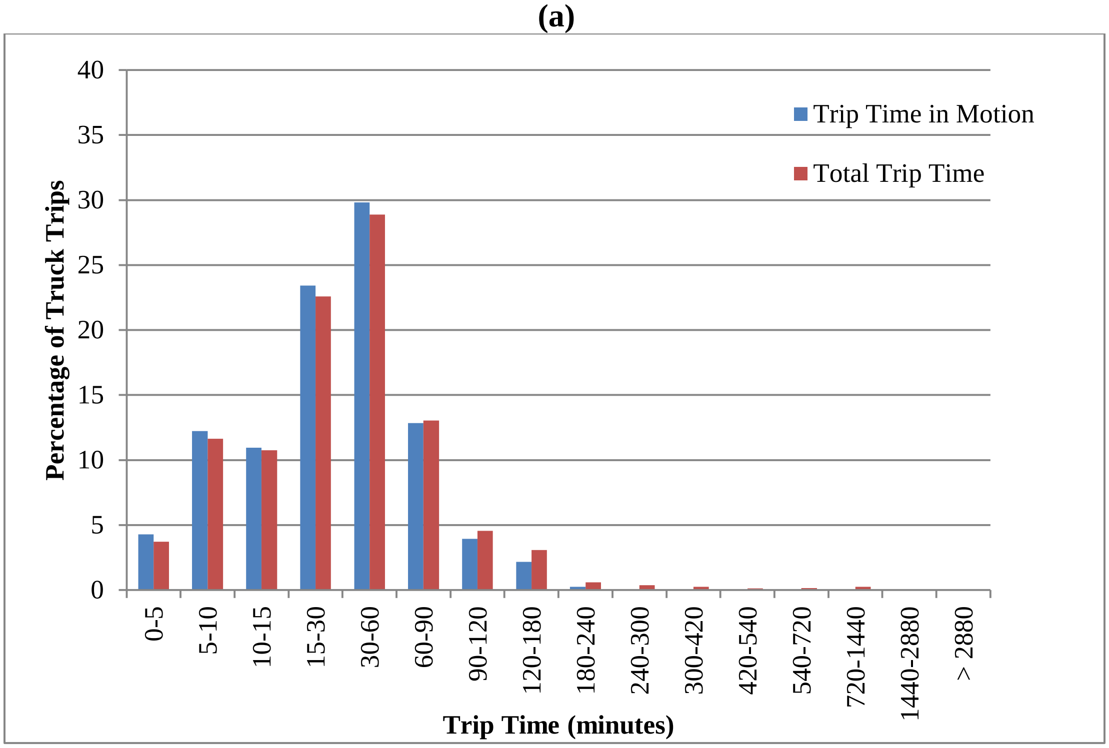


(b)

Figure B.19 Trip Length Distribution of Trips Starting and Ending in Miami FAF Zone during (a) Weekdays (84,301 trips), and (b) Weekend (8,258 trips)

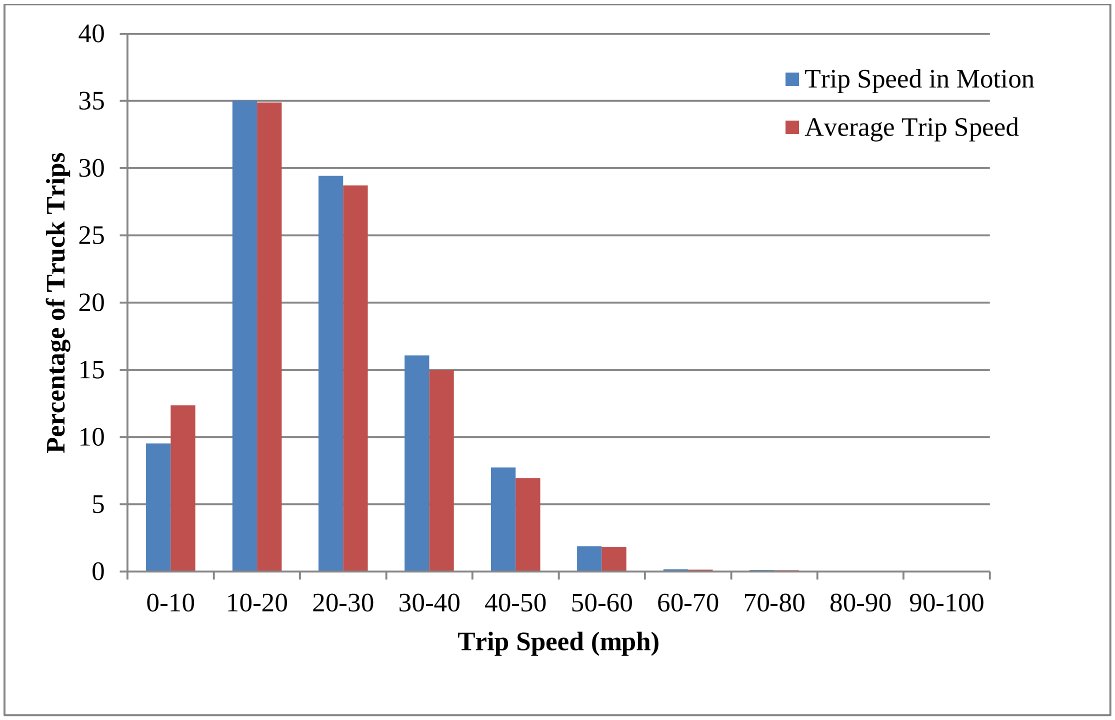


(a)

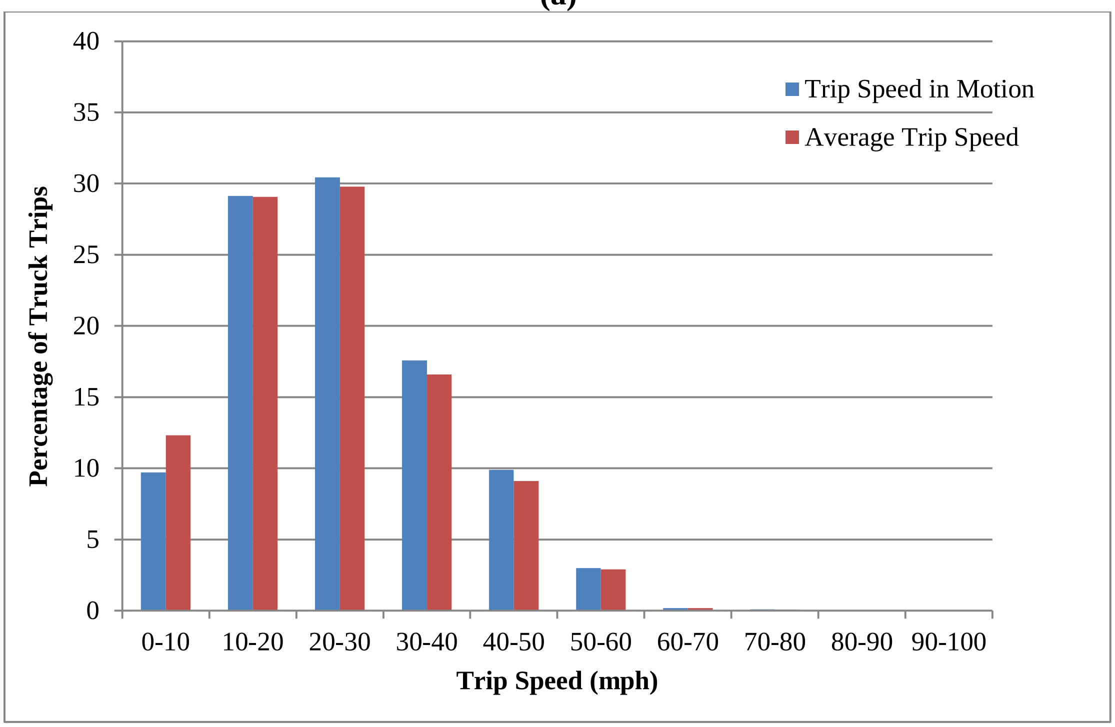


(b)

Figure B.20 Trip Time Distribution of Trips Starting and Ending in Miami FAF Zone during (a) Weekdays (84,301 trips), and (b) Weekend (8,258 trips)

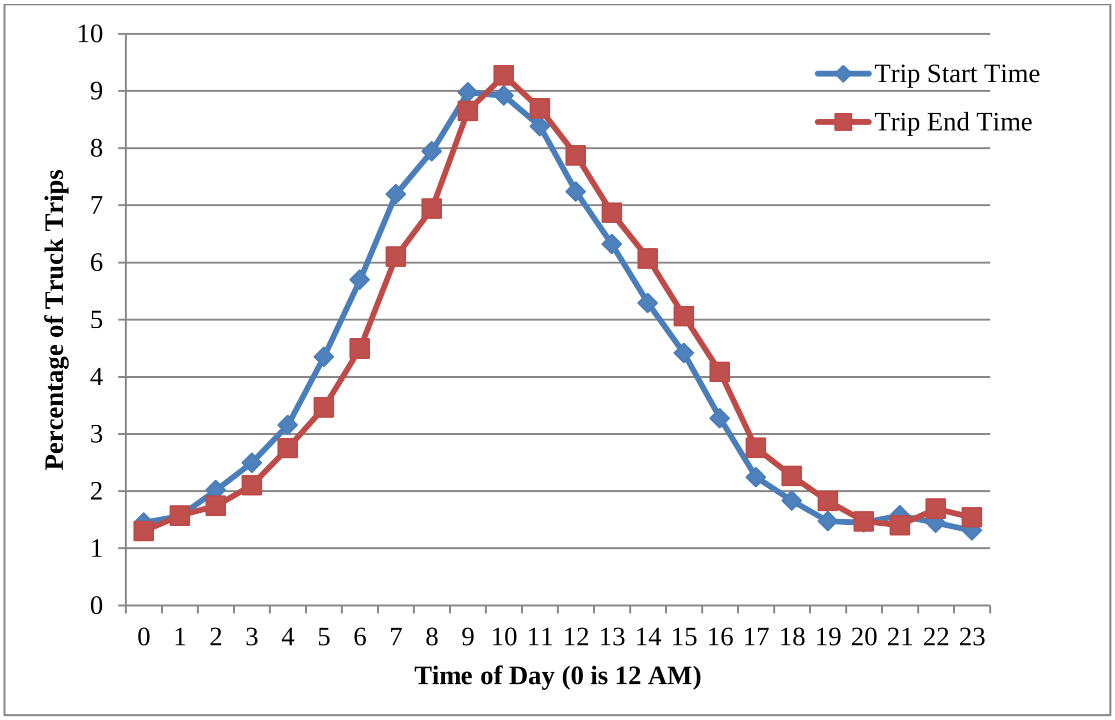


(a)

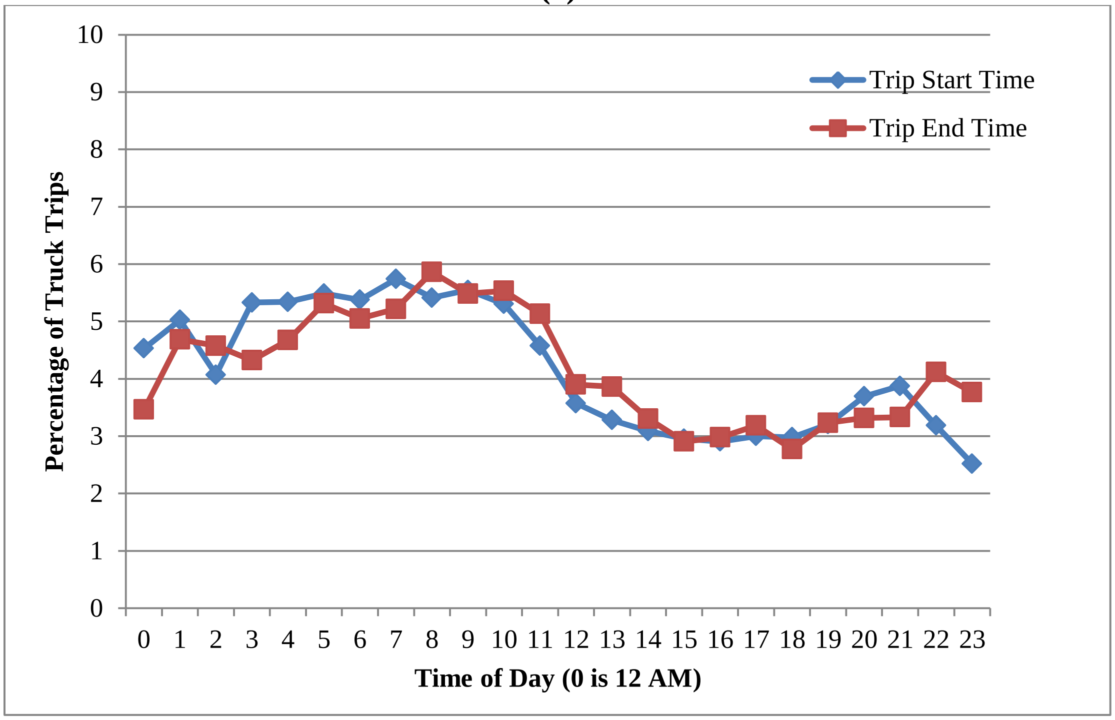


(b)

Figure B.21 Trip Speed Distribution of Trips Starting and Ending in Miami FAF Zone during (a) Weekdays (84,301 trips), and (b) Weekend (8,258 trips)

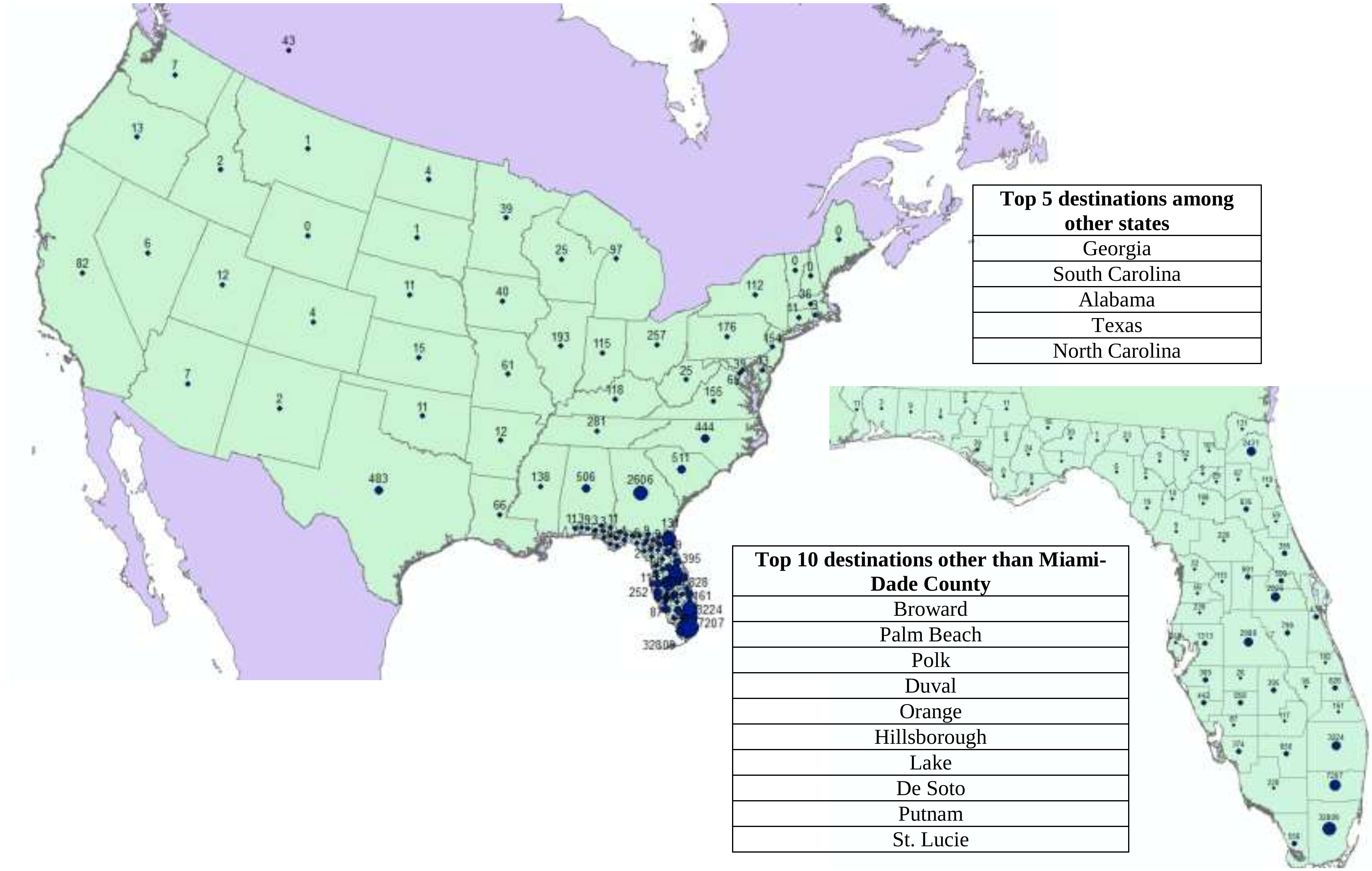


(a)



(b)

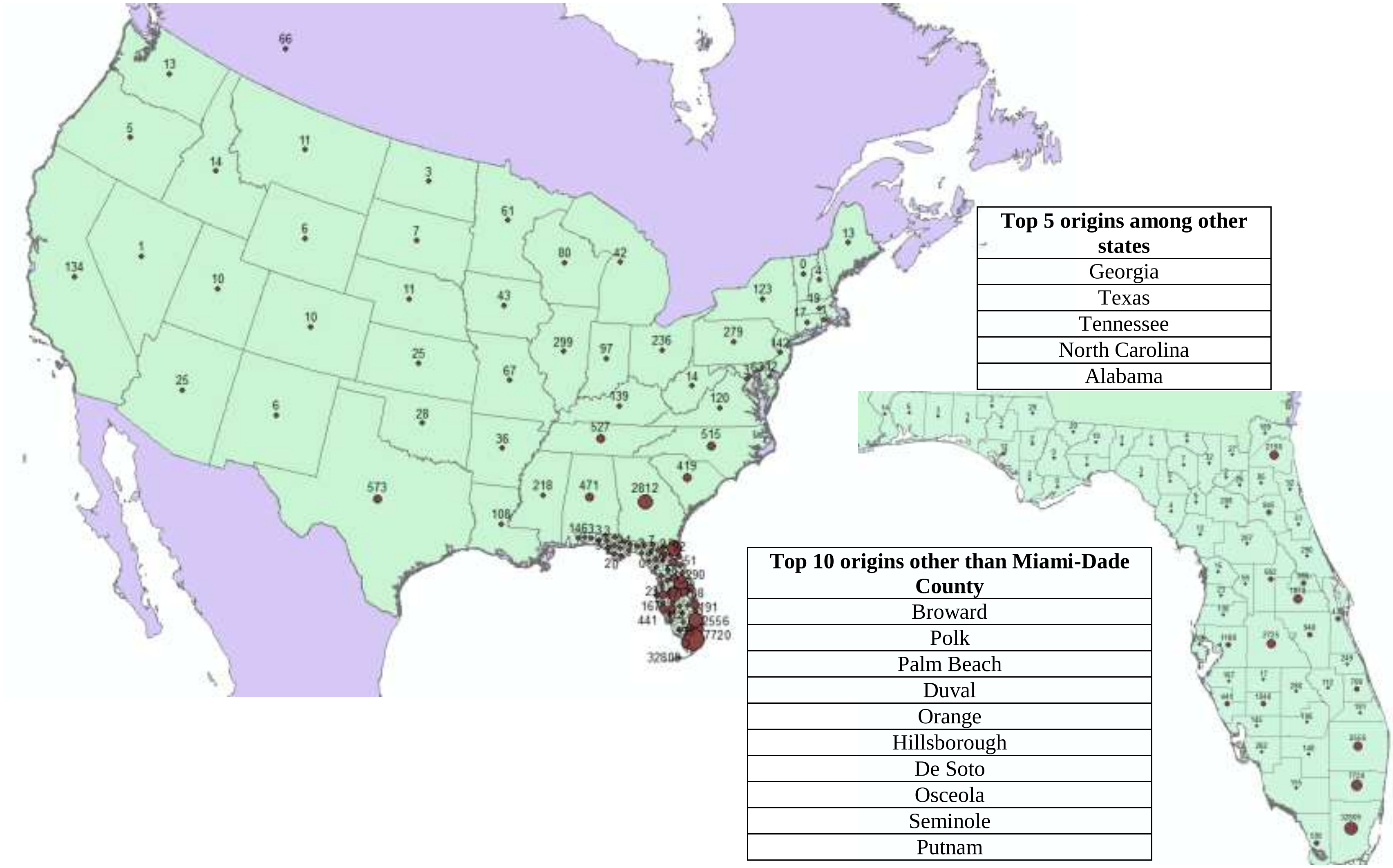
Figure B.22 Time-of-Day Profile of Trips Starting and Ending in Miami FAF Zone during (a) Weekdays (84,301 trips), and (b) Weekend (8,258 trips)



Top 5 destinations among other states
Georgia
South Carolina
Alabama
Texas
North Carolina

Top 10 destinations other than Miami-Dade County
Broward
Palm Beach
Polk
Duval
Orange
Hillsborough
Lake
De Soto
Putnam
St. Lucie

Figure B.23 Destinations of Trips Starting in Miami-Dade County (70,273 Trips)

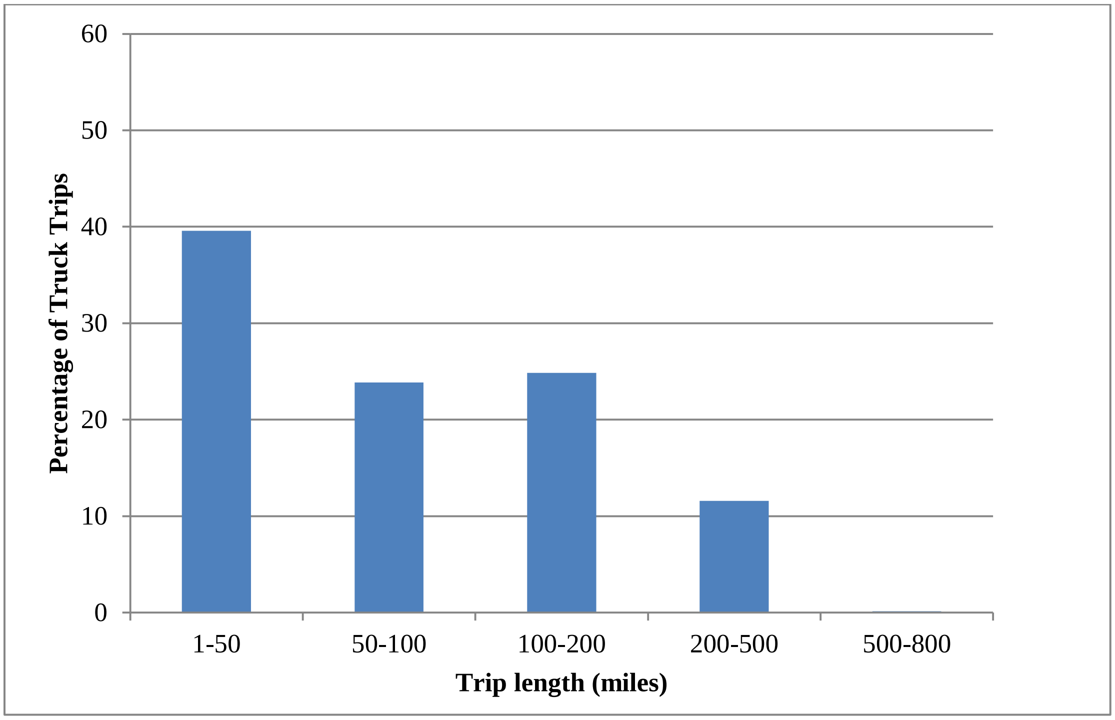


Top 5 origins among other states
Georgia
Texas
Tennessee
North Carolina
Alabama

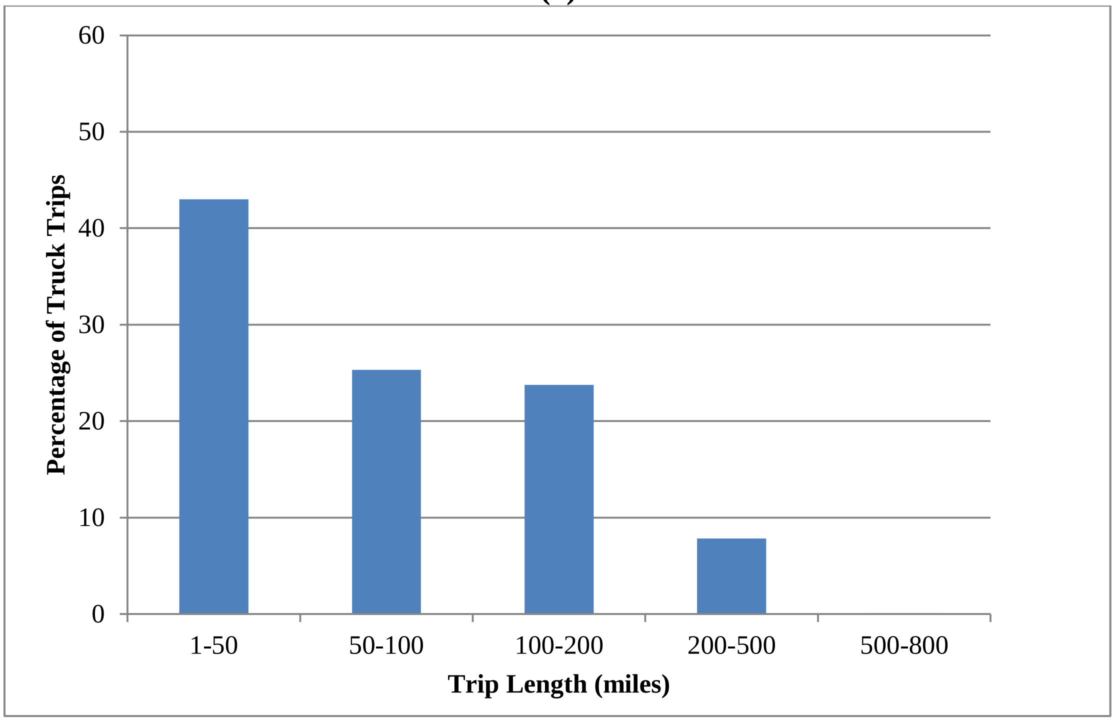
Top 10 origins other than Miami-Dade County
Broward
Polk
Palm Beach
Duval
Orange
Hillsborough
De Soto
Osceola
Seminole
Putnam

Figure B.24 Origins of Trips Ending in Miami-Dade County (69,274 Trips)

Characteristics of Truck Trips Starting and Ending in the Remainder of Florida

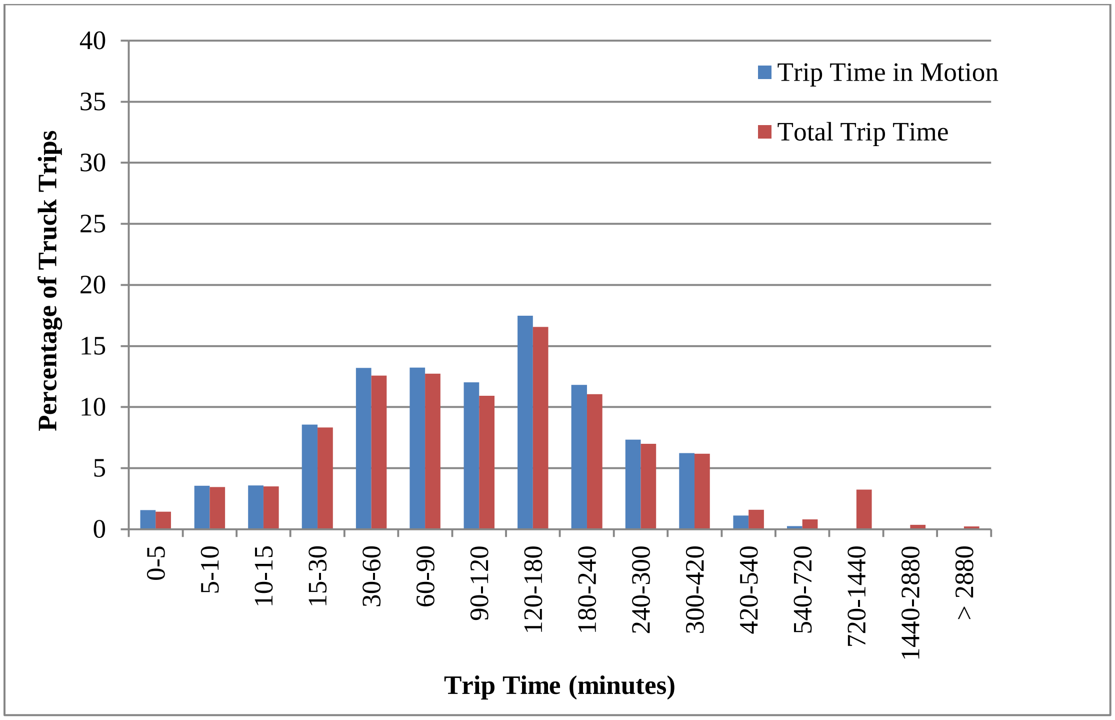


(a)

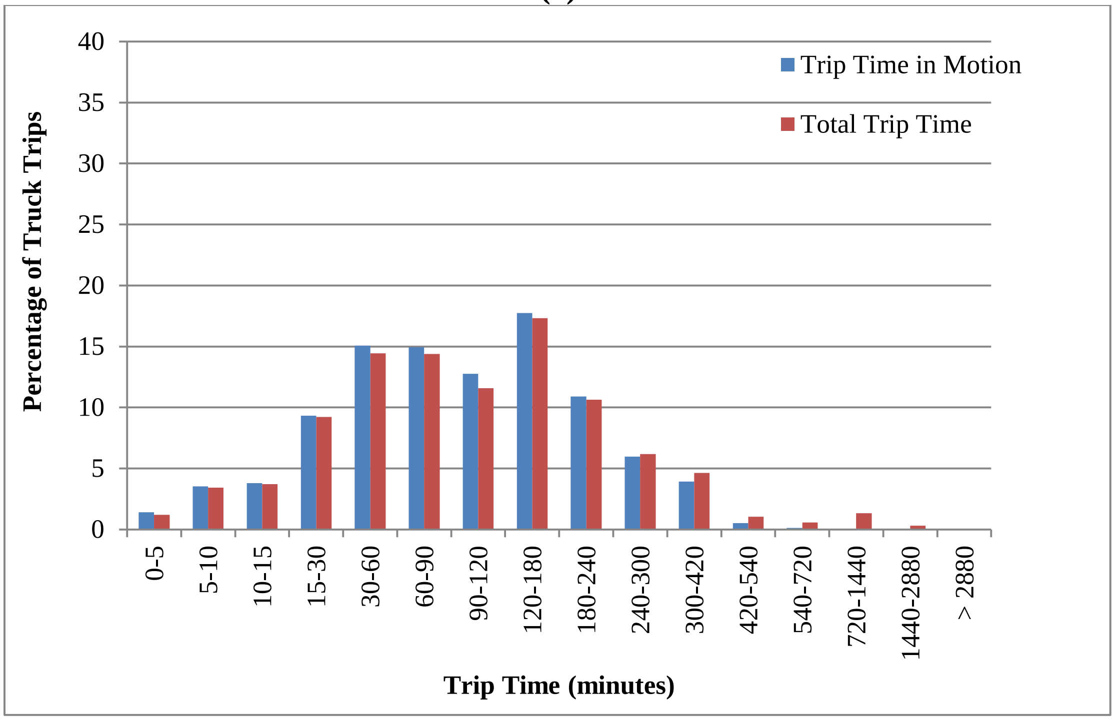


(b)

Figure B.25 Trip Length Distribution of Trips Starting and Ending in Other Regions in Florida during Weekdays (527,484 Trips), and (b) Weekend (73,678 Trips)

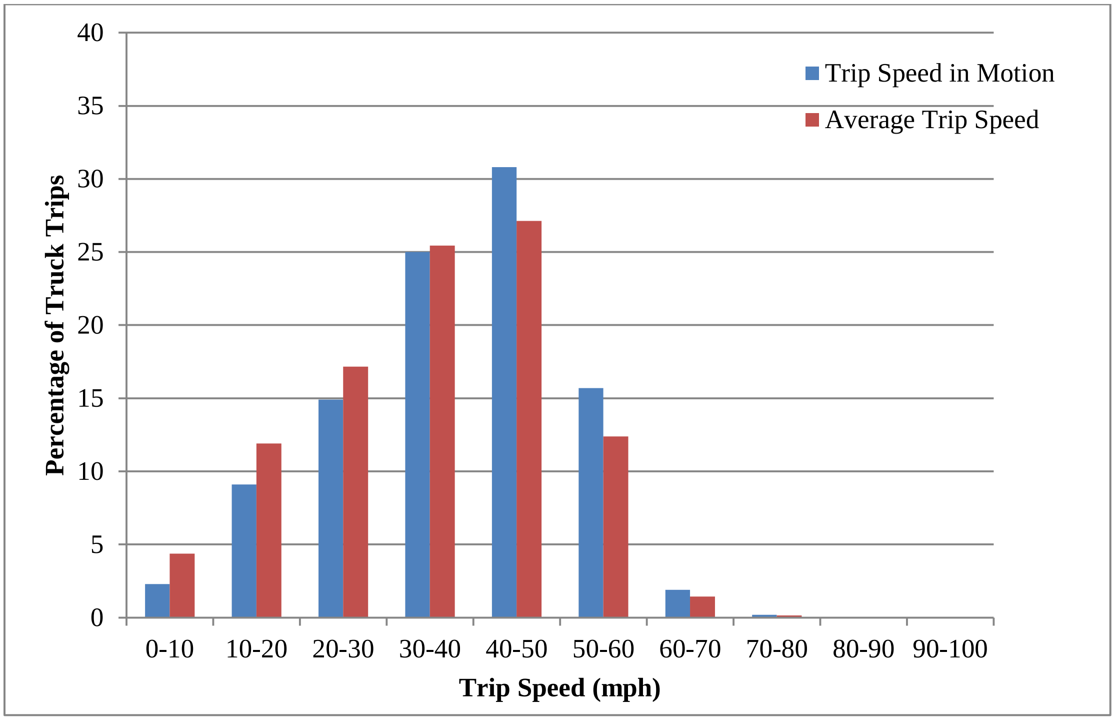


(a)

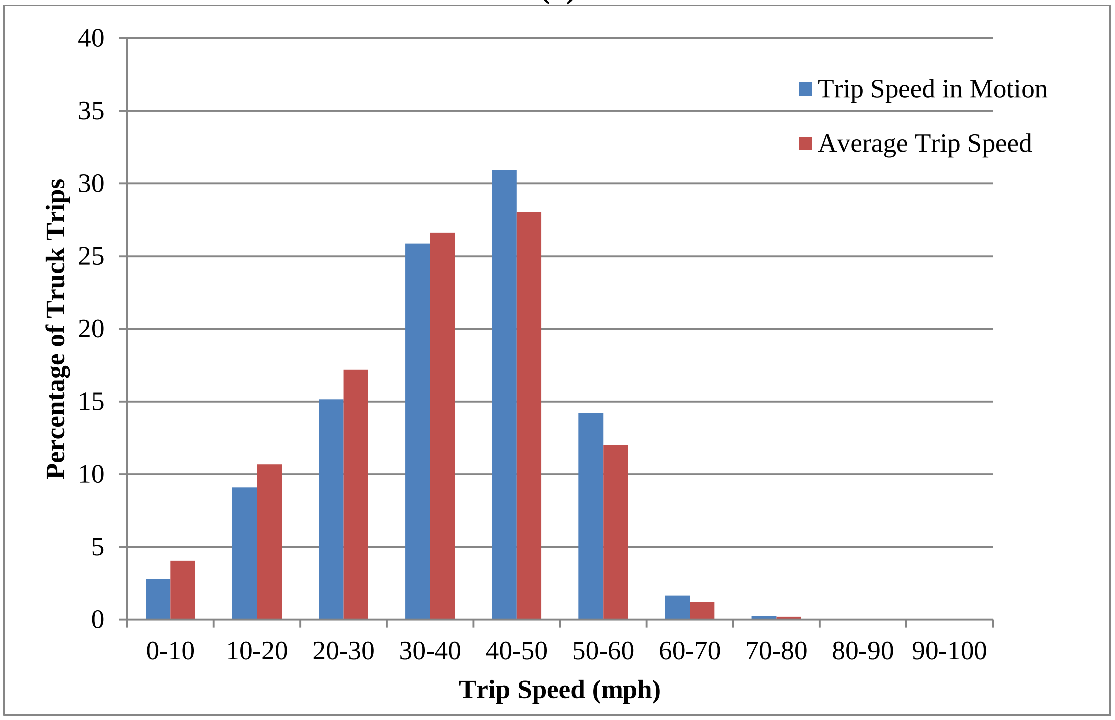


(b)

Figure B.26 Trip Time Distribution of Trips Starting and Ending in Other Regions in Florida during Weekdays (527,484 Trips), and (b) Weekend (73,678 Trips)

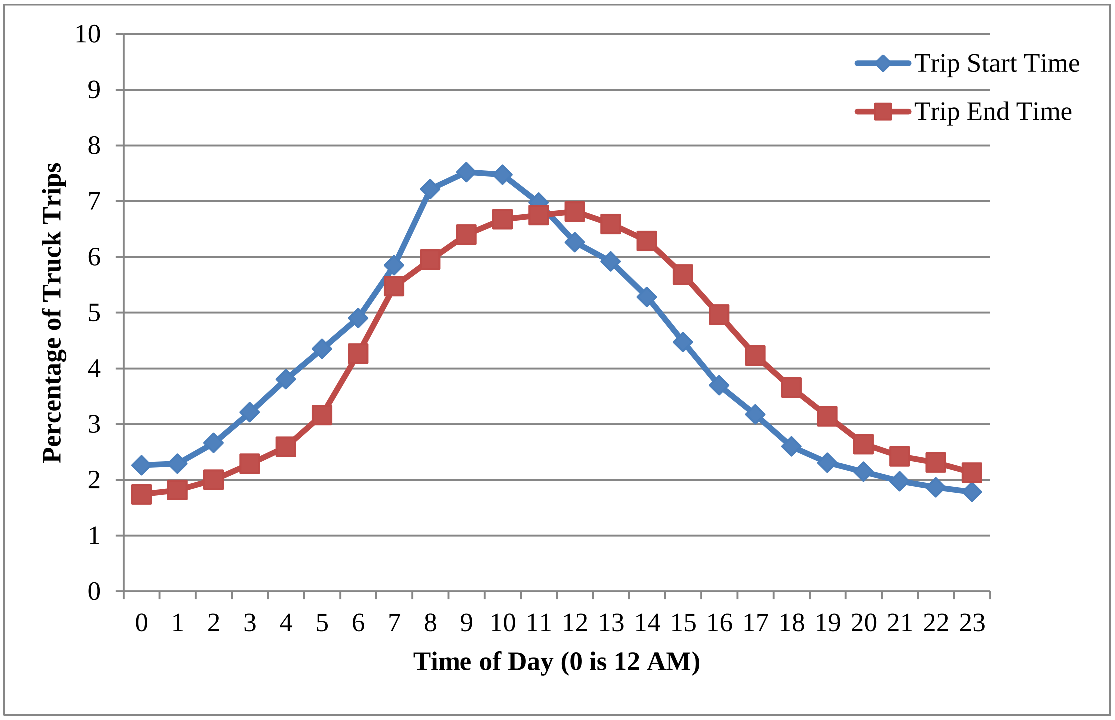


(a)

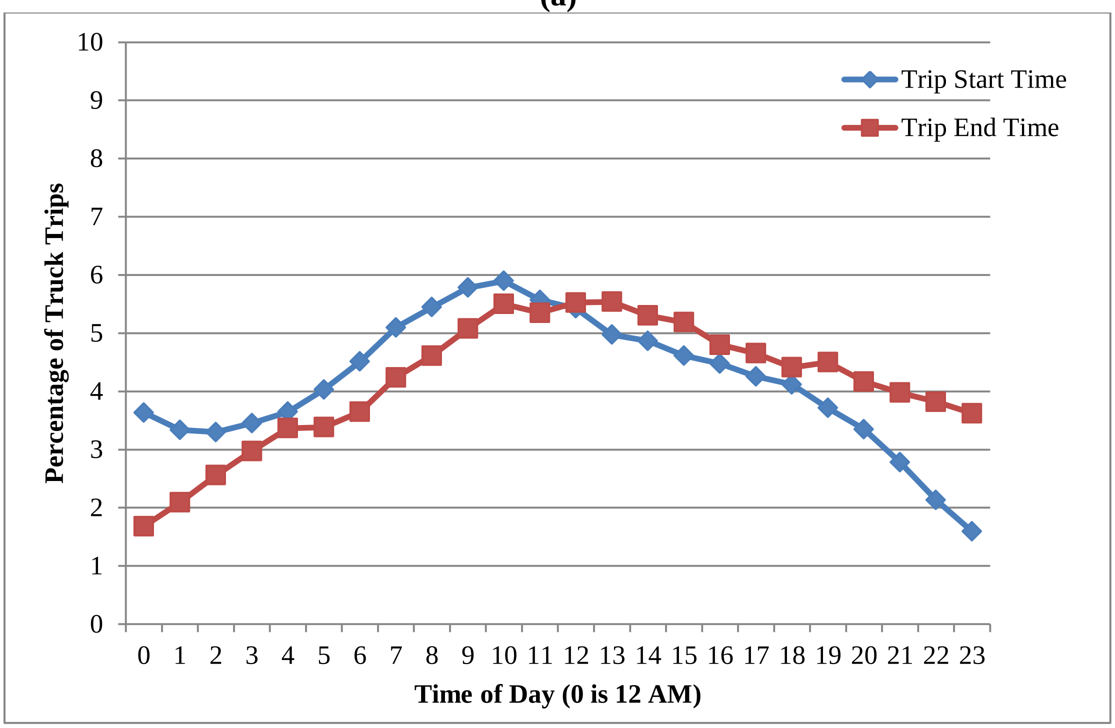


(b)

Figure B.27 Trip Speed Distribution of Trips Starting and Ending in Other Regions in Florida during Weekdays (527,484 Trips), and (b) Weekend (73,678 Trips)

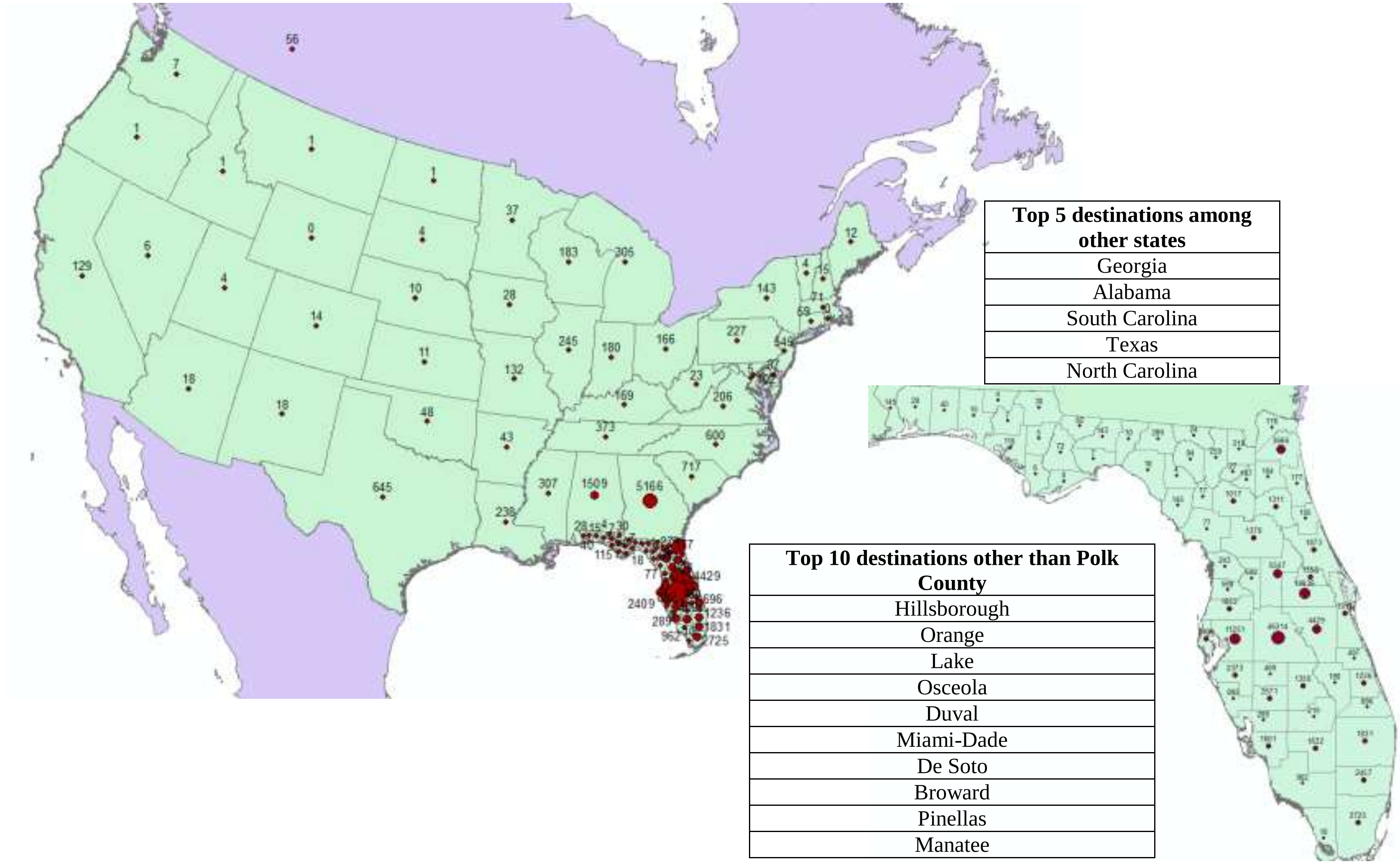


(a)



(b)

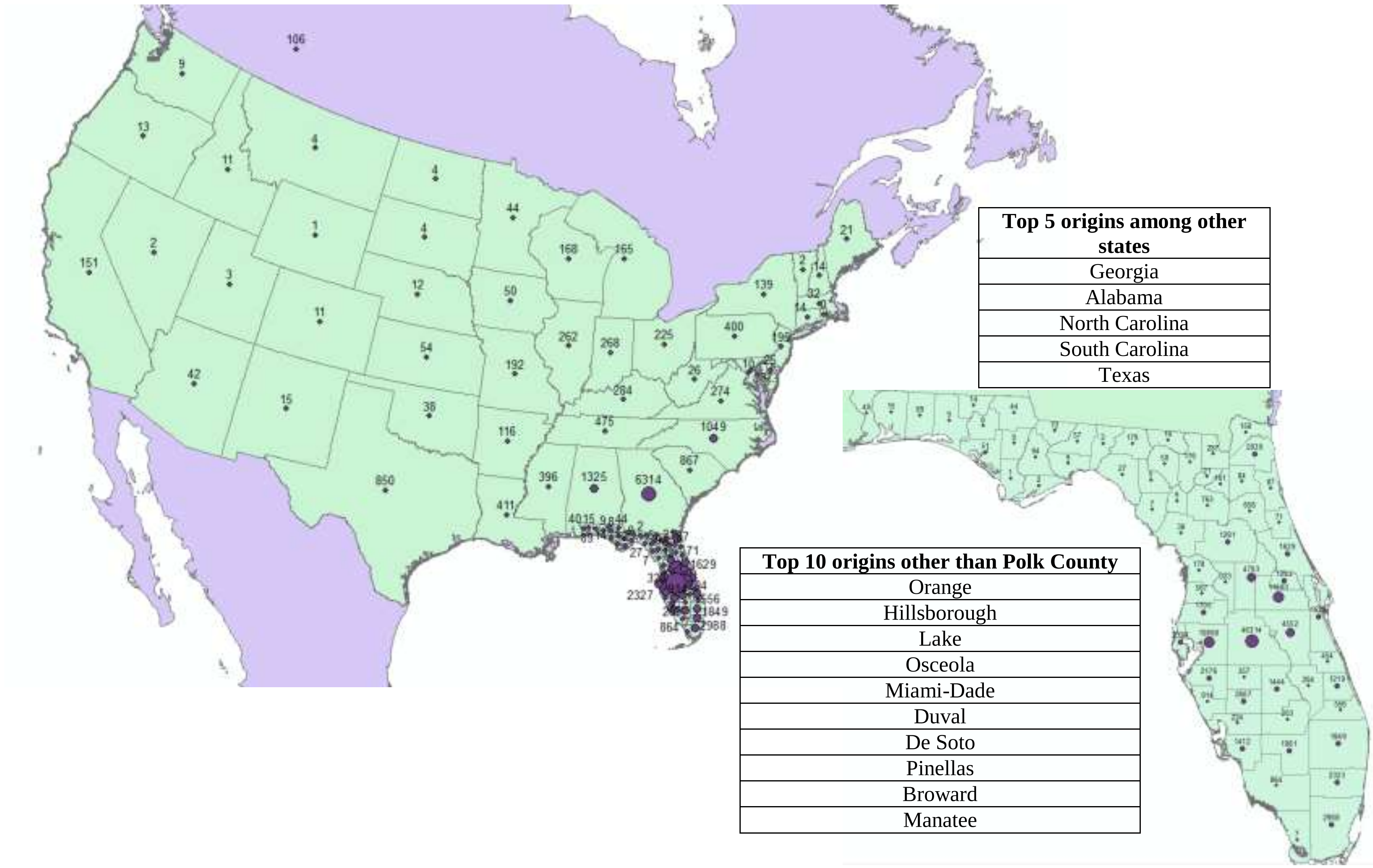
Figure B.28 Time-of-Day Profile of Trips Starting and Ending in Other Regions in Florida during (a) Weekdays (527,484 Trips), and (b) Weekend (73,678 Trips)



Top 5 destinations among other states
Georgia
Alabama
South Carolina
Texas
North Carolina

Top 10 destinations other than Polk County
Hillsborough
Orange
Lake
Osceola
Duval
Miami-Dade
De Soto
Broward
Pinellas
Manatee

Figure B.29 Destinations of Trips Starting in Polk County (133,365 Trips)

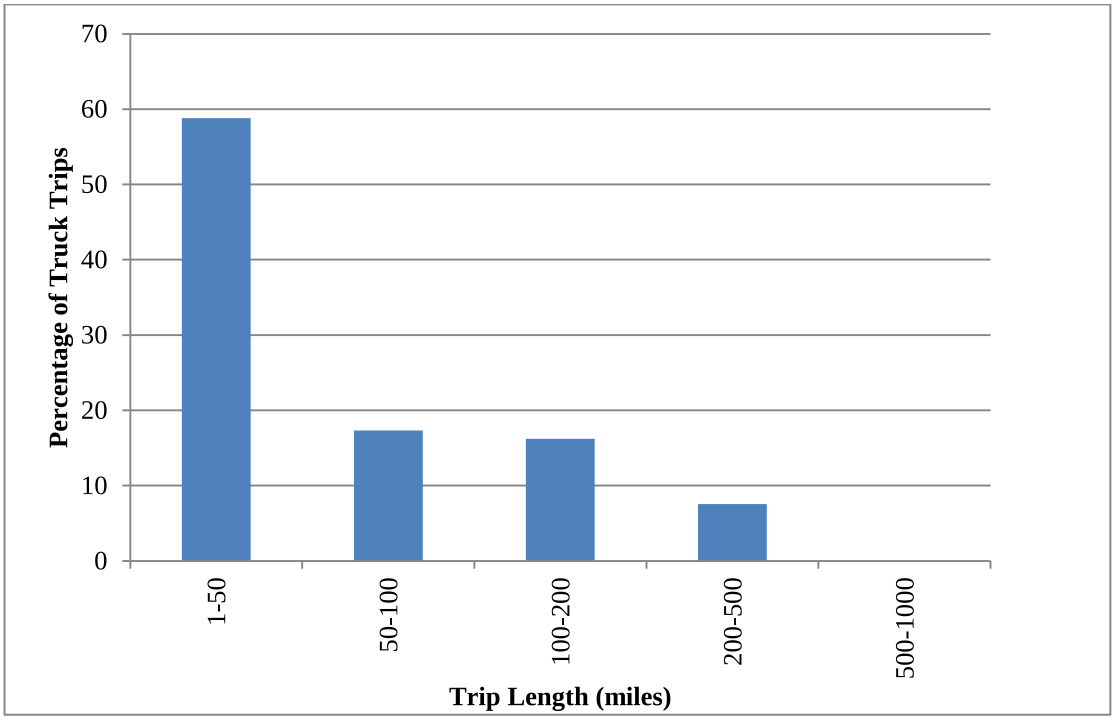


Top 5 origins among other states
Georgia
Alabama
North Carolina
South Carolina
Texas

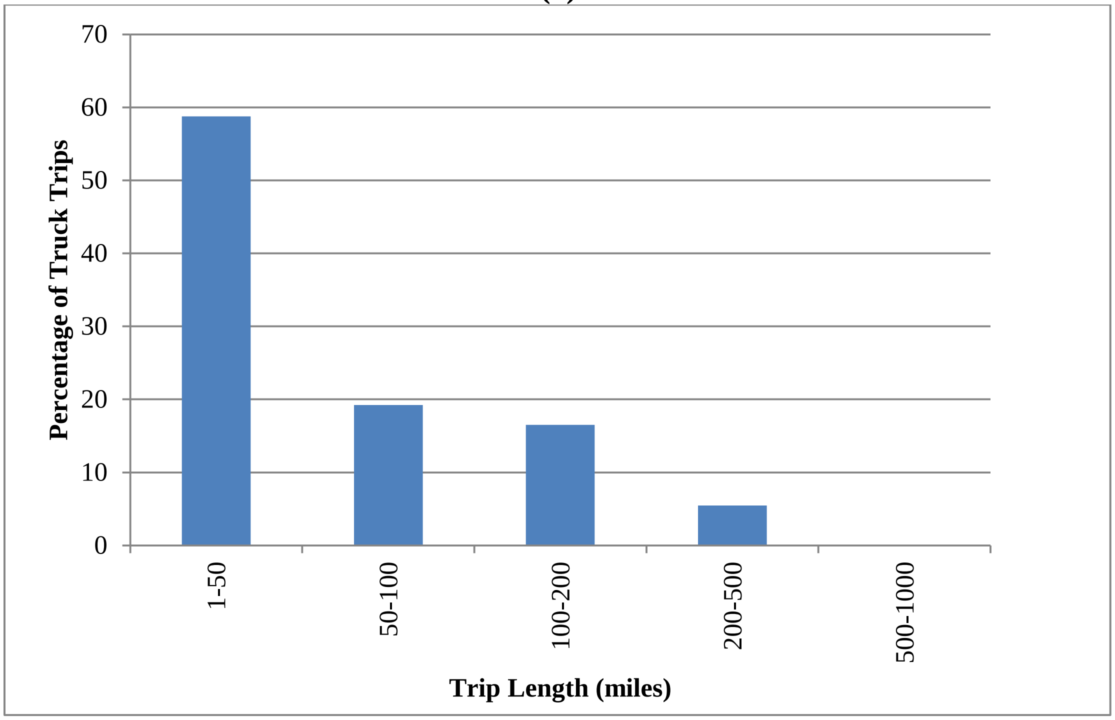
Top 10 origins other than Polk County
Orange
Hillsborough
Lake
Osceola
Miami-Dade
Duval
De Soto
Pinellas
Broward
Manatee

Figure B.30 Origins of Trips Ending in Polk County (132,393 Trips)

Characteristics of Truck Trips Starting and Ending in Florida (I-I Trips for Florida)

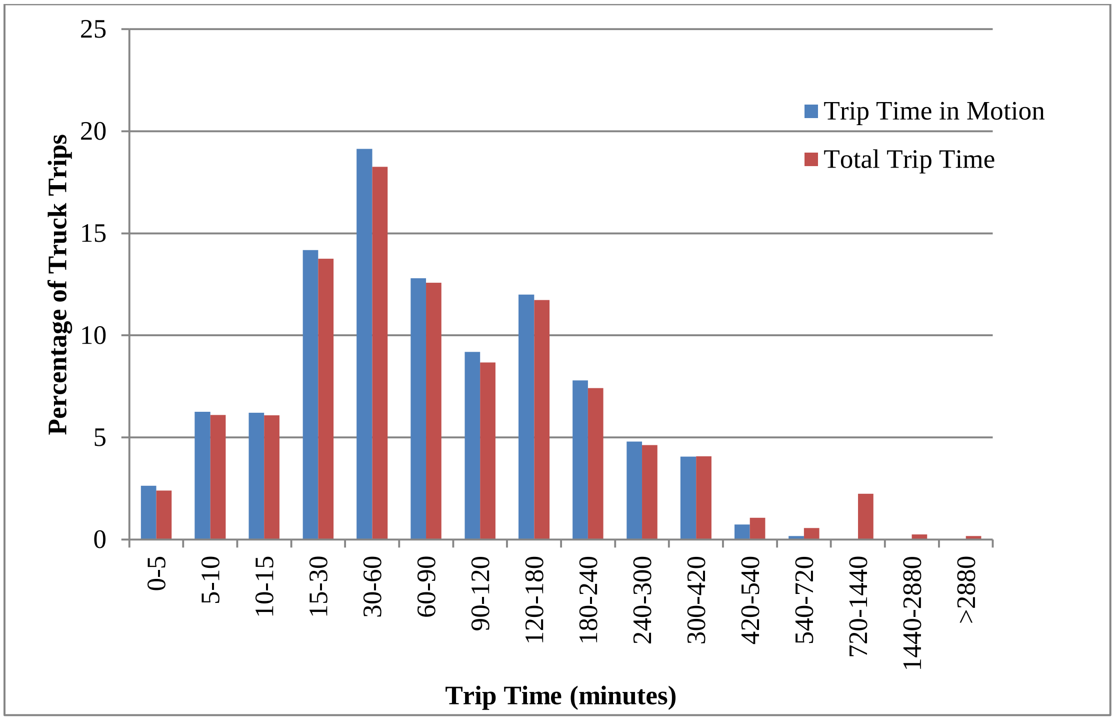


(a)

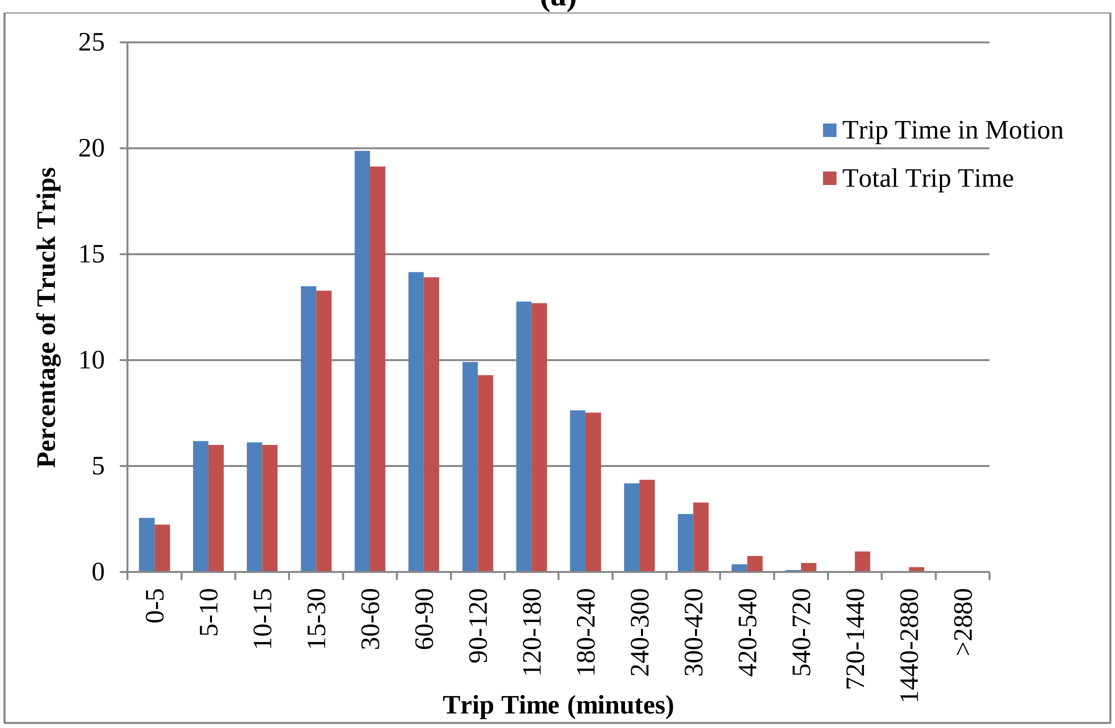


(b)

Figure B.31 Trip Length Distribution of Trips Starting and Ending in Florida during (a) Weekdays (808,673 trips), and (b) Weekend (106,033 trips)

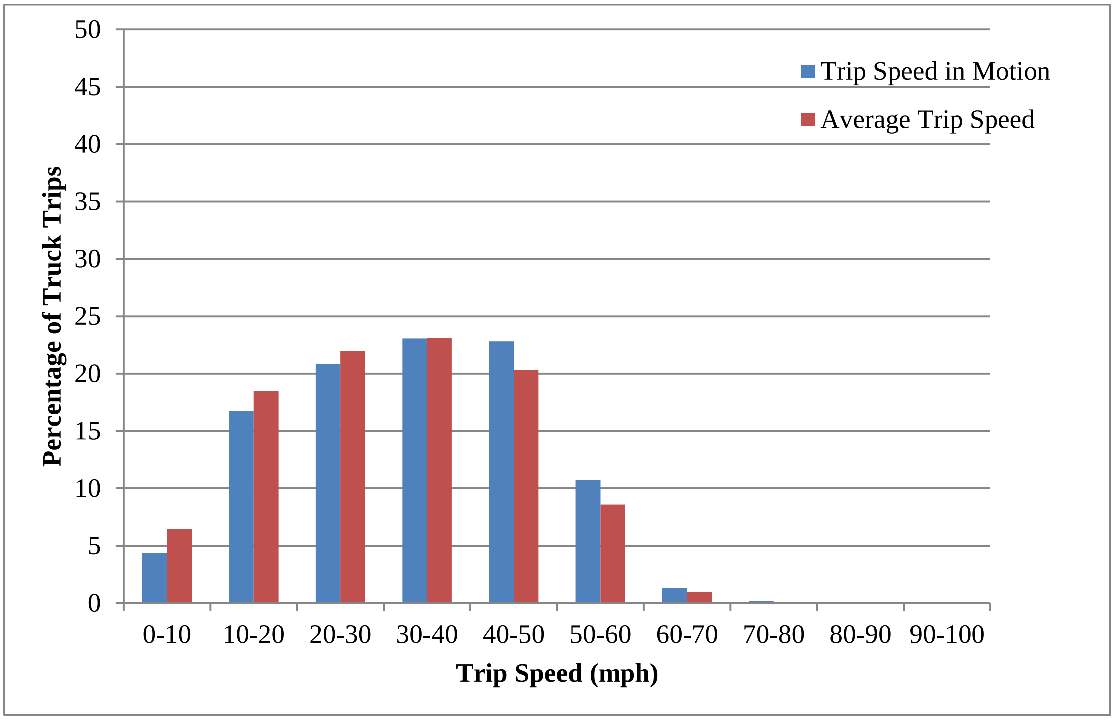


(a)

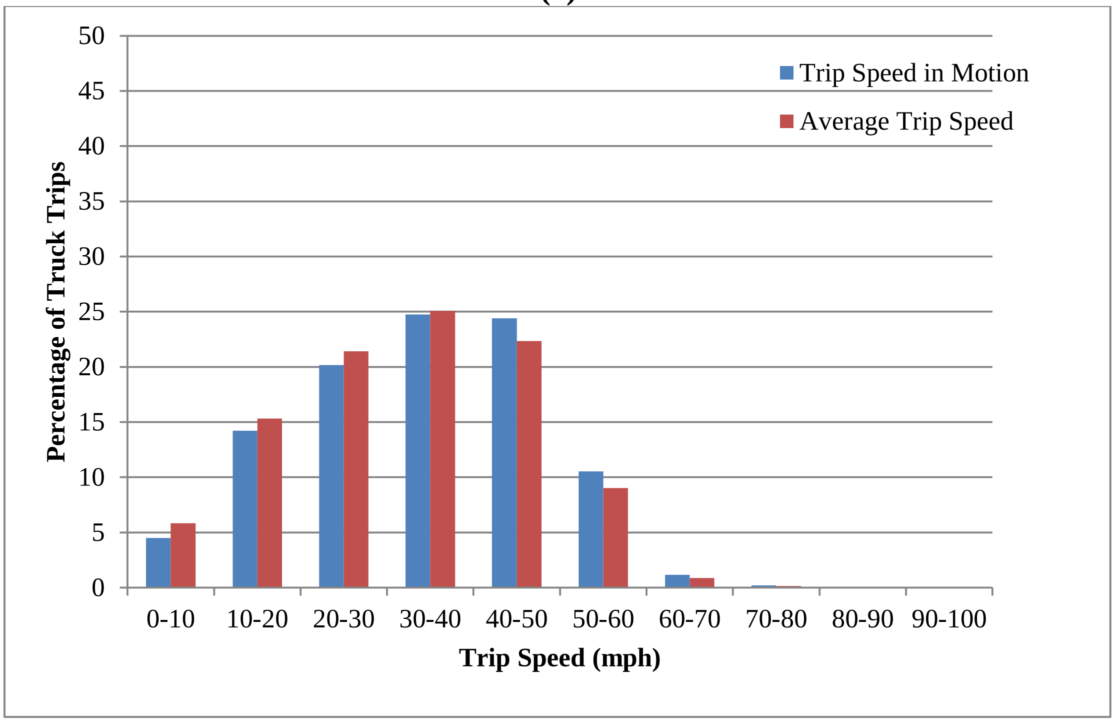


(b)

Figure B.32 Trip Time Distribution of Trips Starting and Ending in Florida during (a) Weekdays (808,673 trips), and (b) Weekend (106,033 trips)

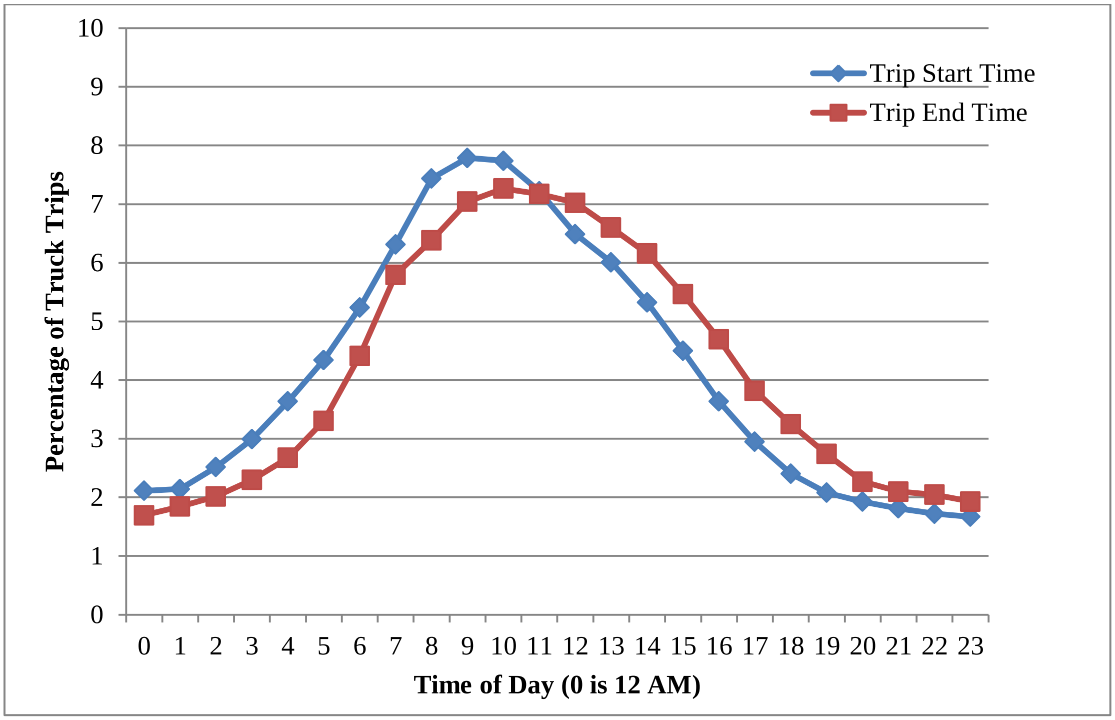


(a)

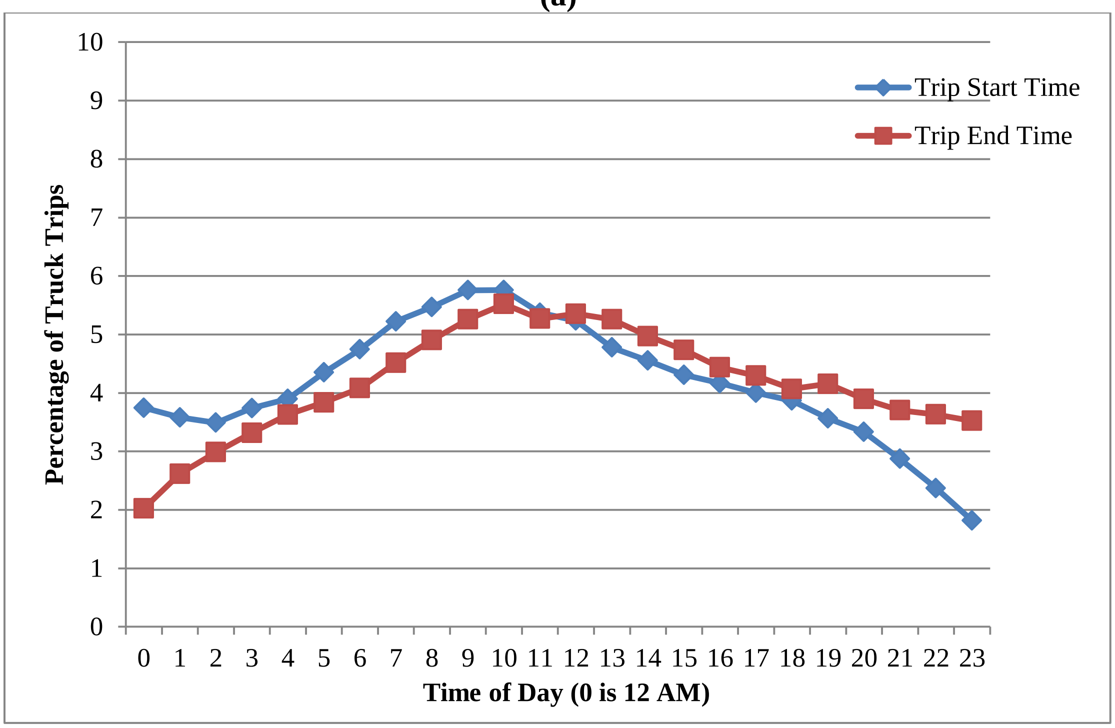


(b)

Figure B.33 Trip Speed Distribution of Trips Starting and Ending in Florida during (a) Weekdays (808,673 trips), and (b) Weekend (106,033 trips)



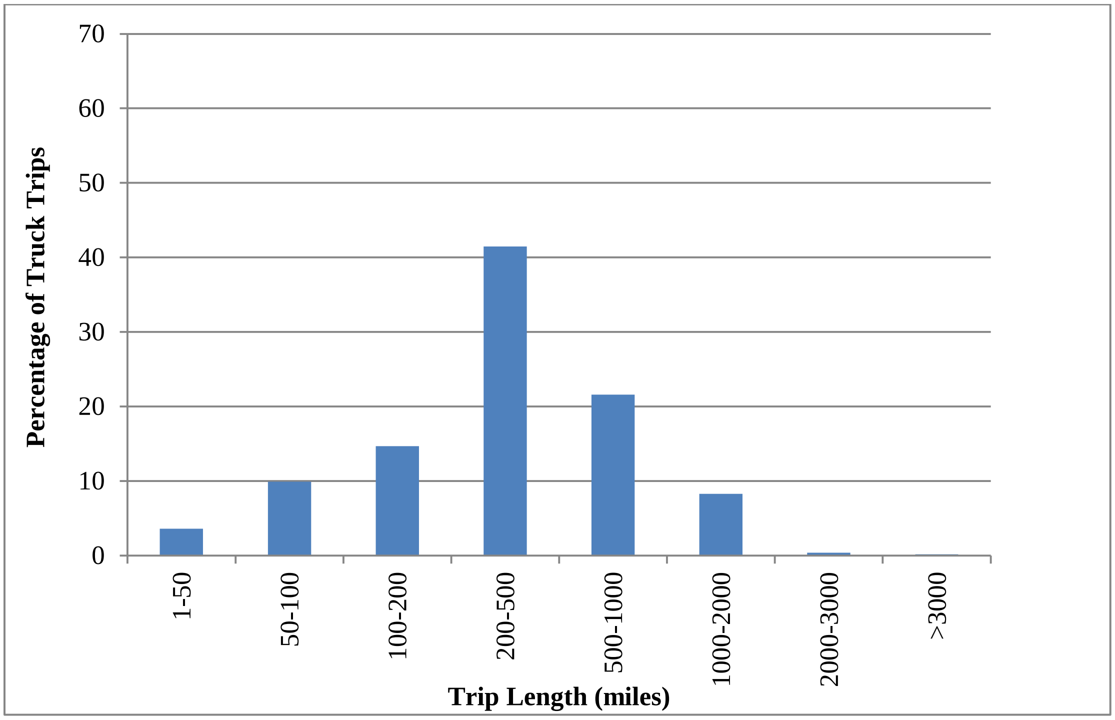
(a)



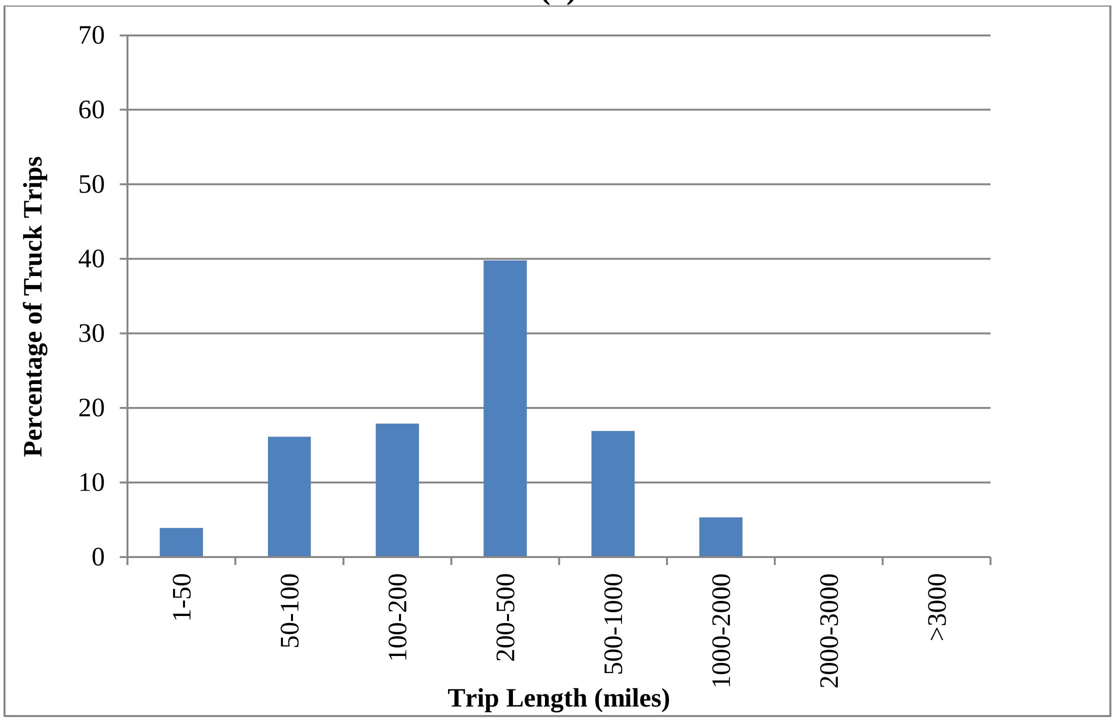
(b)

Figure B.34 Time-of-Day Profile of Trips Starting and Ending in Florida during (a) Weekdays (808,673 trips), and (b) Weekend (106,033 trips)

Characteristics of Truck Trips Starting in Florida and Ending outside Florida (I-E Trips)

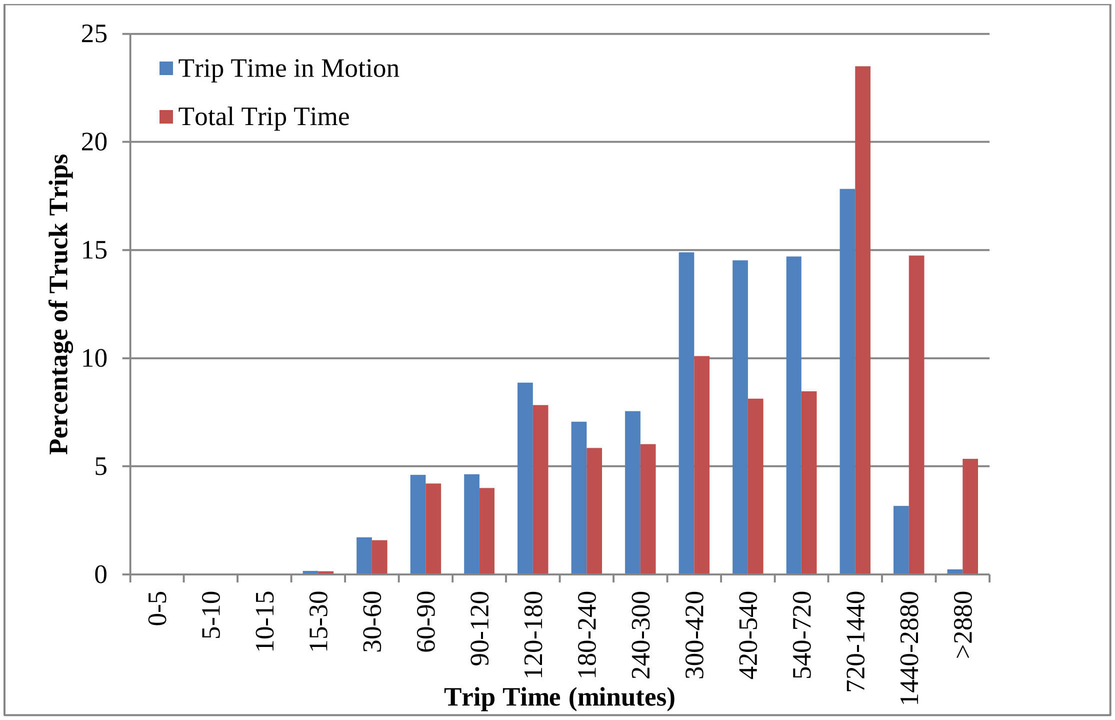


(a)

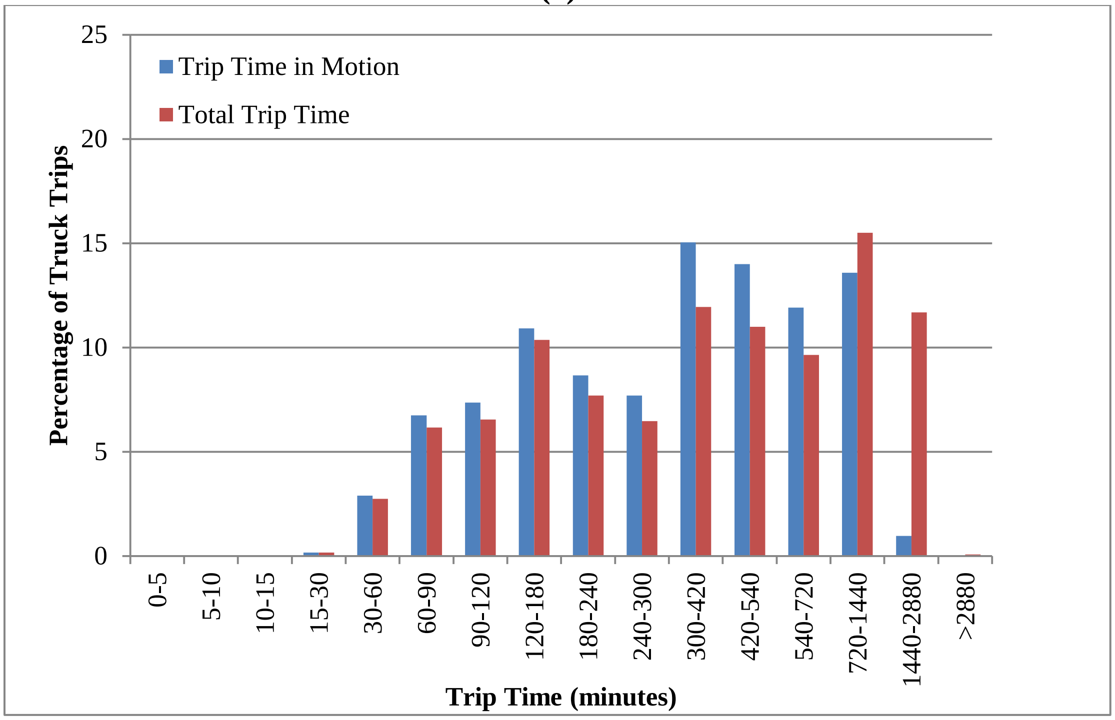


(b)

Figure B.35 Trip Length Distribution of Trips Starting in Florida and Ending outside Florida during (a) Weekdays (138,816 trips), and (b) Weekend (13,900 trips)

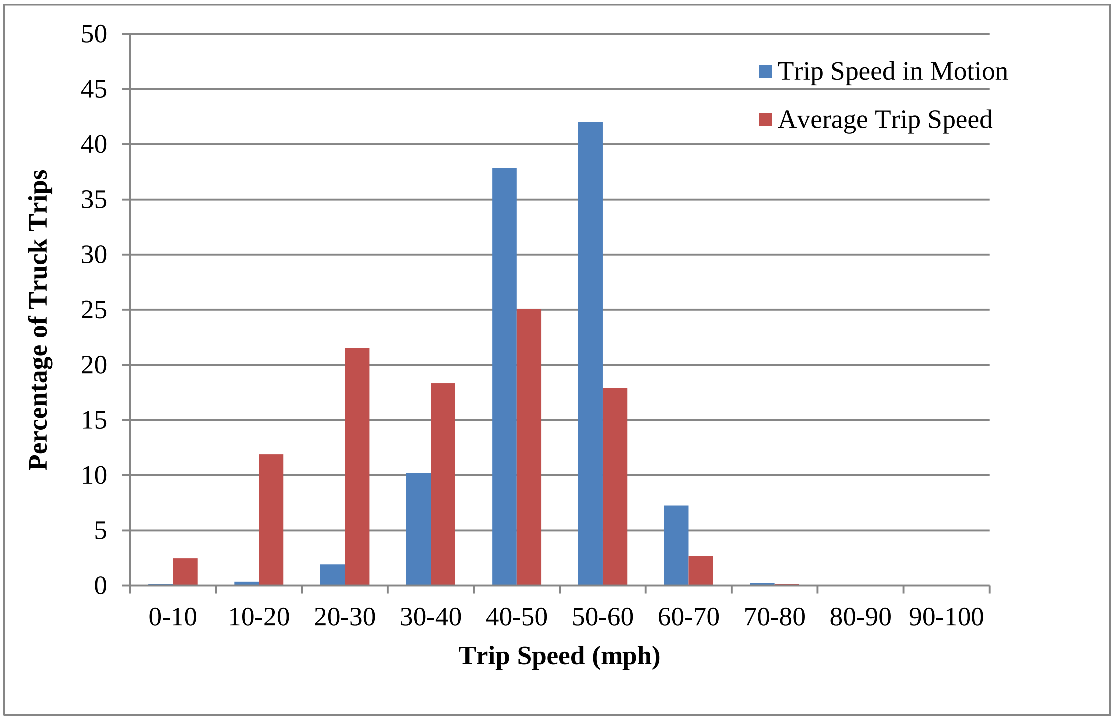


(a)

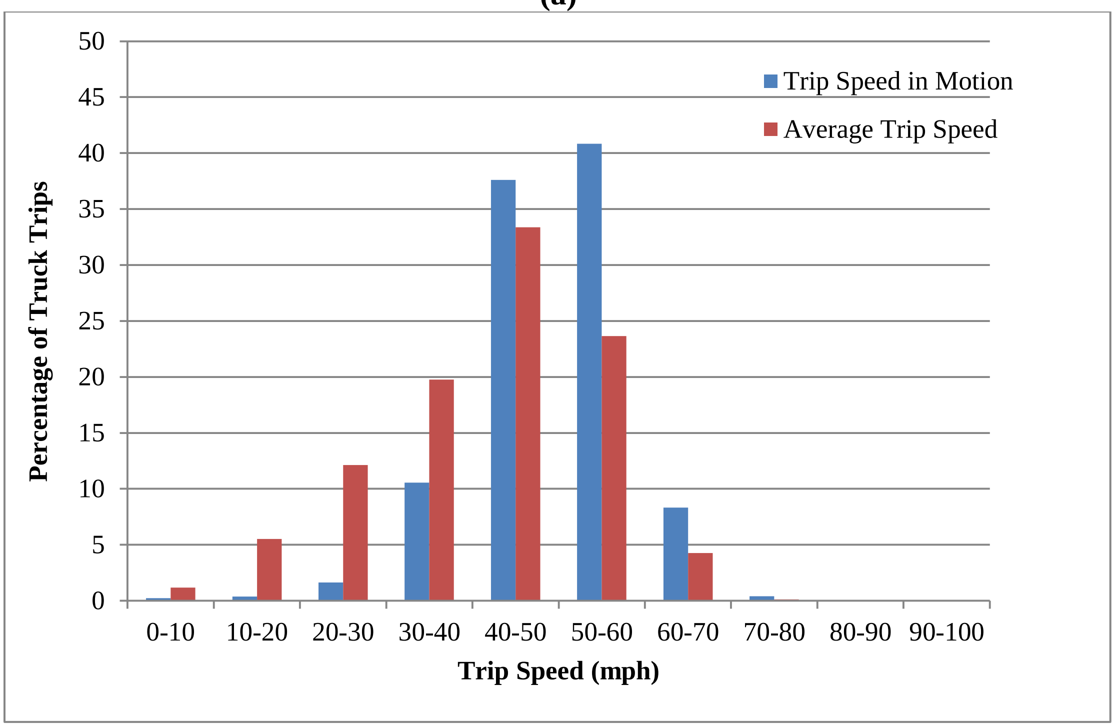


(b)

Figure B.36 Trip Time Distribution of Trips Starting in Florida and Ending outside Florida during (a) Weekdays (138,816 trips), and (b) Weekend (13,900 trips)

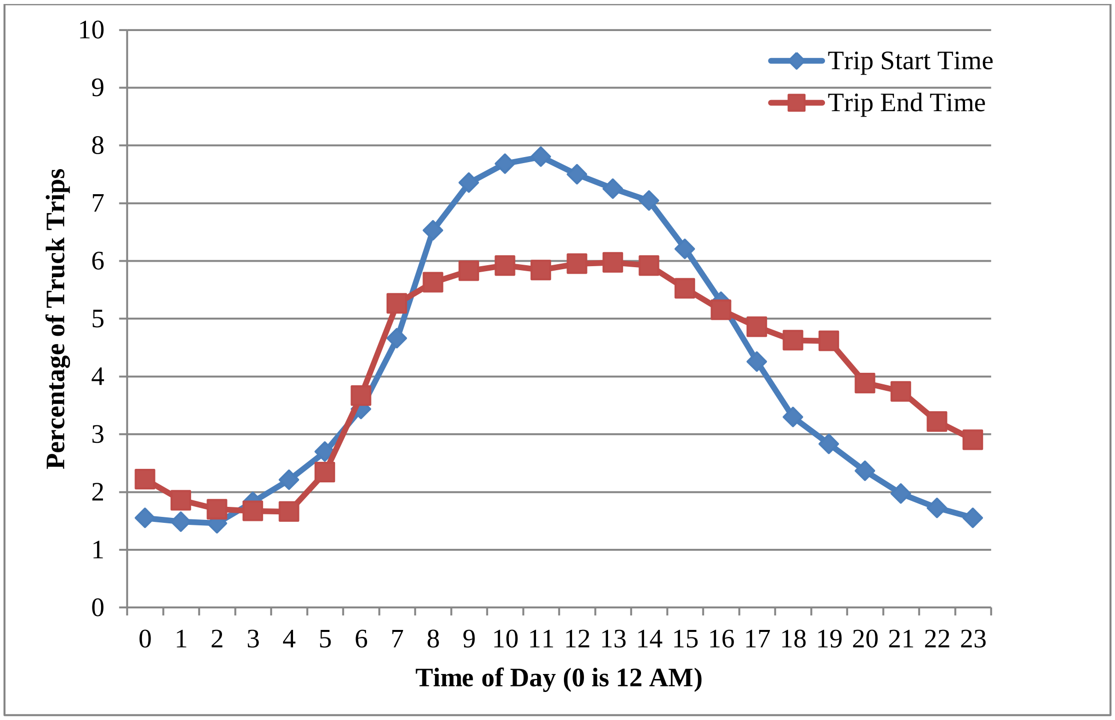


(a)

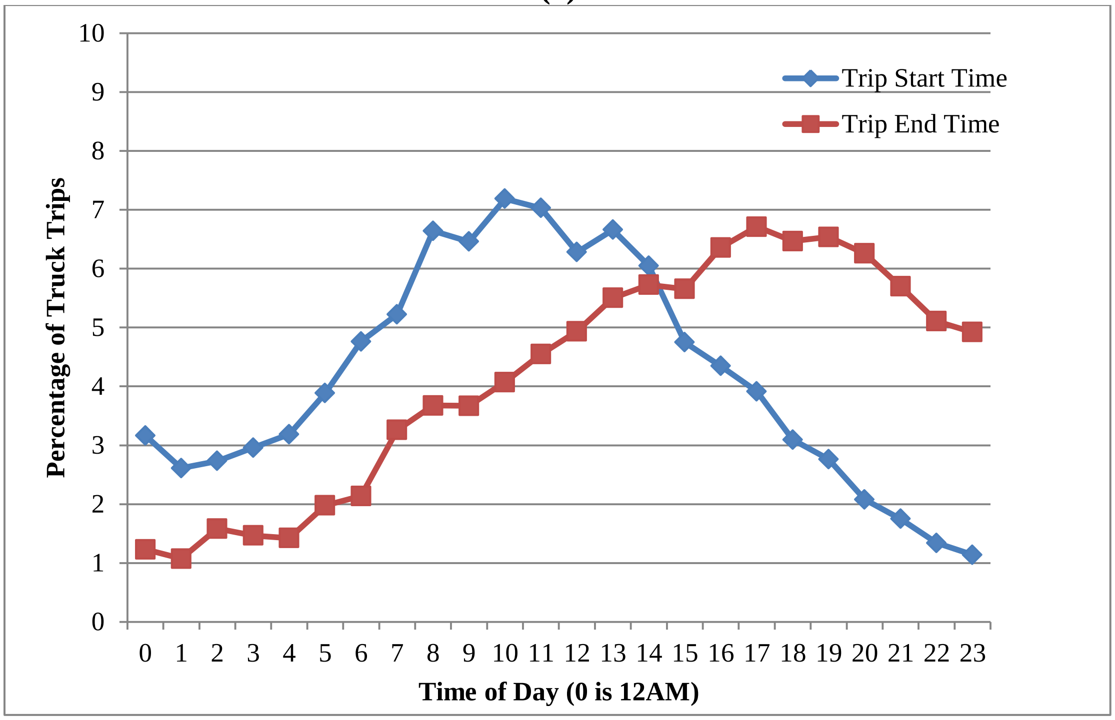


(b)

Figure B.37 Trip Speed Distribution of Trips Starting in Florida and Ending outside Florida during (a) Weekdays (138,816 trips), and (b) Weekend (13,900 trips)

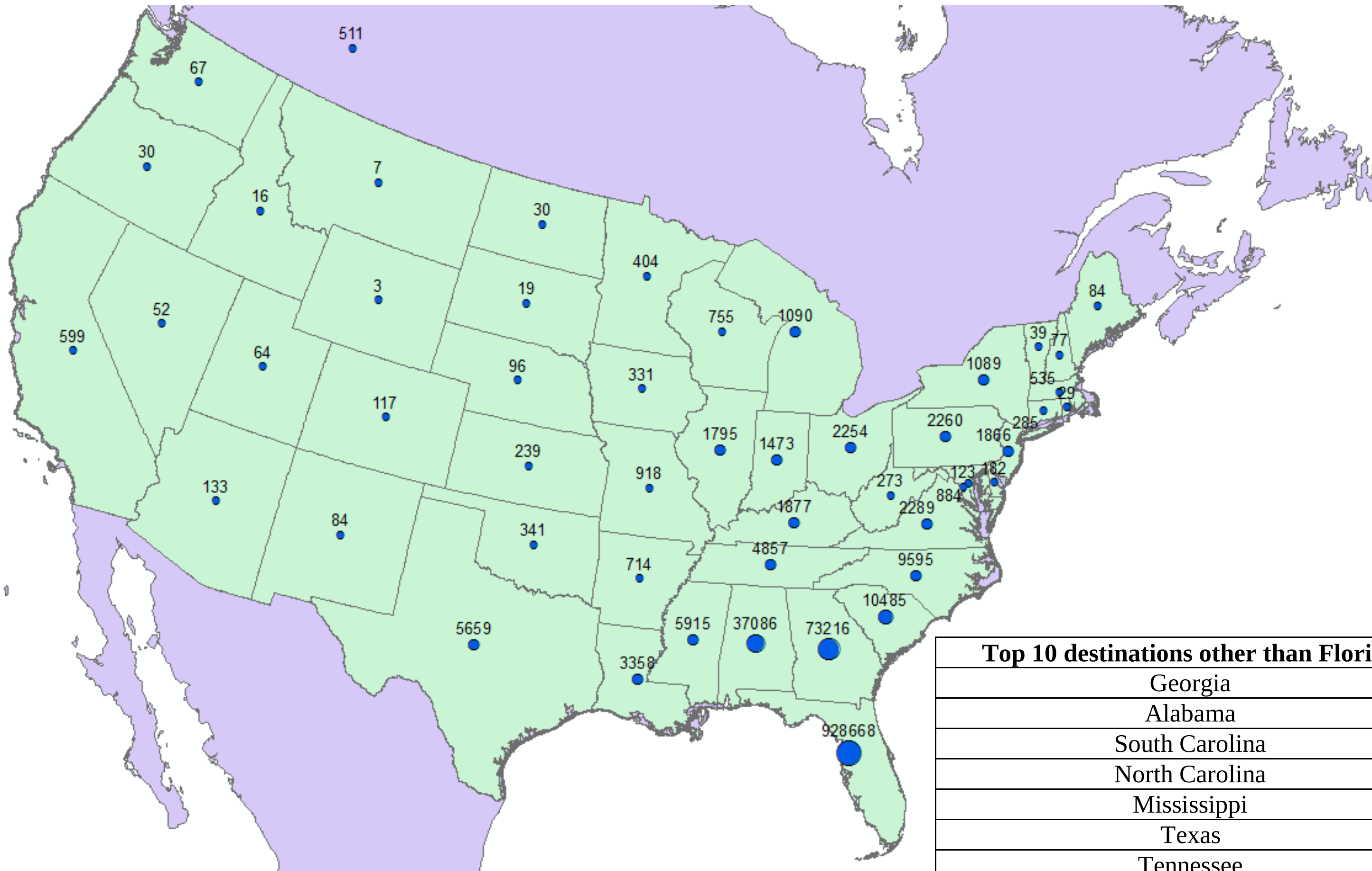


(a)



(b)

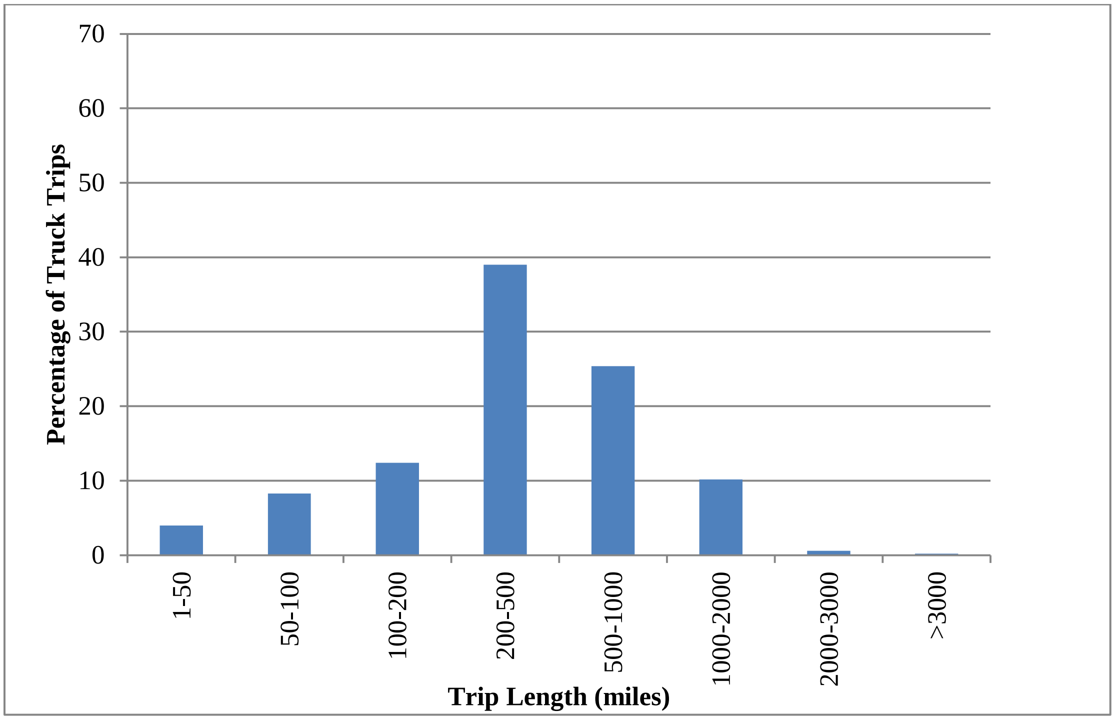
Figure B.38 Time-of-Day Profile of Trips Starting in Florida and Ending outside Florida during (a) Weekdays (138,816 trips), and (b) Weekend (13,900 trips)



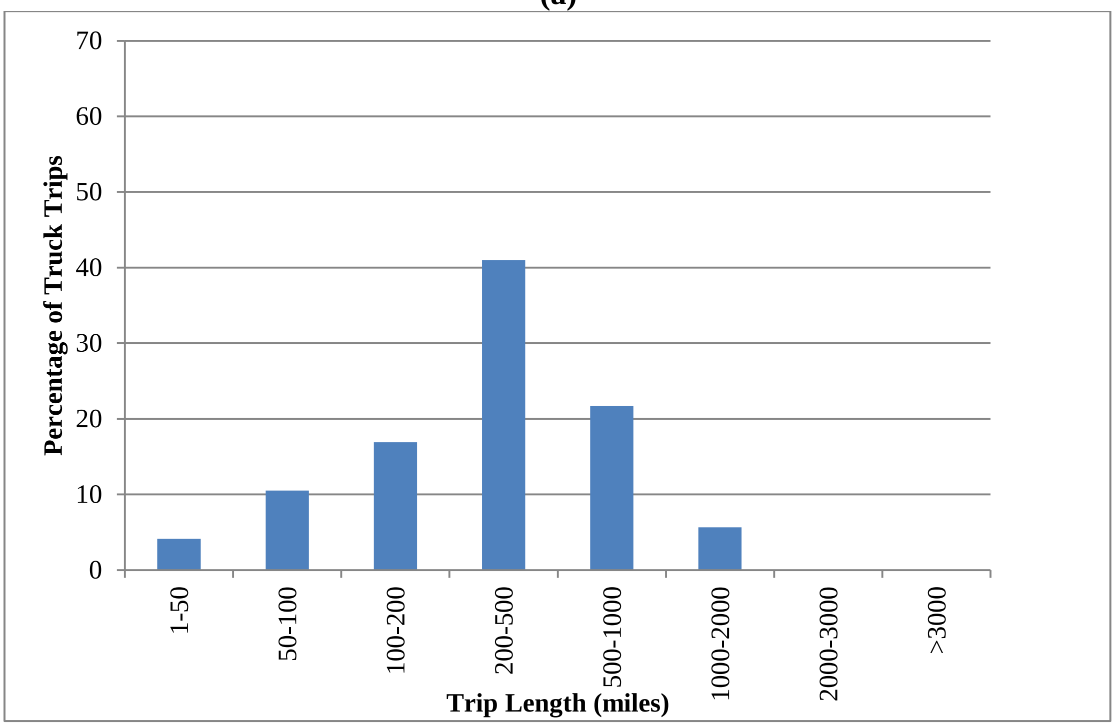
Top 10 destinations other than Florida
Georgia
Alabama
South Carolina
North Carolina
Mississippi
Texas
Tennessee
Louisiana
Virginia
Pennsylvania

Figure B.39 Destinations of Trips Starting in Florida (1,102,873 Trips)

Characteristics of Truck Trips Starting outside Florida and Ending in Florida (E-I Trips)

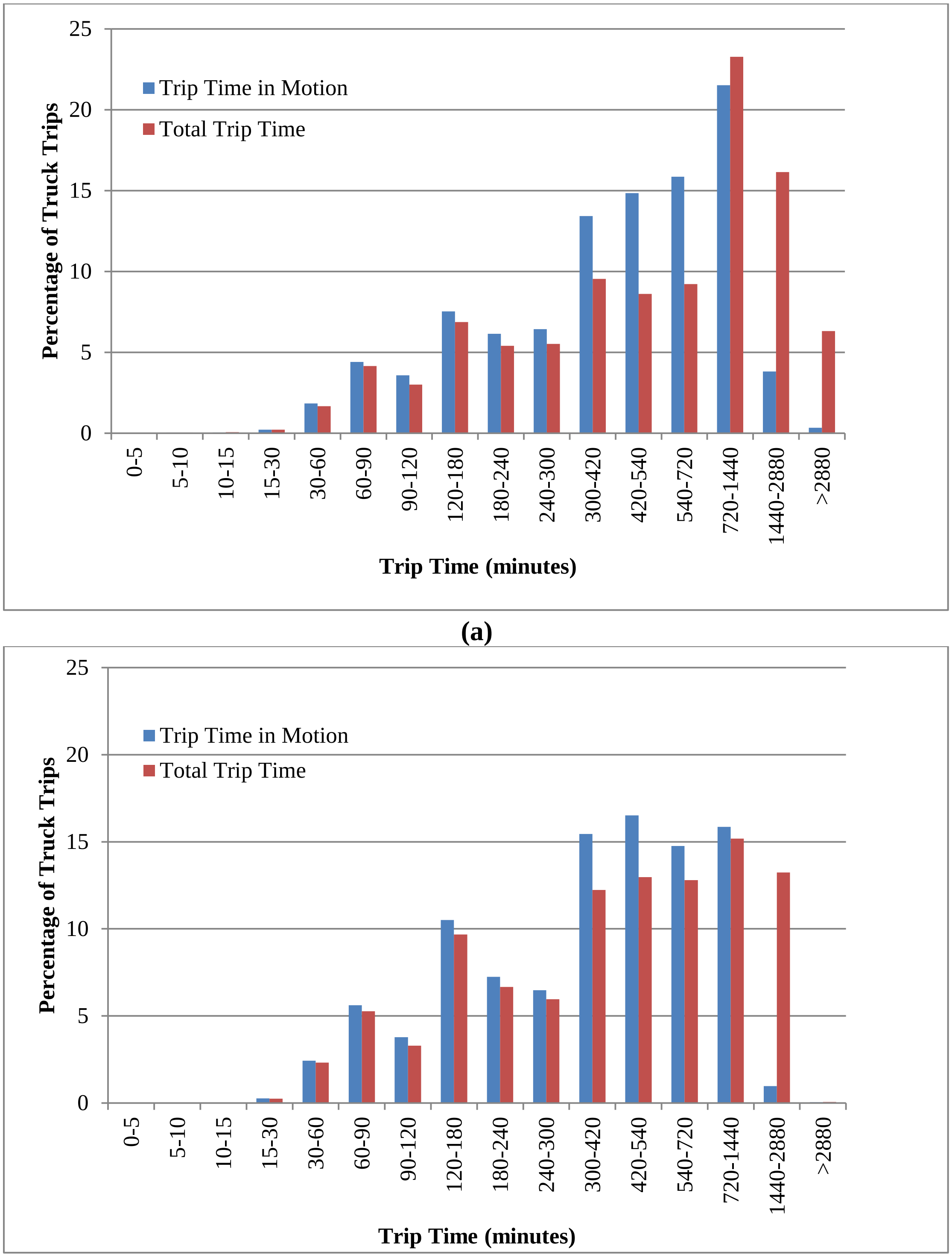


(a)



(b)

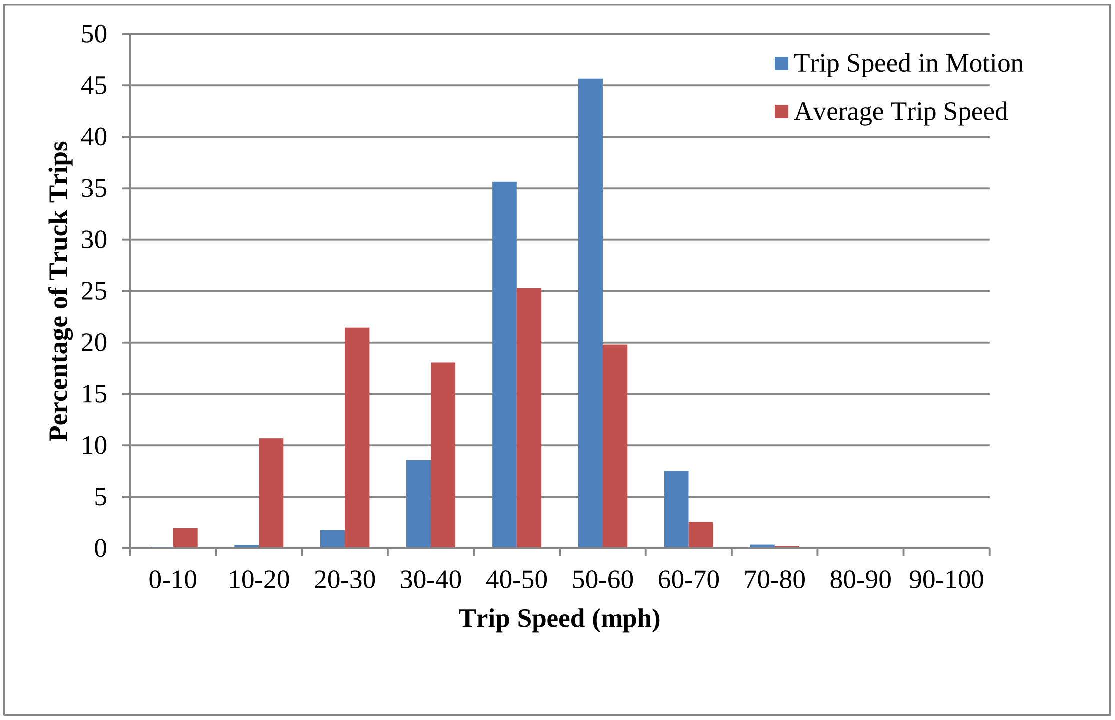
Figure B.40 Trip Length Distribution of Trips Starting outside Florida and Ending in Florida during (a) Weekdays (127,796 trips), and (b) Weekend (15,635 trips)



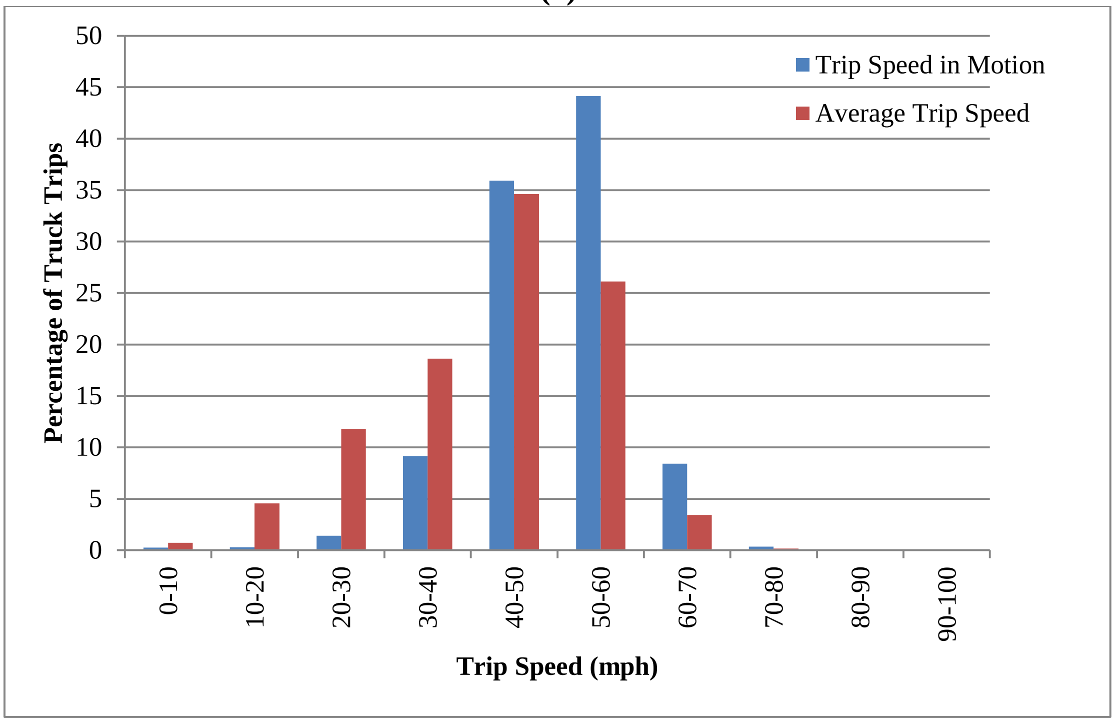
(a)

(b)

Figure B.41 Trip Time Distribution of Trips Starting outside Florida and Ending in Florida during (a) Weekdays (127,796 trips), and (b) Weekend (15,635 trips)

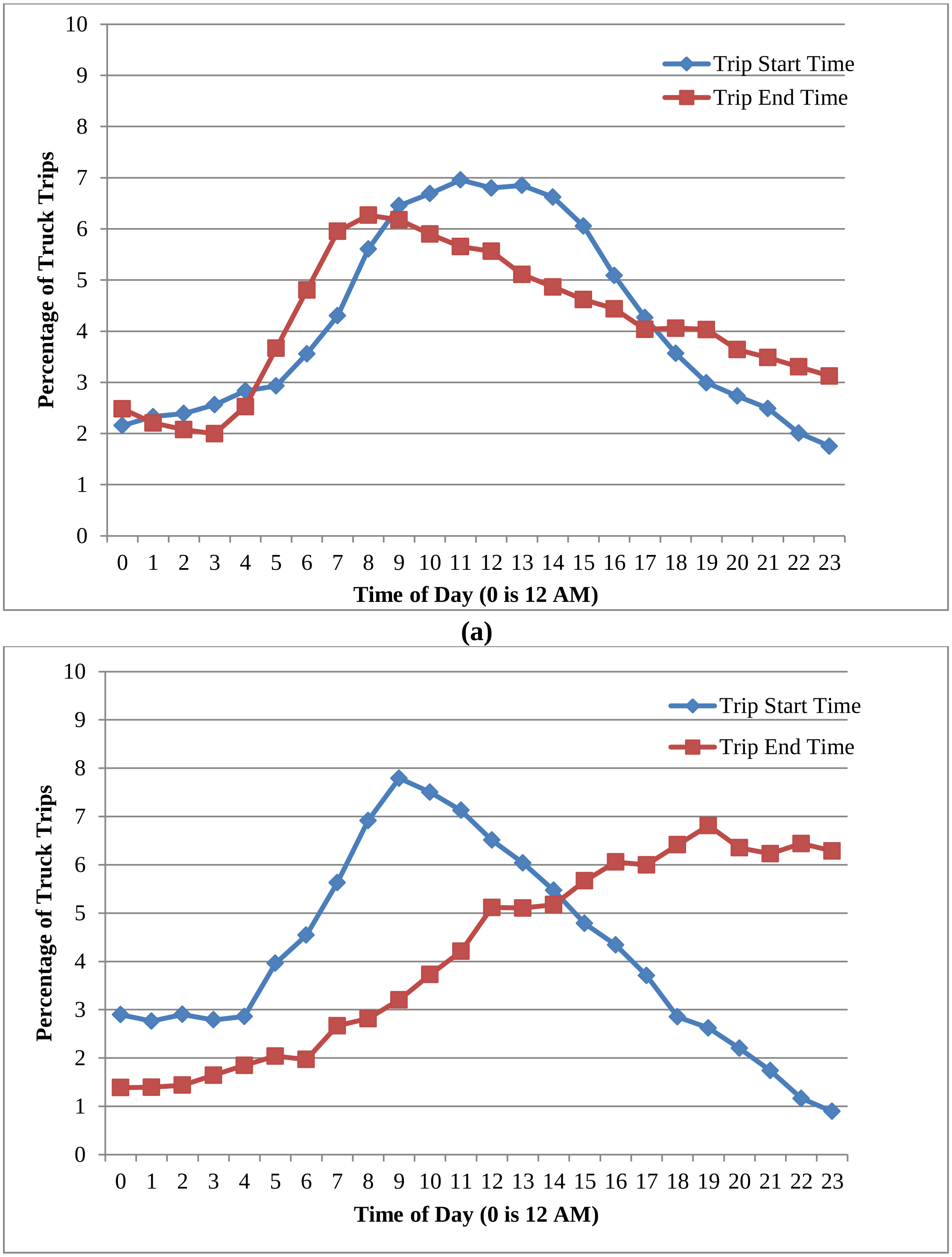


(a)



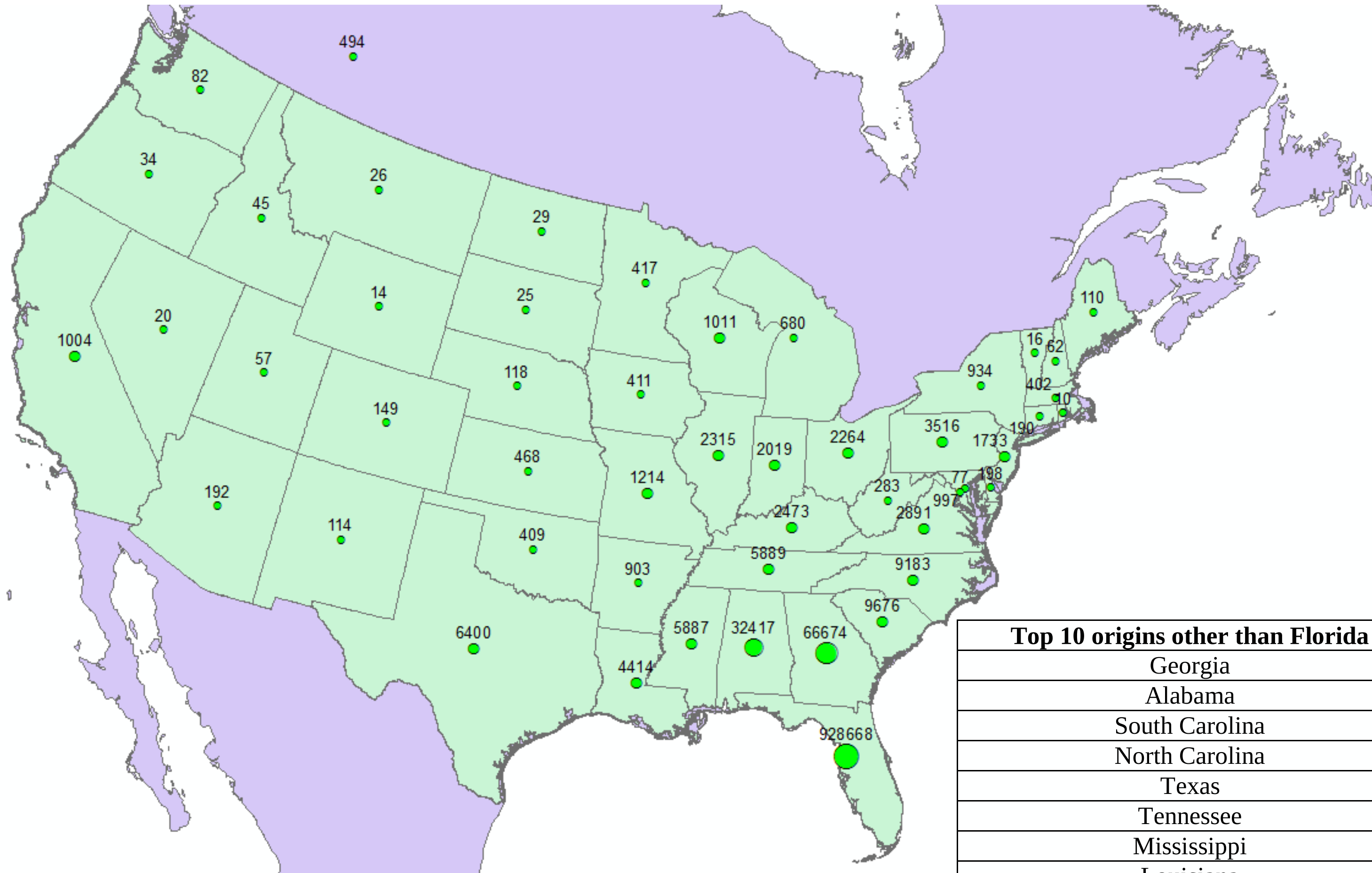
(b)

Figure B.42 Trip Speed Distribution of Trips Starting outside Florida and Ending in Florida during (a) Weekdays (127,796 trips), and (b) Weekend (15,635 trips)



(b)

Figure B.43 Time-of-Day Profile of Trips Starting outside Florida and Ending in Florida during (a) Weekdays (127,796 trips), and (b) Weekend (15,635 trips)



Top 10 origins other than Florida
Georgia
Alabama
South Carolina
North Carolina
Texas
Tennessee
Mississippi
Louisiana
Pennsylvania
Virginia

Figure B.44 Origins of Trips Ending in Florida (1,097,614 Trips)

APPENDIX C: TRAVEL ROUTES AND TRAVEL TIME MEASUREMENTS FOR 10 OD PAIRS

This appendix provides maps of travel routes and histograms of travel time distributions between 10 TAZ-to-TAZ OD pairs in FLSWM. The 10 OD pairs were selected strategically to include a randomly-selected sample of 2 OD pairs in each of the following five travel distance bands: within 100 miles, 100–200 miles, 200–500 miles, 500–1000 miles, and above 1,000 miles. For each of these OD pairs, the route choices of all trips extracted from the data are depicted as on-route GPS coordinates. Specifically, Figures D.1 through D.10 show maps with the route choices, one figure for each OD pair. These maps can be used to gain a preliminary understanding of the route choice patterns of long-haul trucks.

In addition to route choice maps, the appendix provides histograms of OD travel time distributions for the same 10 OD pairs. Specifically, the distributions for three different types of travel times are provided: (1) total travel time, which measures the time between trip start and tripe end, including the time spent at all intermediate stops such as rest stops, traffic congestion stops, and fueling stops; (2) travel time in motion including non-significant stops, which measures the travel time excluding significant stops such as rest stops but includes non-significant stops such as traffic congestion stops and fueling stops; and (3) travel time in motion excluding non-significant stops, which excludes the time spent all intermediate stops, including rest stops, traffic congestion stops and fueling stops. These distributions are provided for different time periods of the day such as AM peak, mid-day, PM peak, and night-time. This information can be used to validate the freight component of the new FLSWM recently developed by FDOT (by comparing the measured travel times provided in this appendix with the travel times estimated or output from the model).

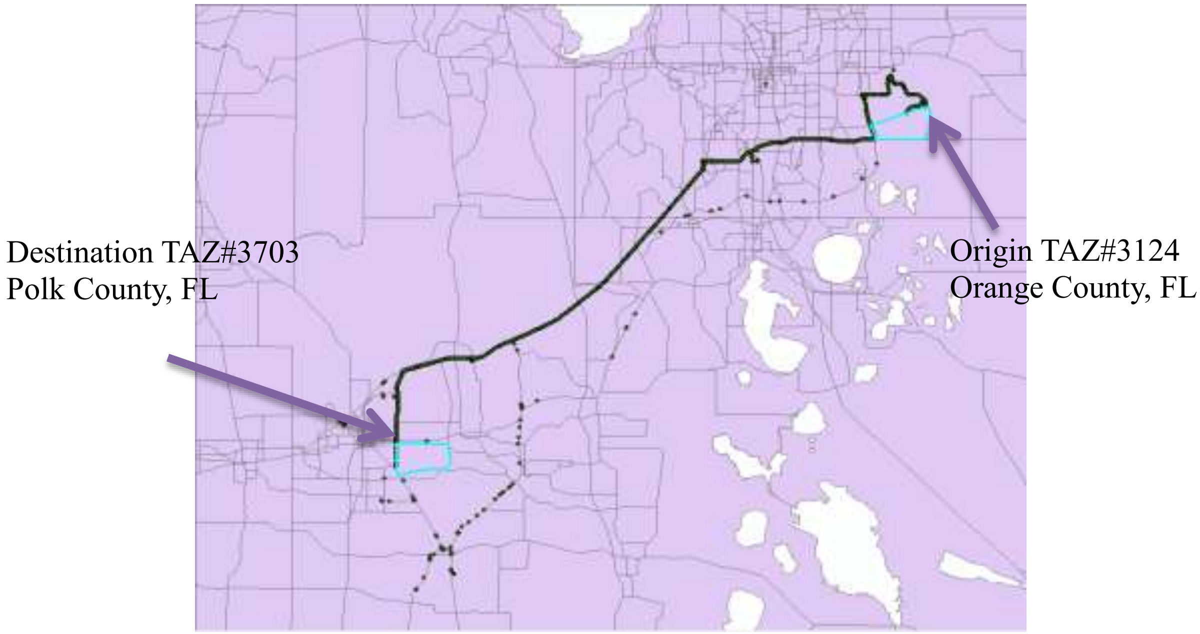


Figure C.1 Route Choice for 365 Trips for OD Pair "3124-3703"

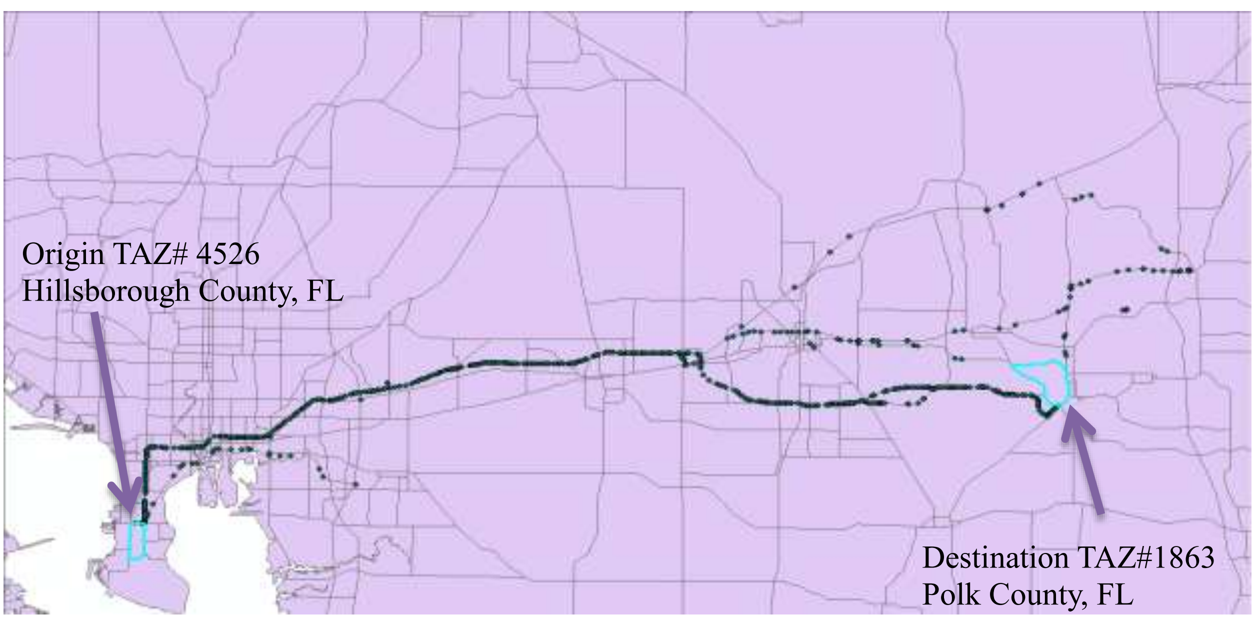


Figure C.2 Route Choice for 134 Trips for OD Pair "4526-1863"

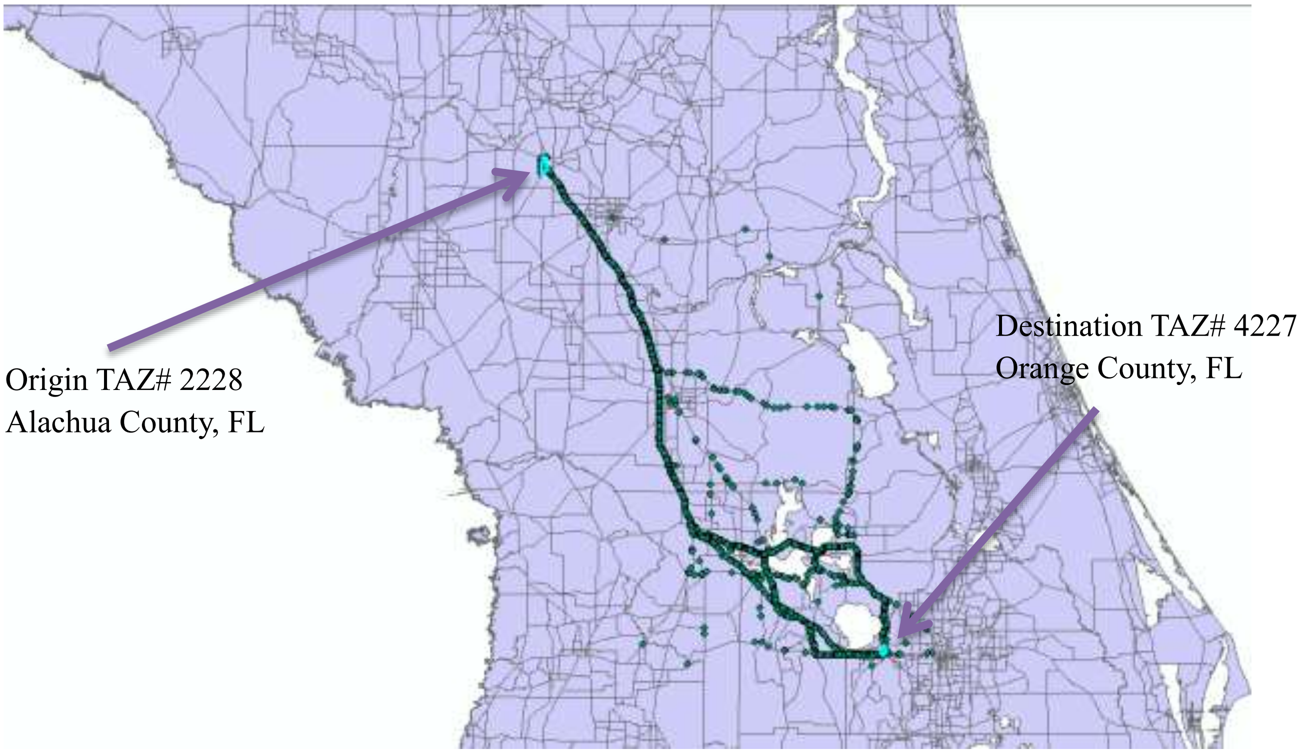


Figure C.3 Route Choice for 327 Trips between OD Pair "2228-4227"

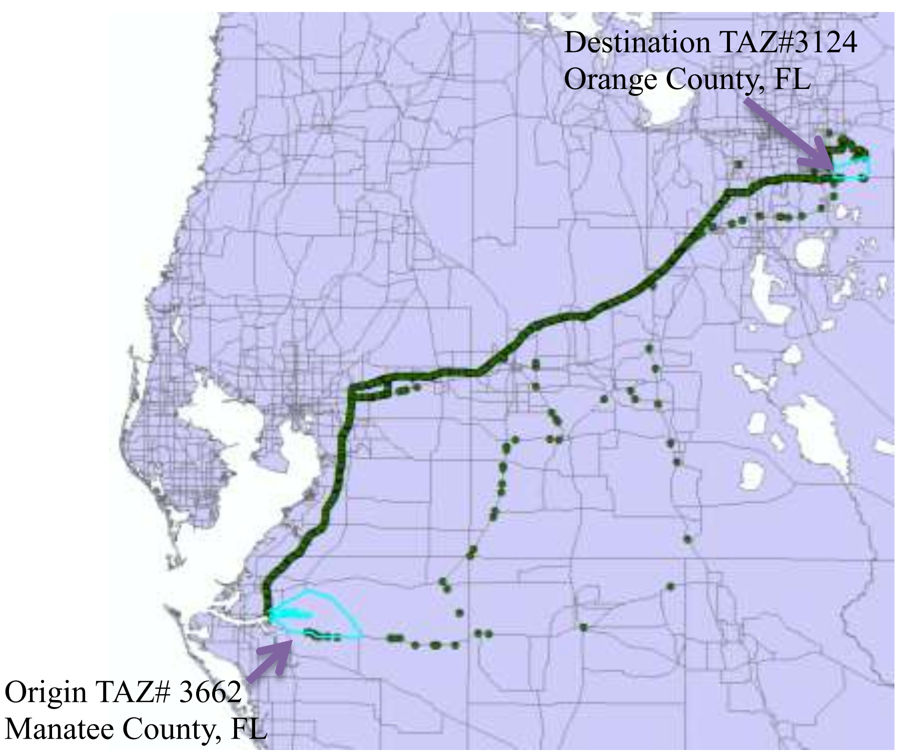


Figure C.4 Route Choice for 151 Trips for OD Pair "3662-3124"

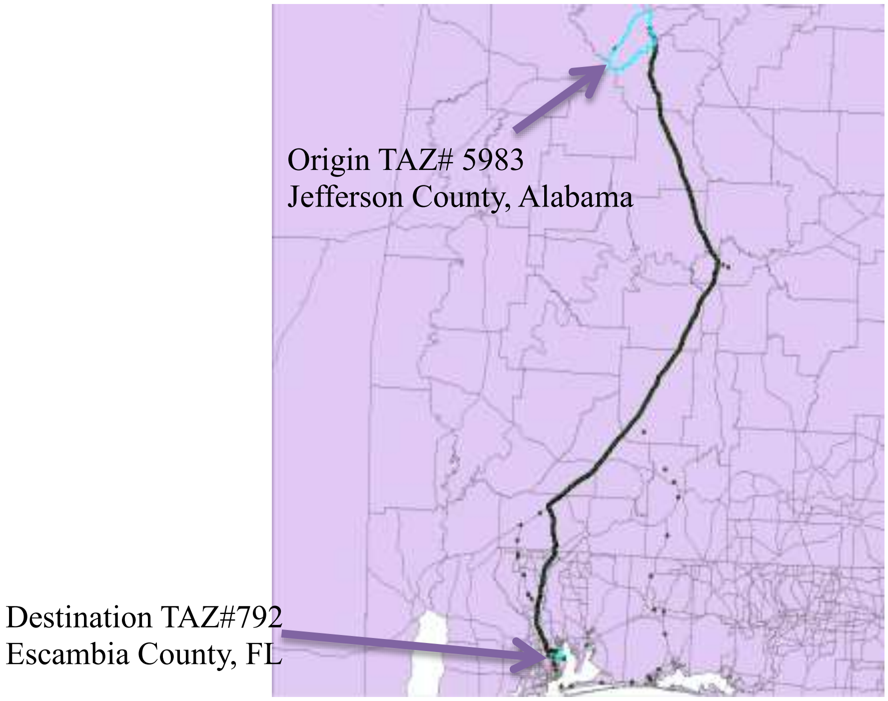


Figure C.5 Route Choice for 386 Trips for OD Pair "5983-792"

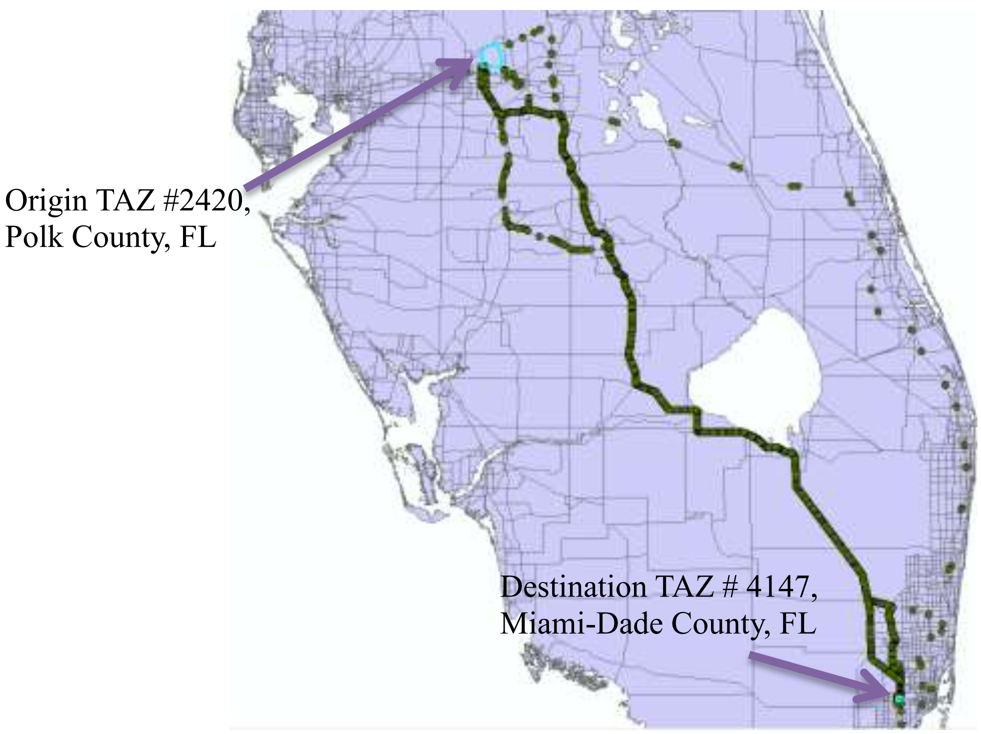


Figure C.6 Route Choice for 217 Trips for OD Pair "2420-4147"

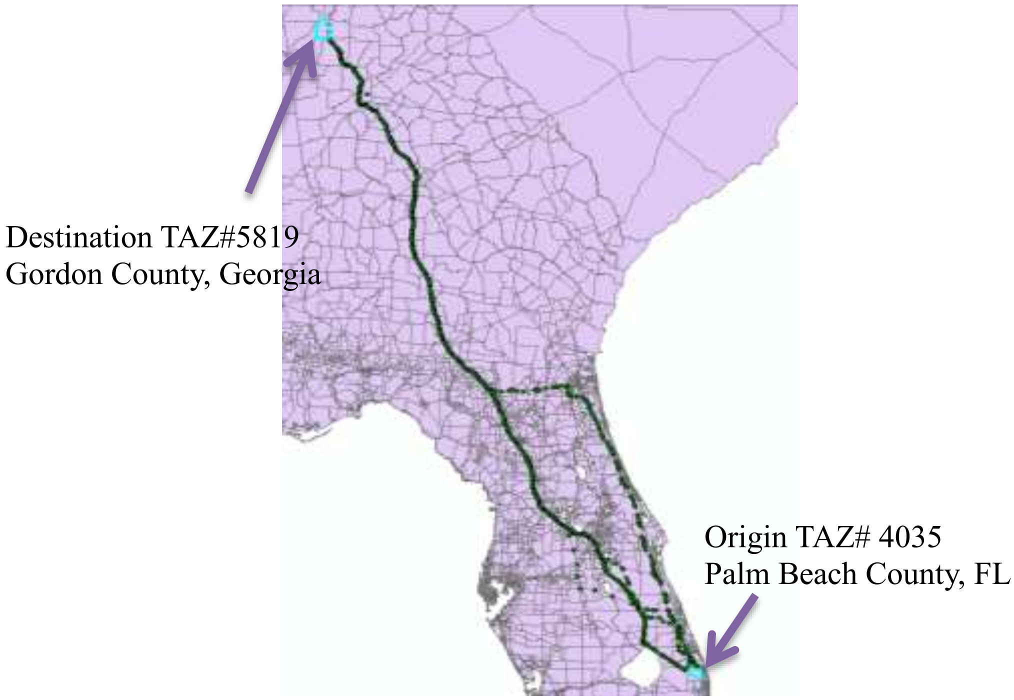


Figure C.7 Route Choice for 28 Trips for OD Pair "4035-5819"

Figure C.8 Route Choice 38 Trips between OD Pair "5073-6117"

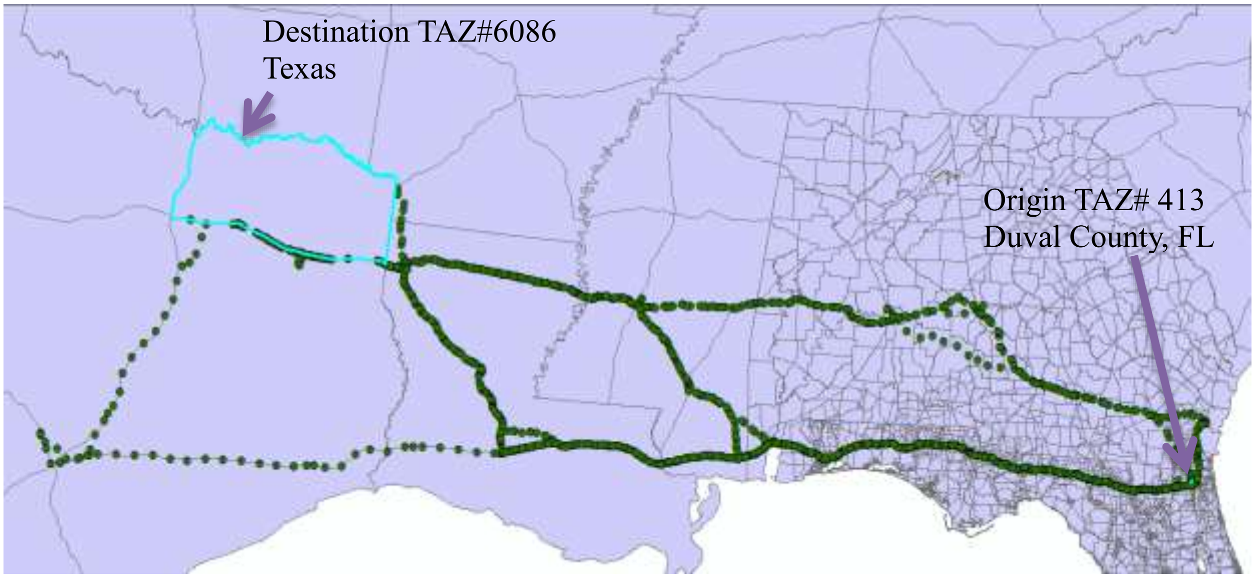


Figure C.9 Route Choice for 23 Trips for OD Pair "413-6086"

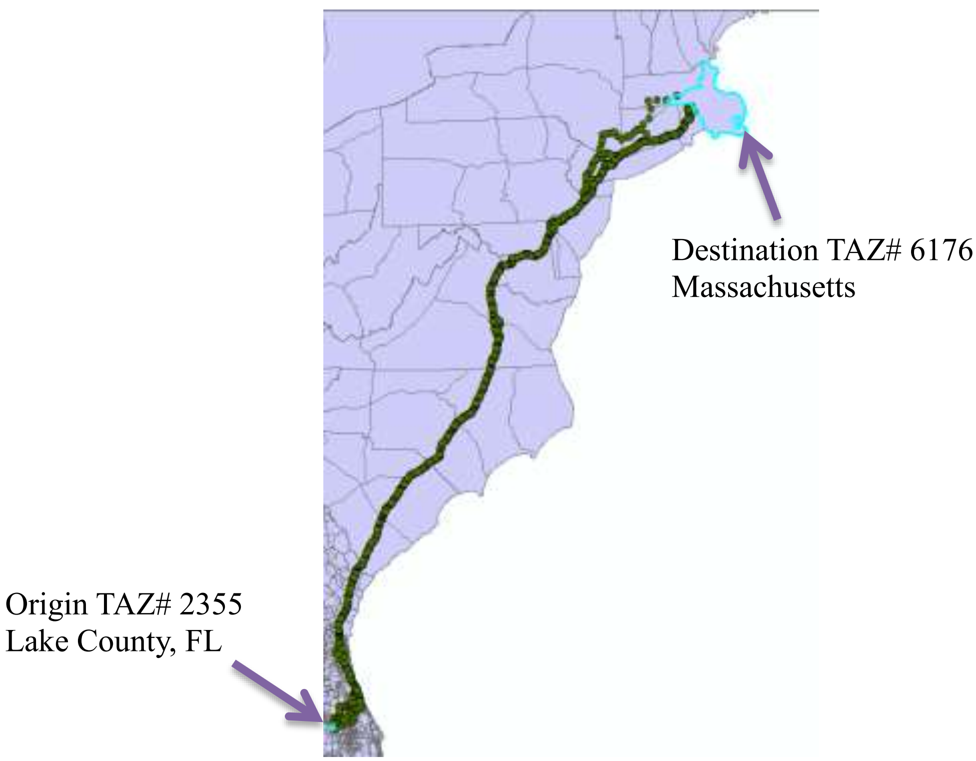


Figure C.10 Route Choice for 28 Trips between OD Pair "2355-6176"

Origin TAZ: 3124, Destination TAZ: 3703

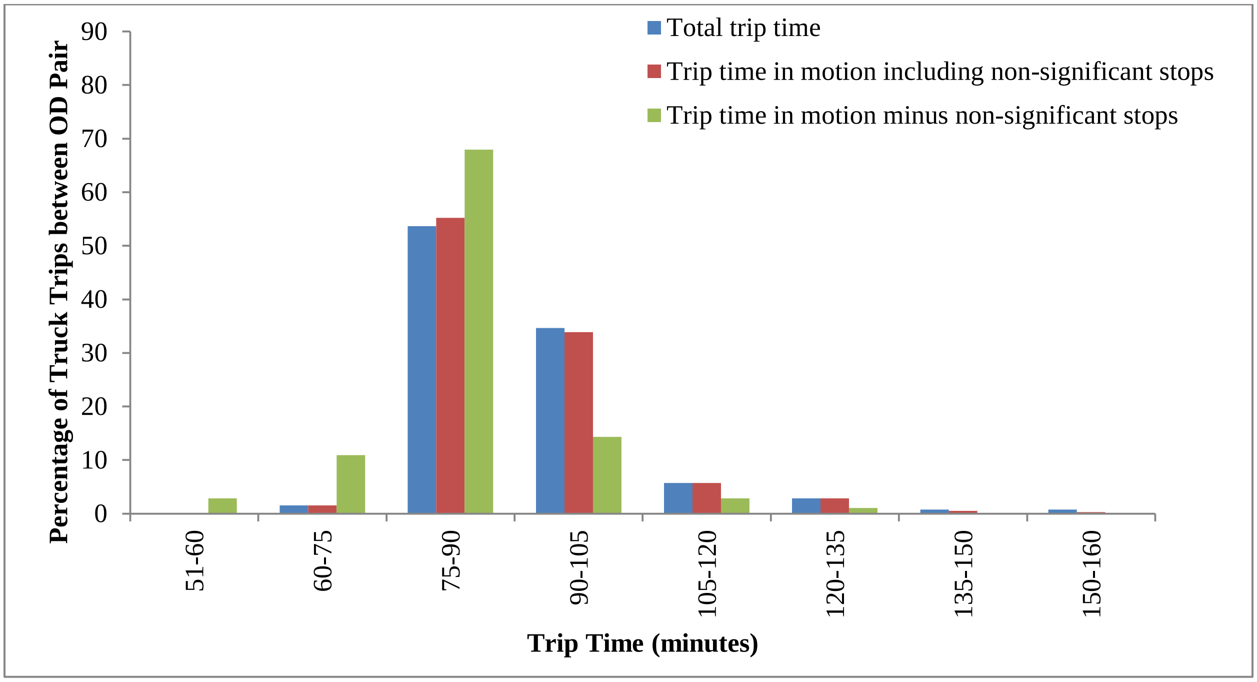


Figure C.11 Travel Time Distribution for Trips between OD Pair "3124-3703" (384 Trips)

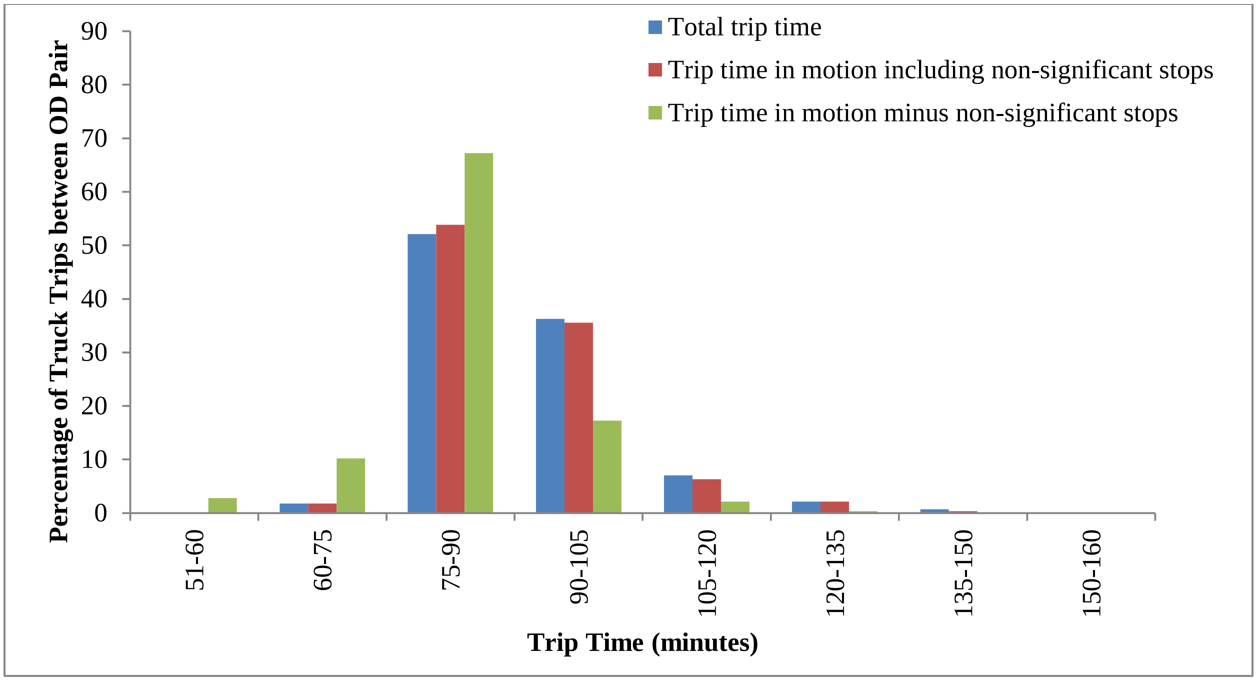


Figure C.12 Trips between OD Pair "3124-3703" during Weekdays (284 Trips)

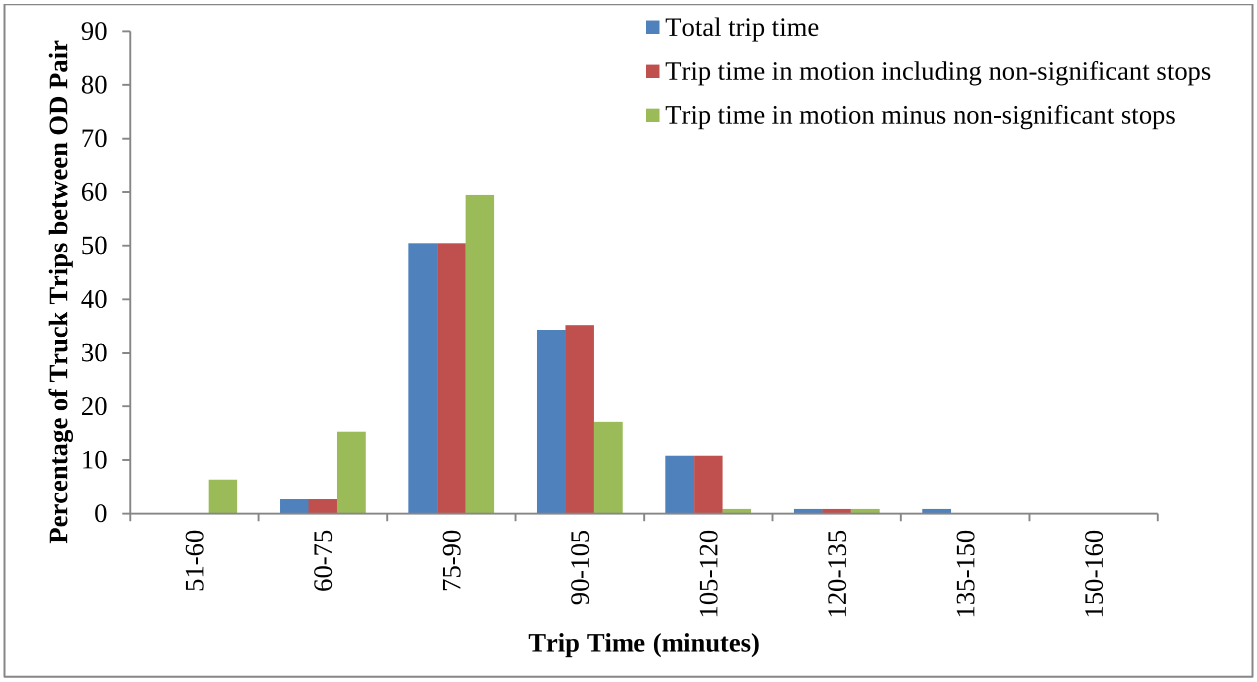


Figure C.13 Mid-day Trips between OD Pair "3124-3703" during Weekdays (111 Trips)

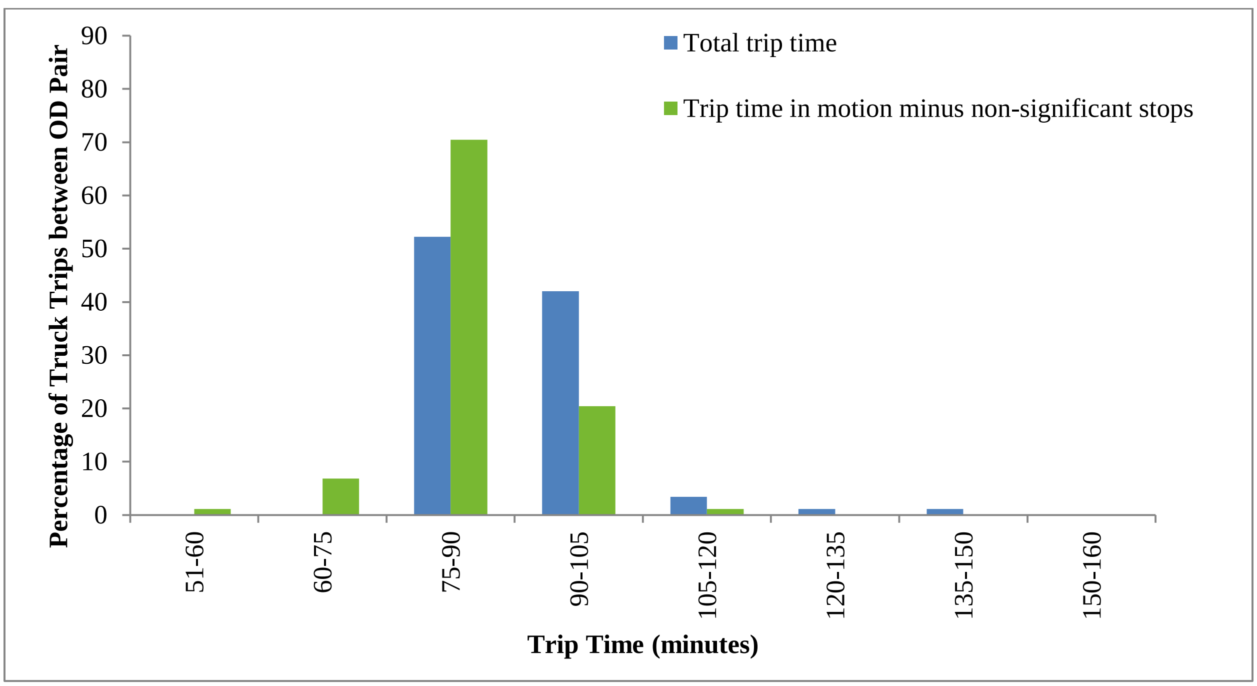


Figure C.14 PM Peak Trips between OD Pair "3124-3703" during Weekdays (88 Trips)

Note: In this case, total trip time and trip time in motion including non-significant stops are equal since the trucks did not make any significant stops in rest areas/gas stations.

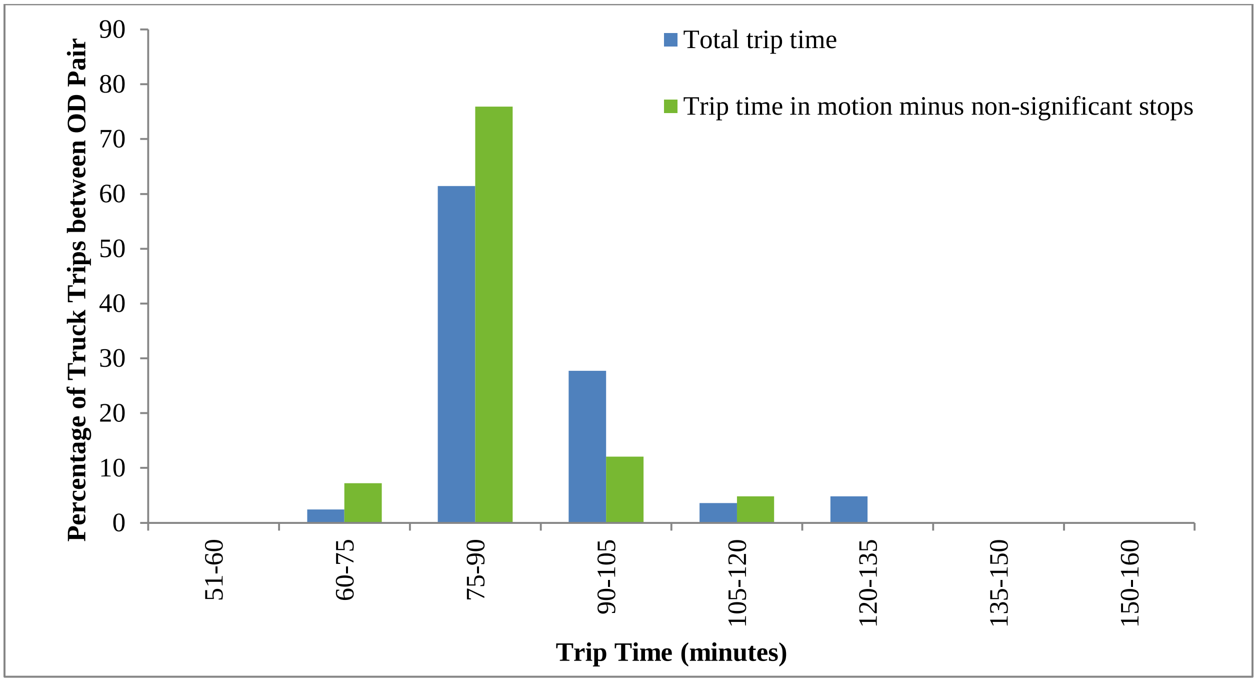


Figure C.15 Night-time Trips between OD Pair "3124-3703" during Weekdays (83 Trips)

Note: In this case, the total trip time and trip time in motion including non-significant stops are equal since the trucks did not make any significant stops in rest areas/gas stations. Therefore, a separate histogram is not provided for trip time in motion including non-significant stops.

Origin TAZ: 4526, Destination TAZ: 1863

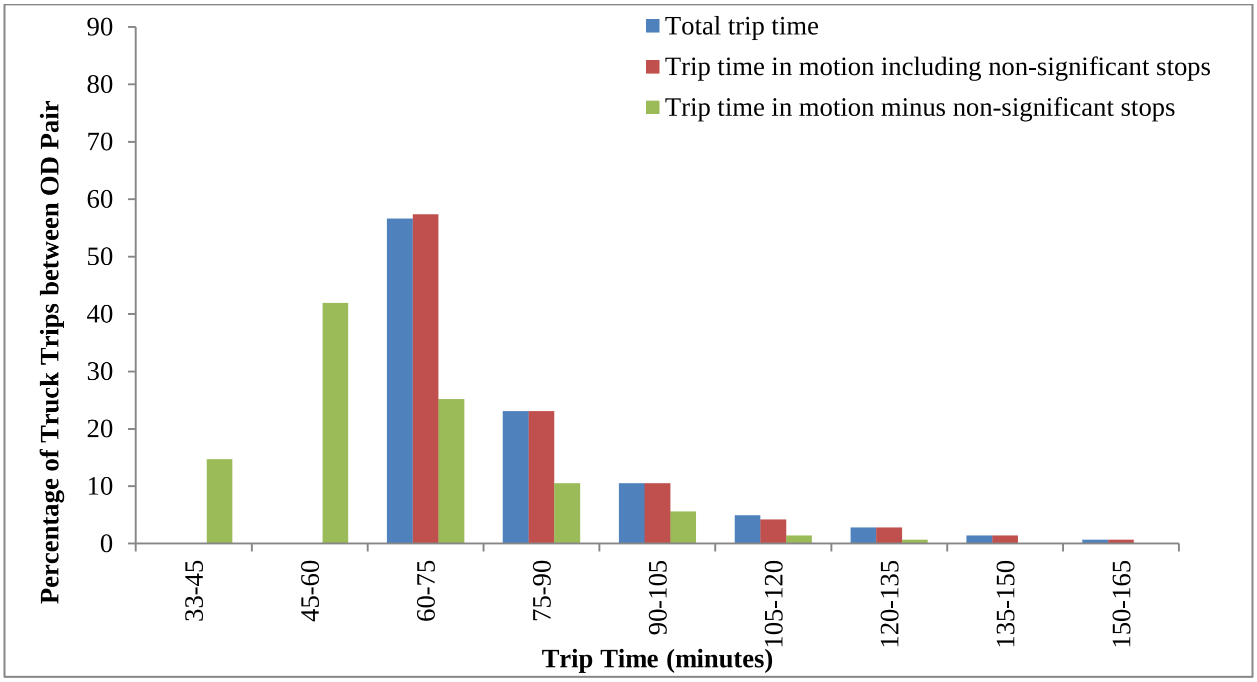


Figure C.16 Travel Time Distribution for Trips between OD Pair "4526-1863" (143 Trips)

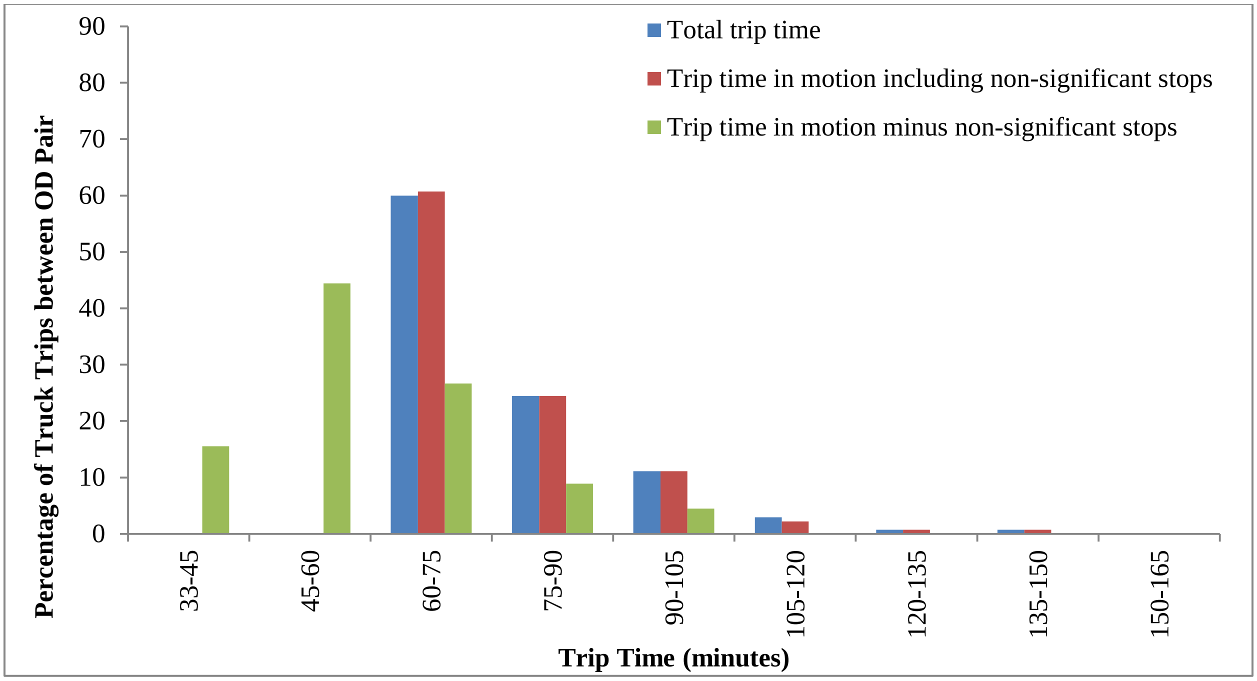


Figure C.17 Trips between OD Pair "4526-1863" during Weekdays (135 Trips)

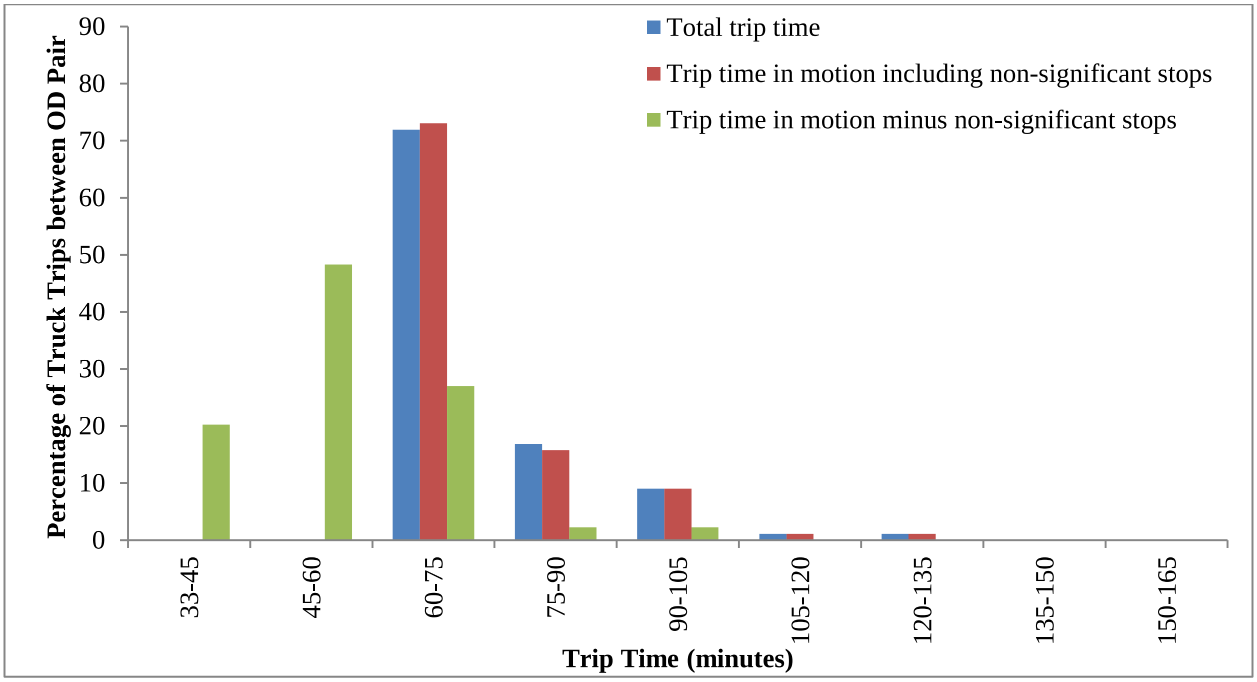


Figure C.18 Night-time Trips between OD Pair "4526-1863" during Weekdays (89 Trips)

Origin TAZ: 2228, Destination TAZ: 4227

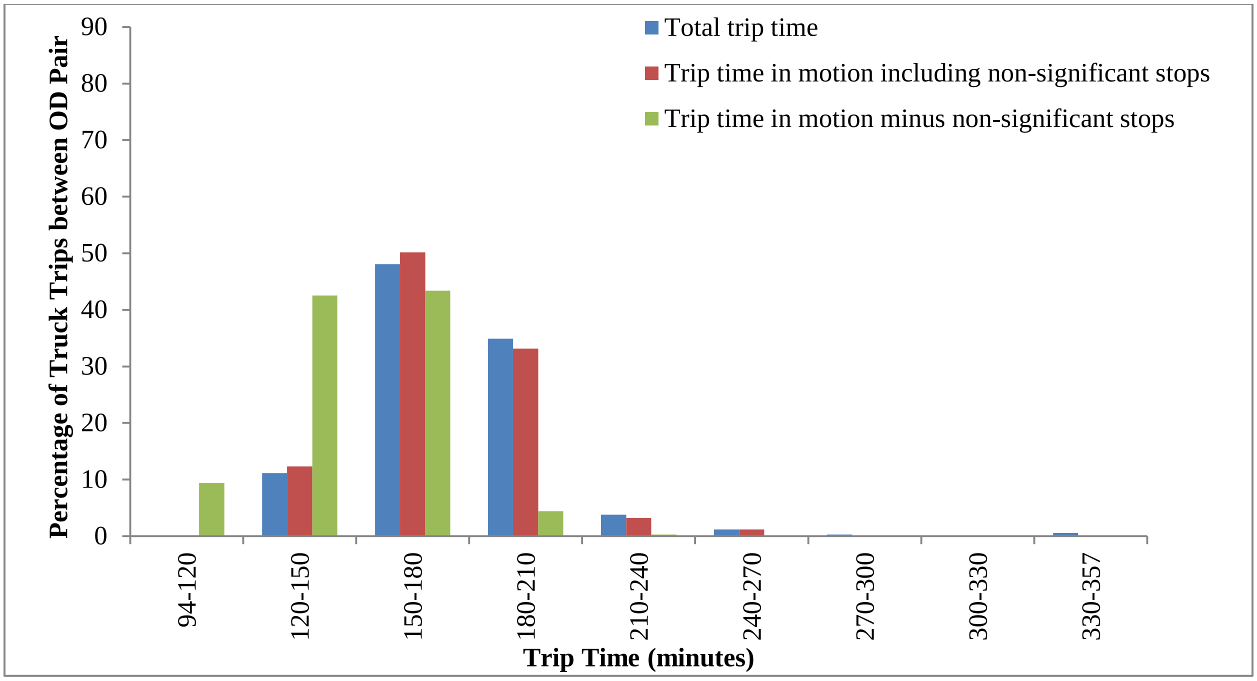


Figure C.19 Travel Time Distribution for Trips between OD Pair "2228-4227" during Weekdays (341 Trips)

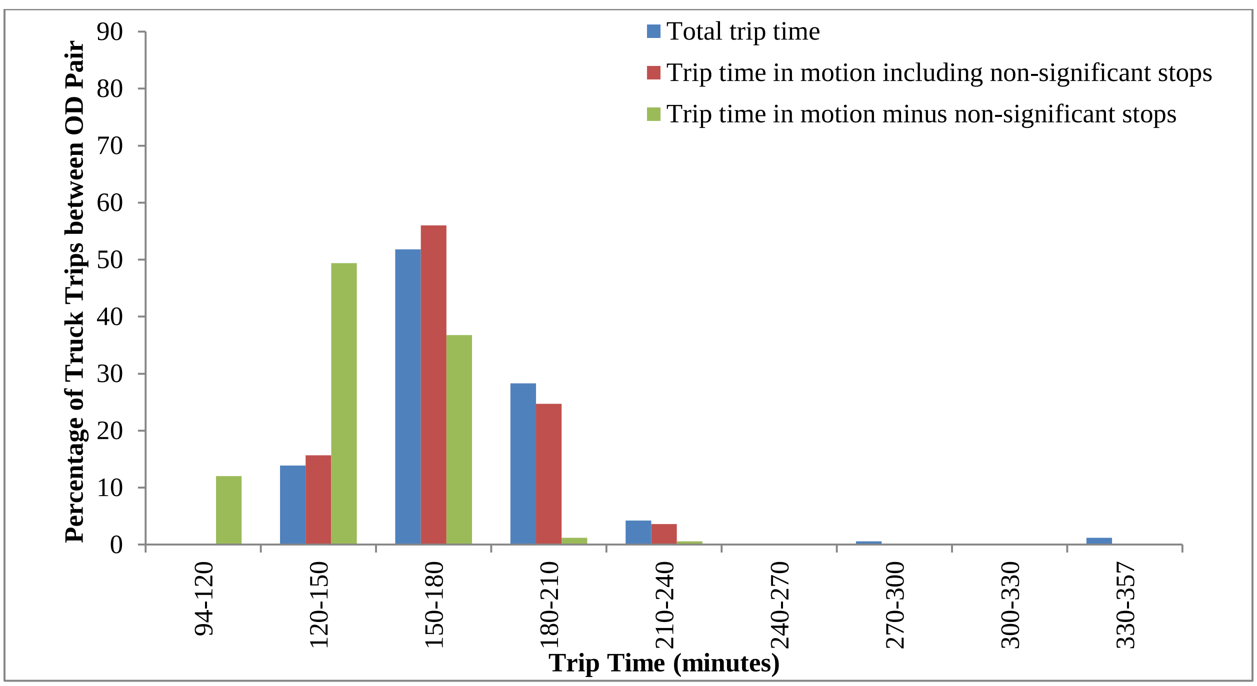


Figure C.20 Night-time Trips between OD Pair "2228-4227" during Weekdays (166 Trips)

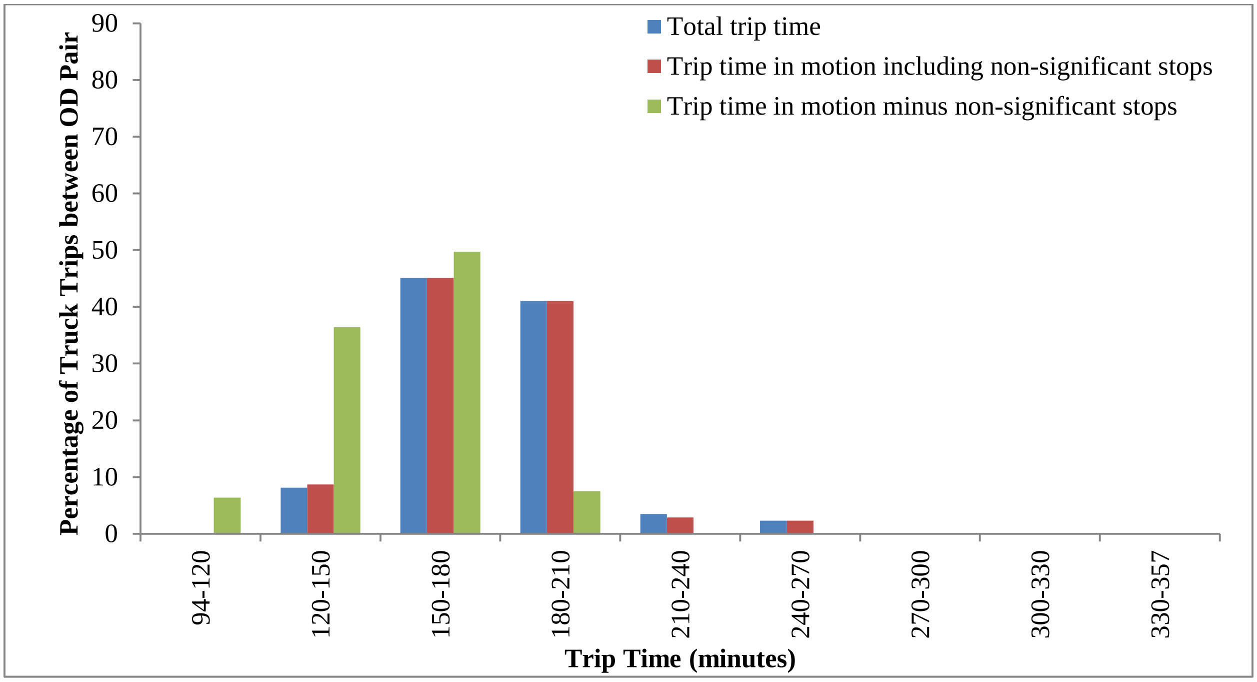


Figure C.21 AM Peak Trips between OD Pair "2228-4227" during Weekdays (173 Trips)

Origin TAZ: 3662, Destination TAZ: 3124

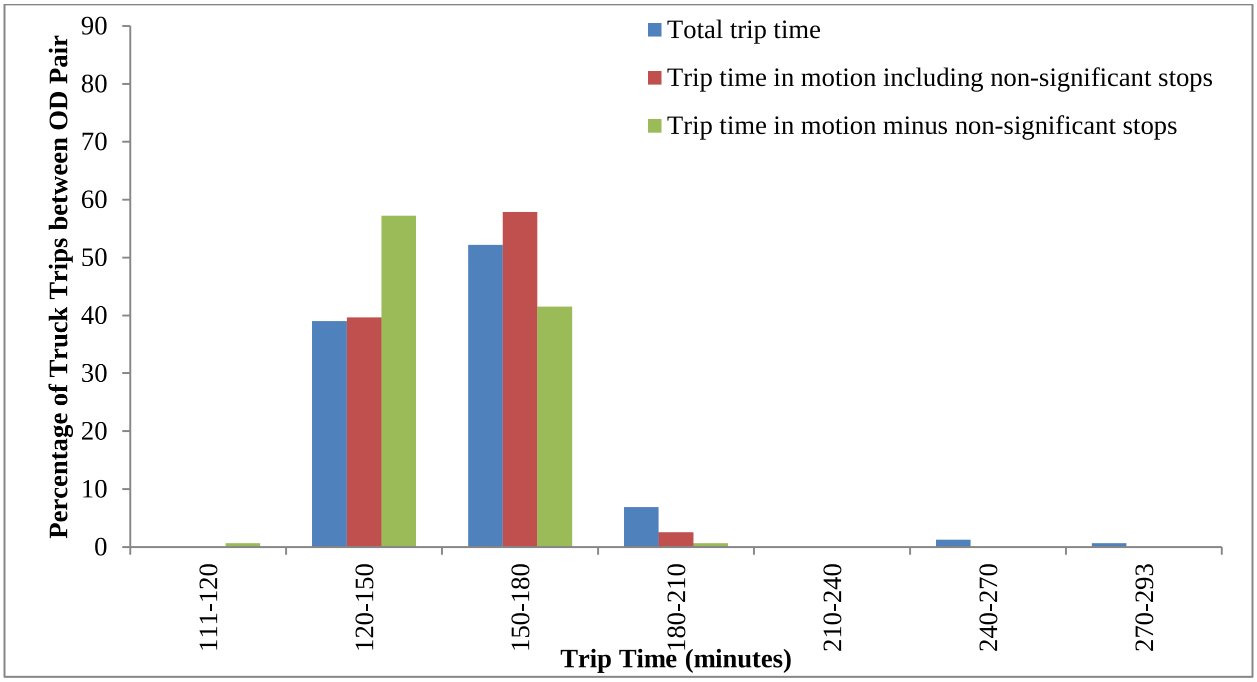


Figure C.22 Travel Time Distribution for Trips between OD Pair "3662-3124" (159 Trips)

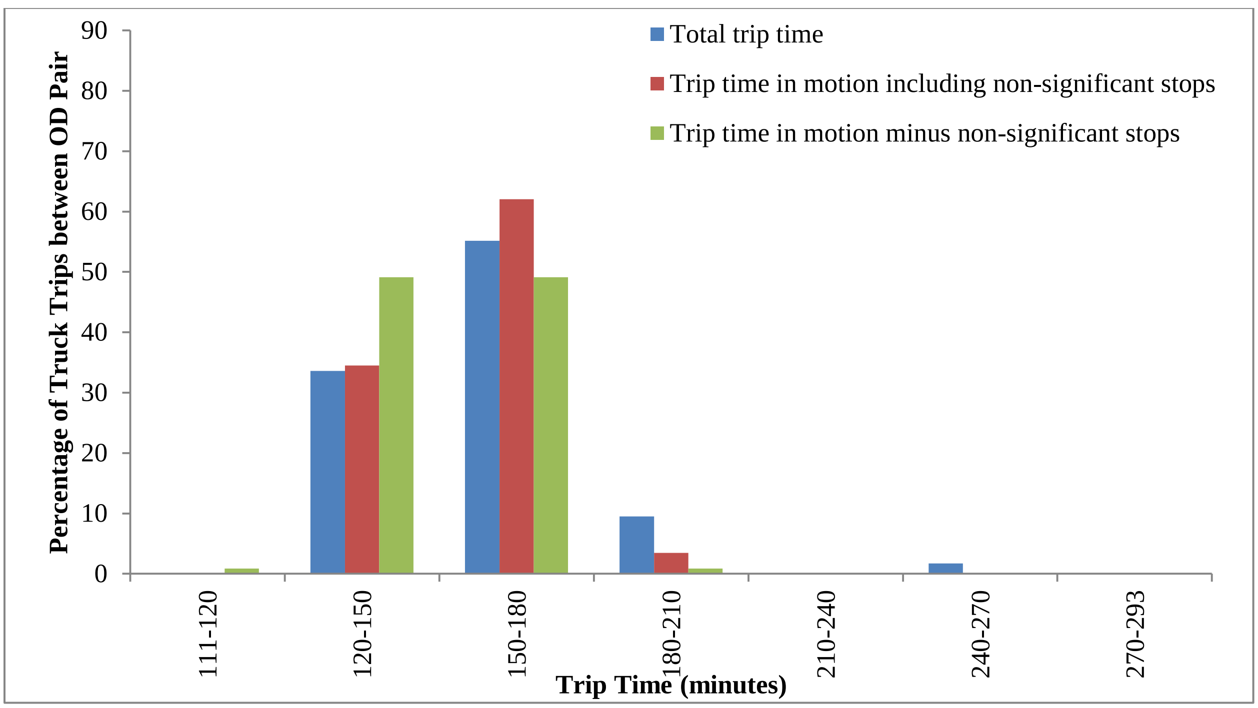


Figure C.23 Trips between OD Pair "3662-3124" during Weekdays (116 Trips)

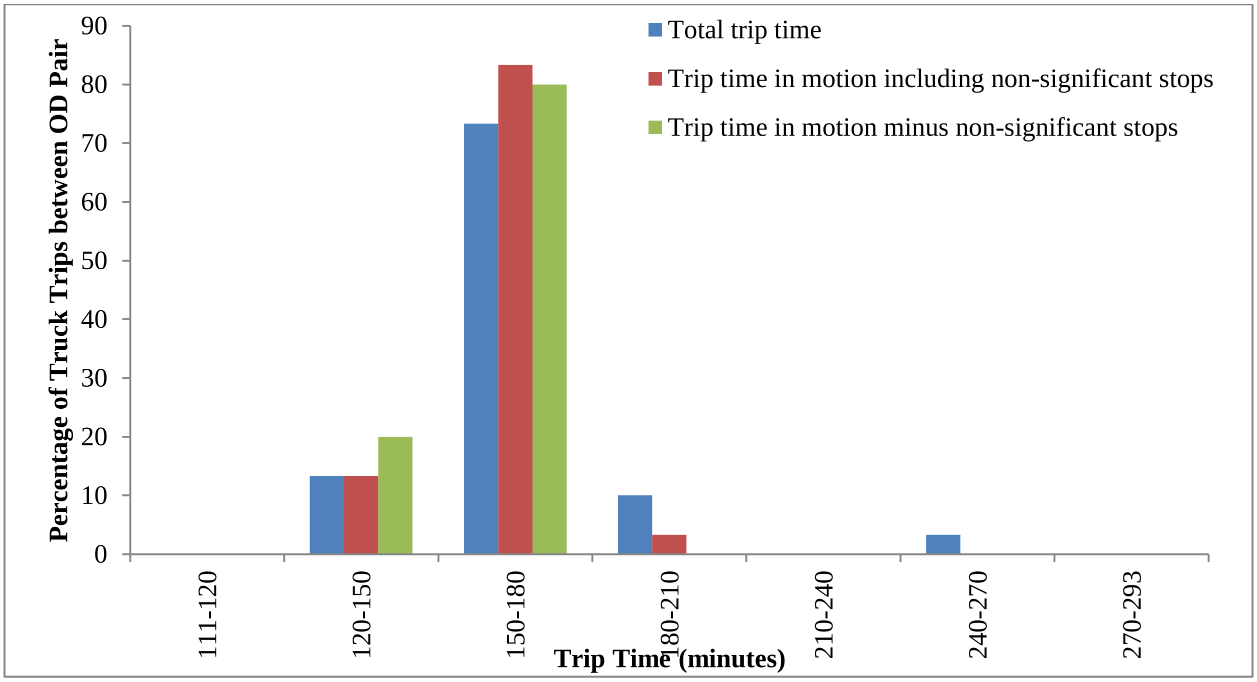


Figure C.24 AM Peak Trips between OD Pair "3662-3124" during Weekdays (30 Trips)

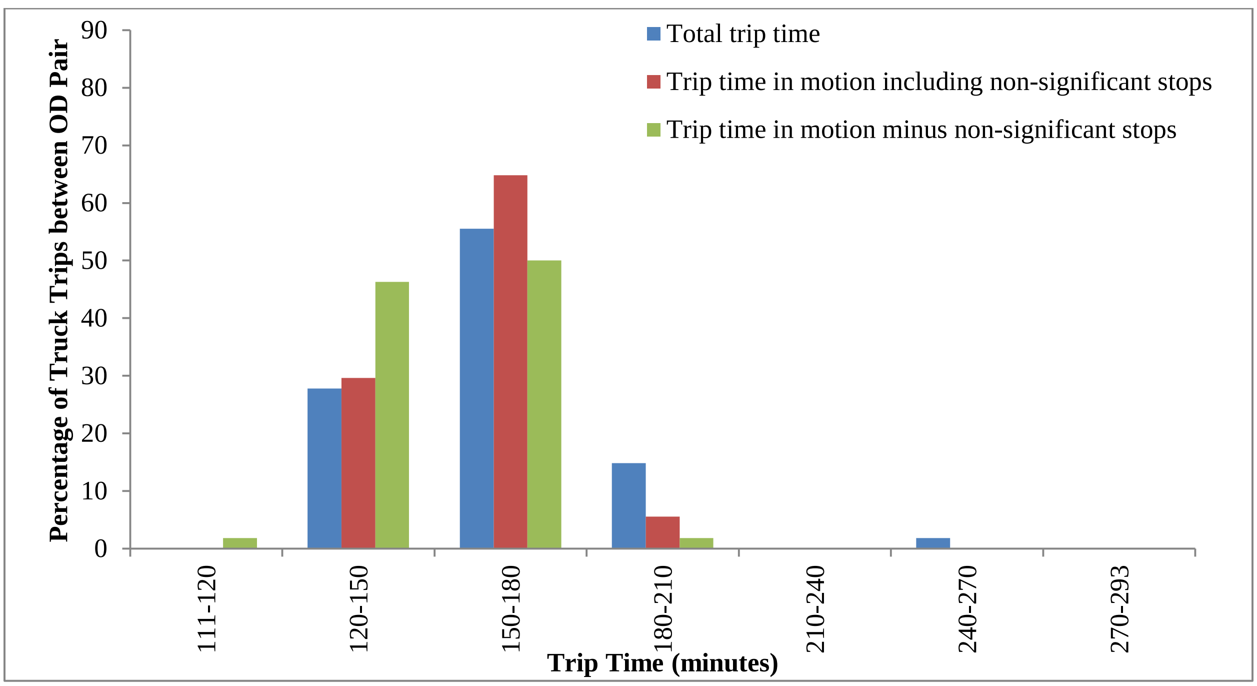


Figure C.25 Mid-day Trips between OD Pair "3662-3124" during Weekdays (54 Trips)

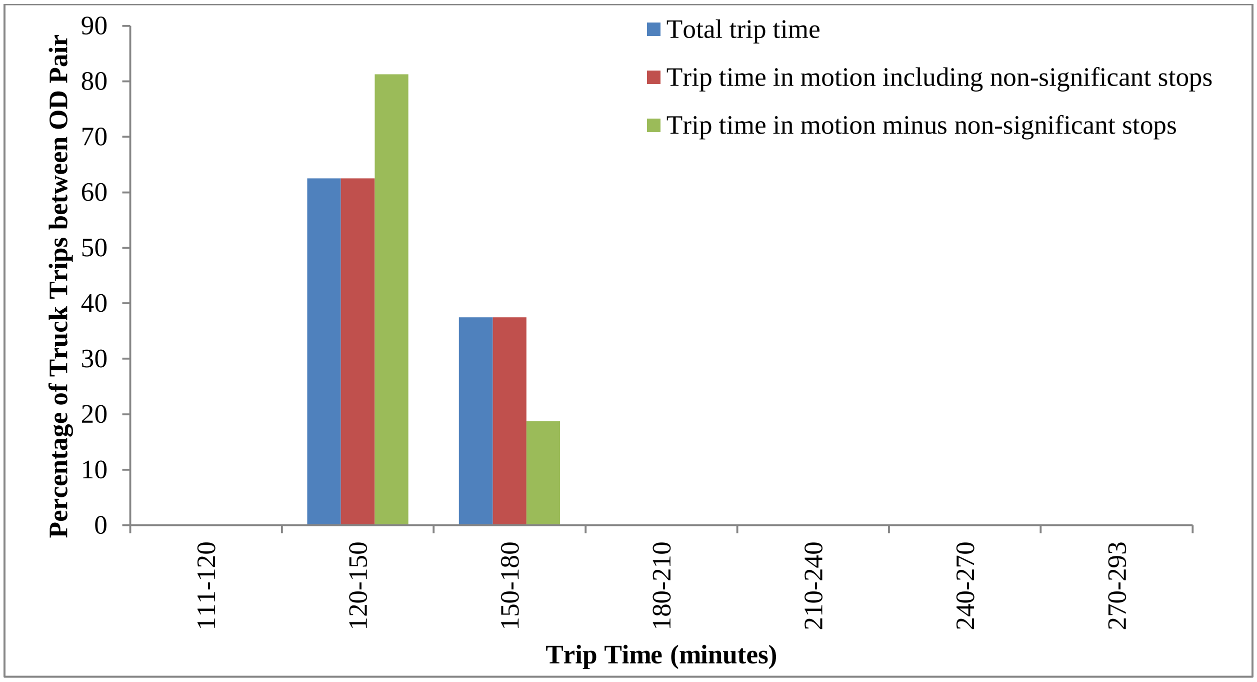


Figure C.26 Night-time Trips between OD Pair "3662-3124" during Weekdays (32 Trips)

Origin TAZ: 5983, Destination TAZ: 792

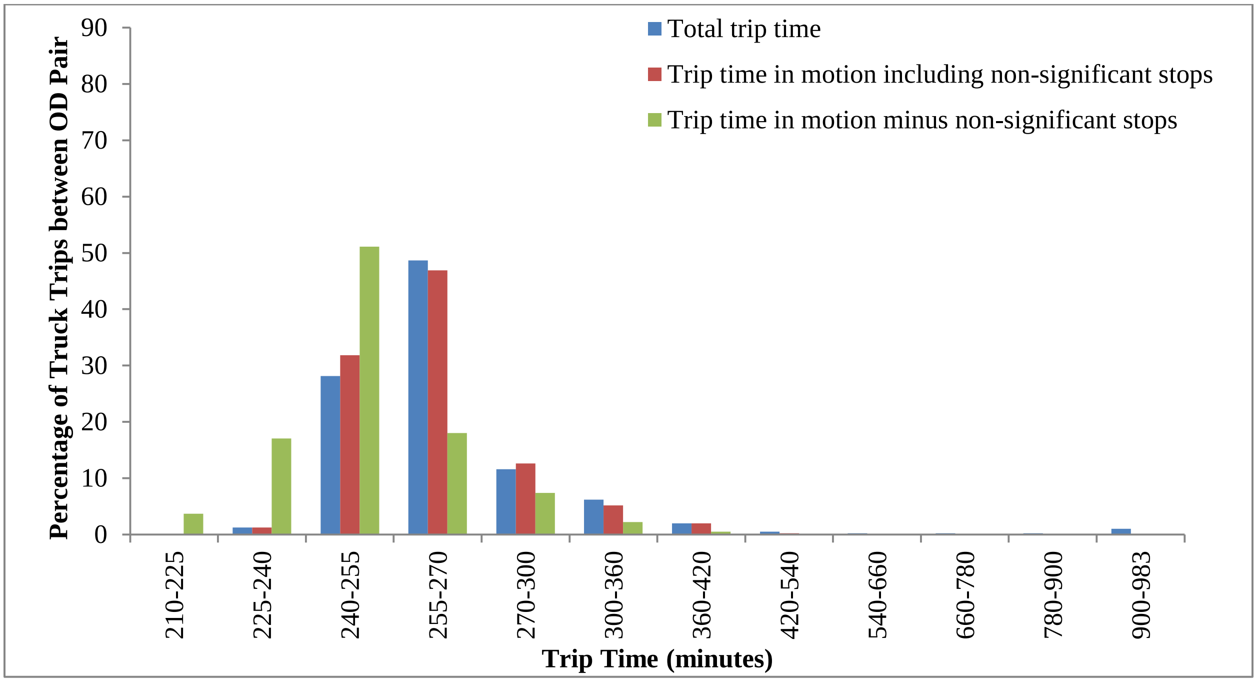


Figure C.27 Travel Time Distribution for Trips between OD Pair "5983-792" (405 Trips)

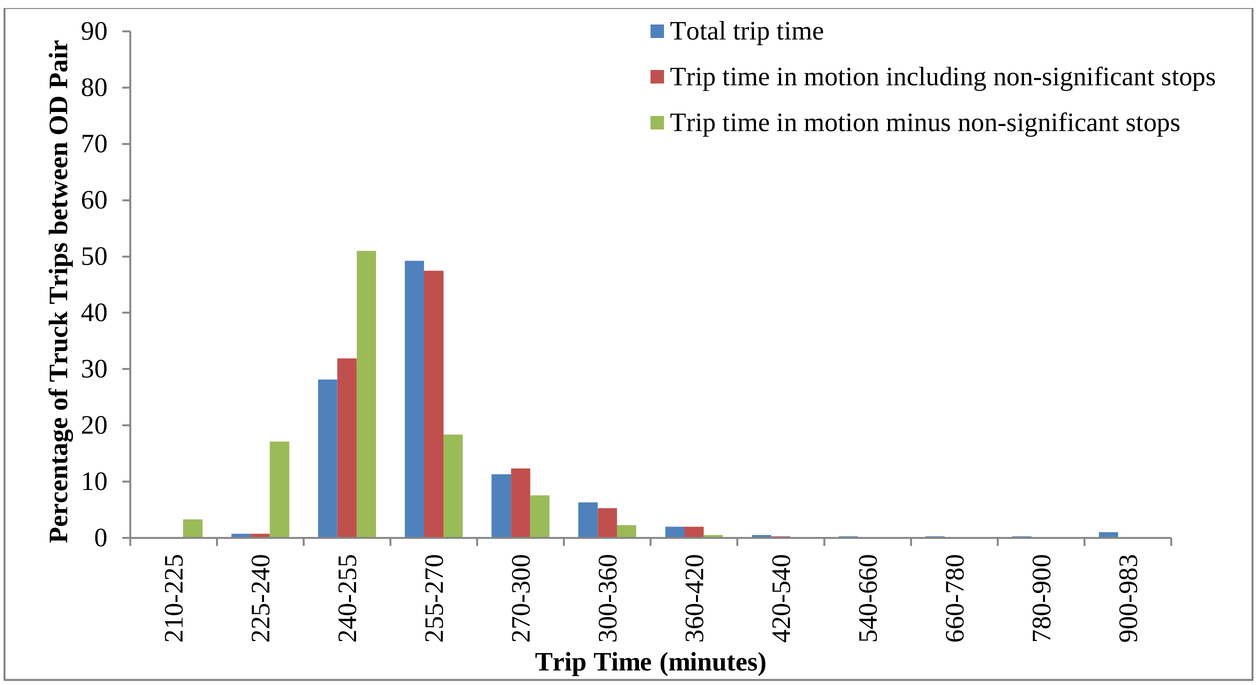


Figure C.28 Trips between OD Pair "5983-792" during Weekdays (398 Trips)

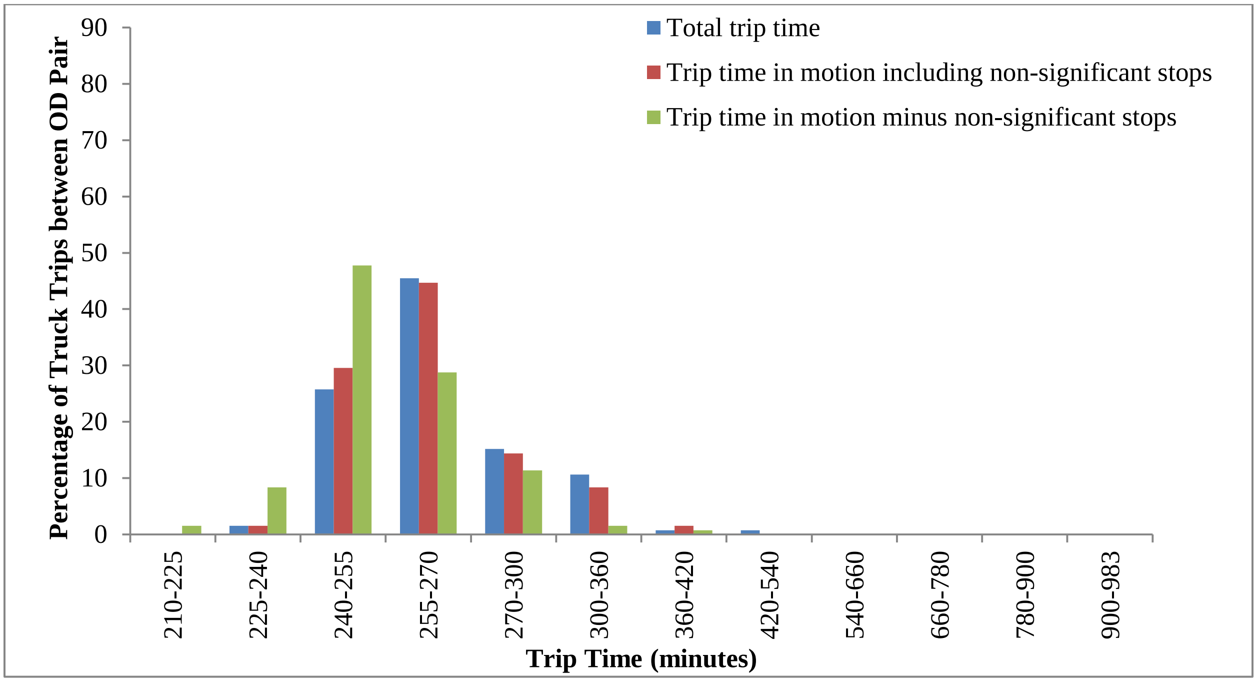


Figure C.29 AM Peak Trips between OD Pair "5983-792" during Weekdays (132 Trips)

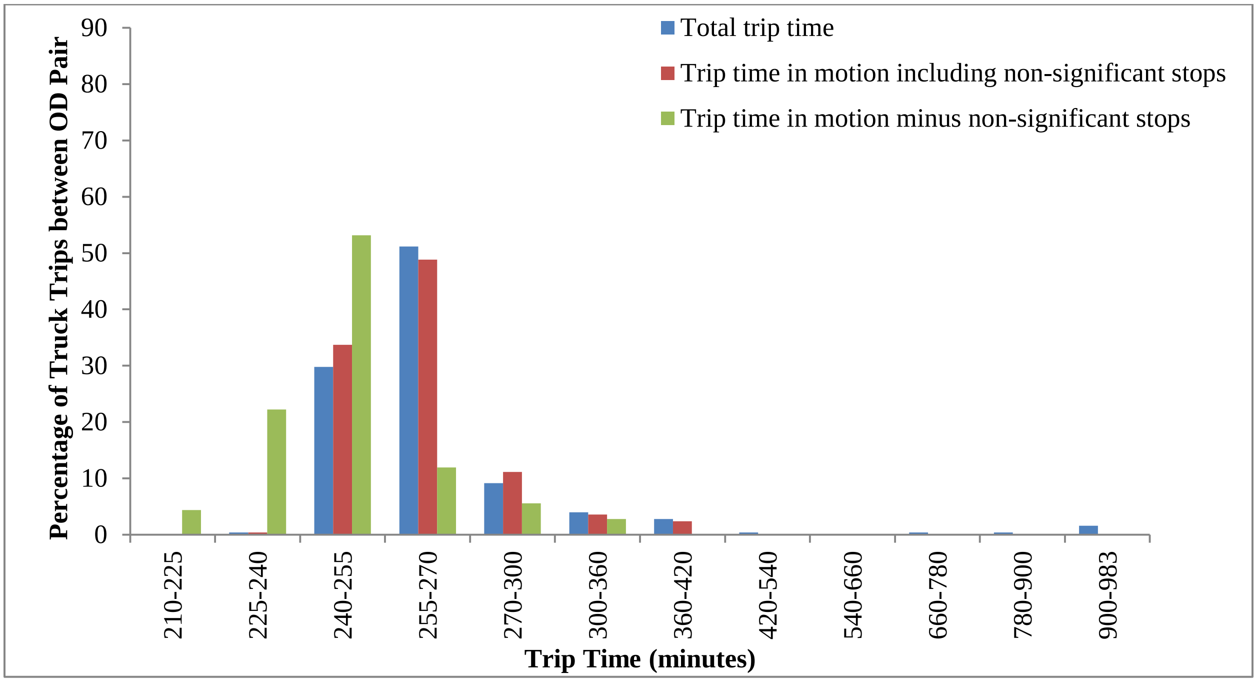


Figure C.30 Night-time Trips between OD Pair "5983-792" during Weekdays (252 Trips)

Origin TAZ: 2420, Destination TAZ: 4147 [12]

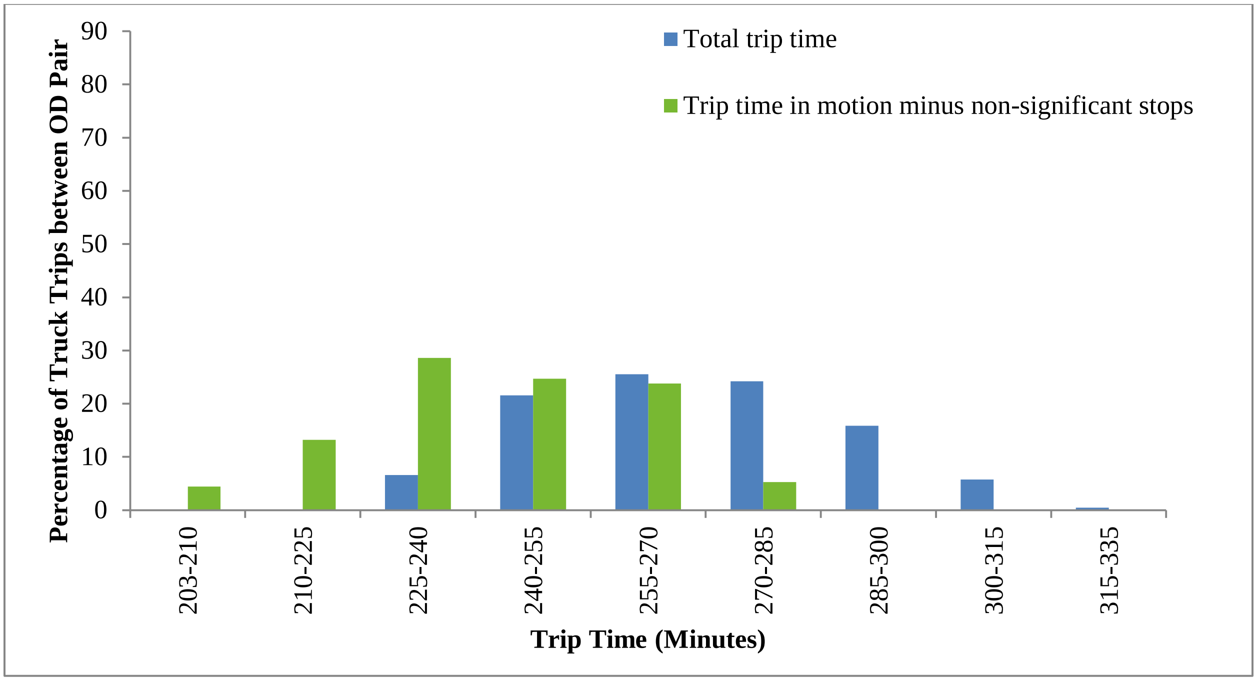


Figure C.31 Travel Time Distribution for Trips between OD Pair "2420-4147" (227 Trips)

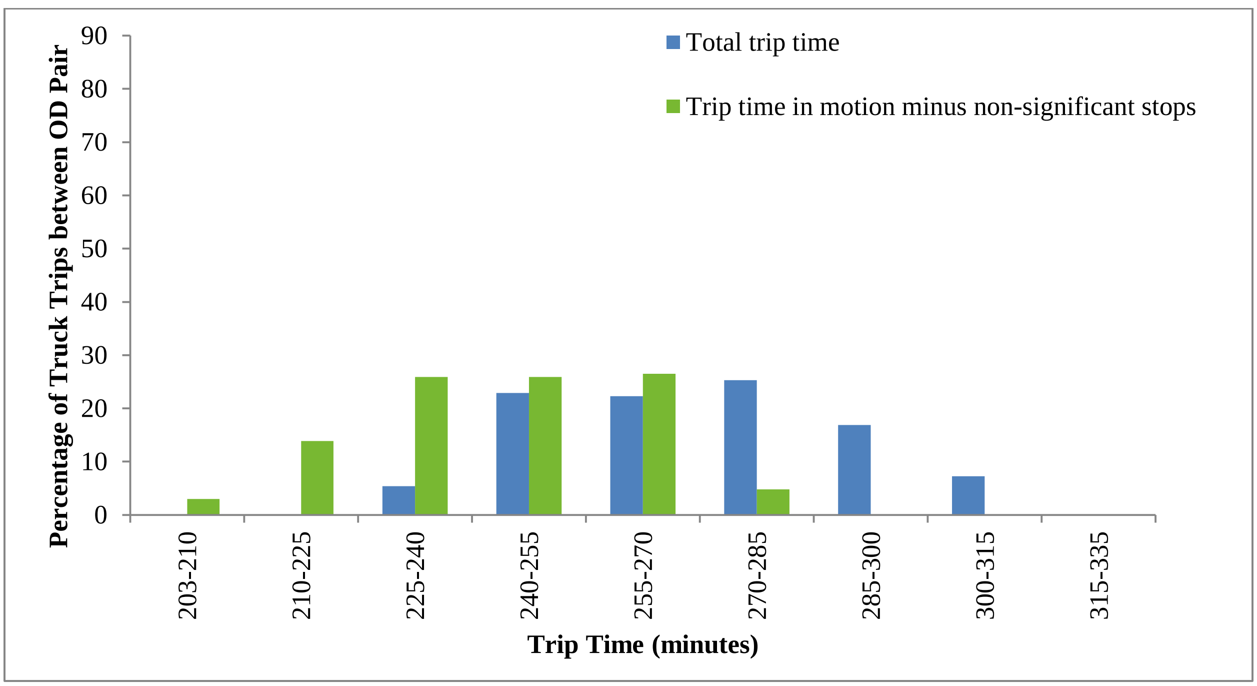


Figure C.32 Trips between OD Pair "2420-4147" during Weekdays (166 Trips)

[12] In this case, total trip time and trip time in motion including non-significant stops are equal since the trucks did not make any significant stops in rest areas/gas stations.

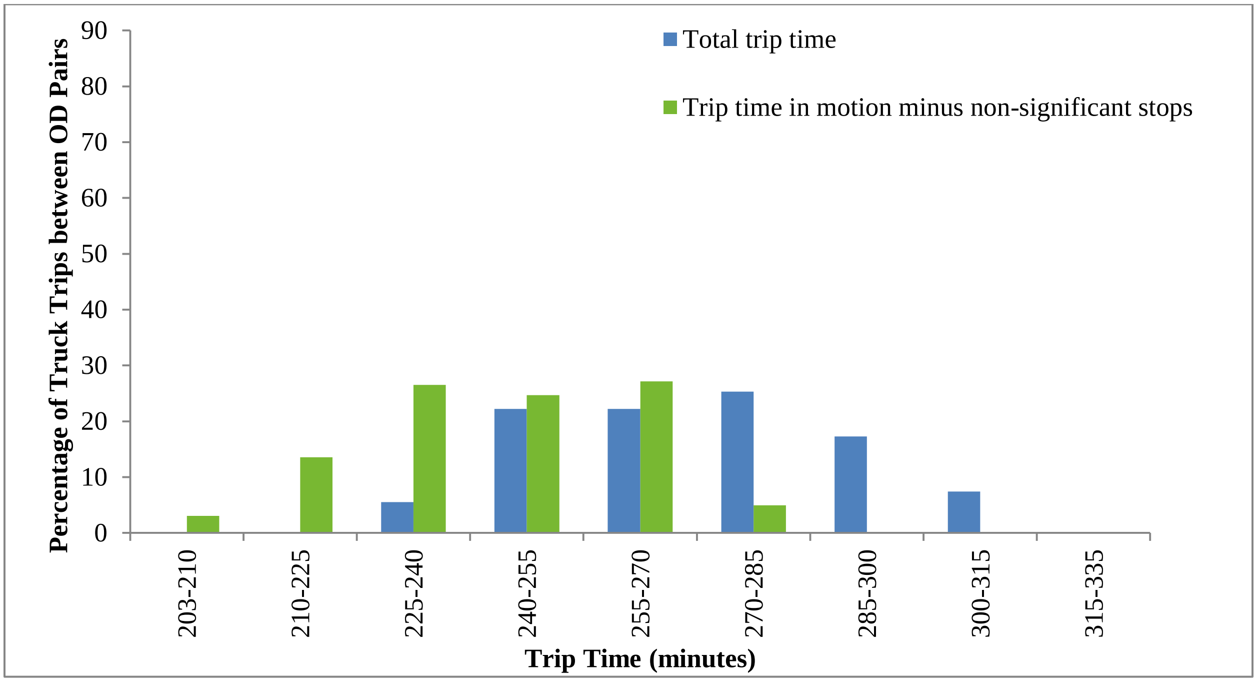


Figure C.33 Night-time Trips between OD Pair "2420-4147" during Weekdays (162 Trips)

Origin TAZ: 4035, Destination TAZ: 5819

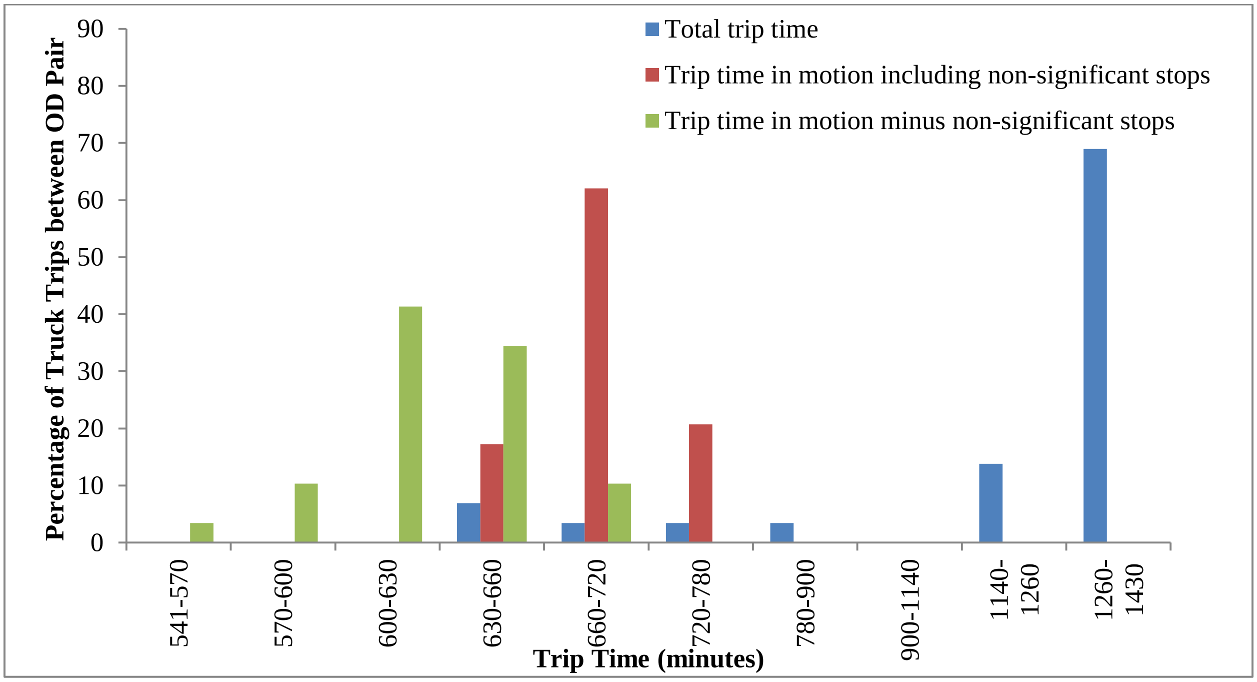


Figure C.34 Travel Time Distribution for Trips between OD Pair "4035-5819" during Weekdays (29 Trips)

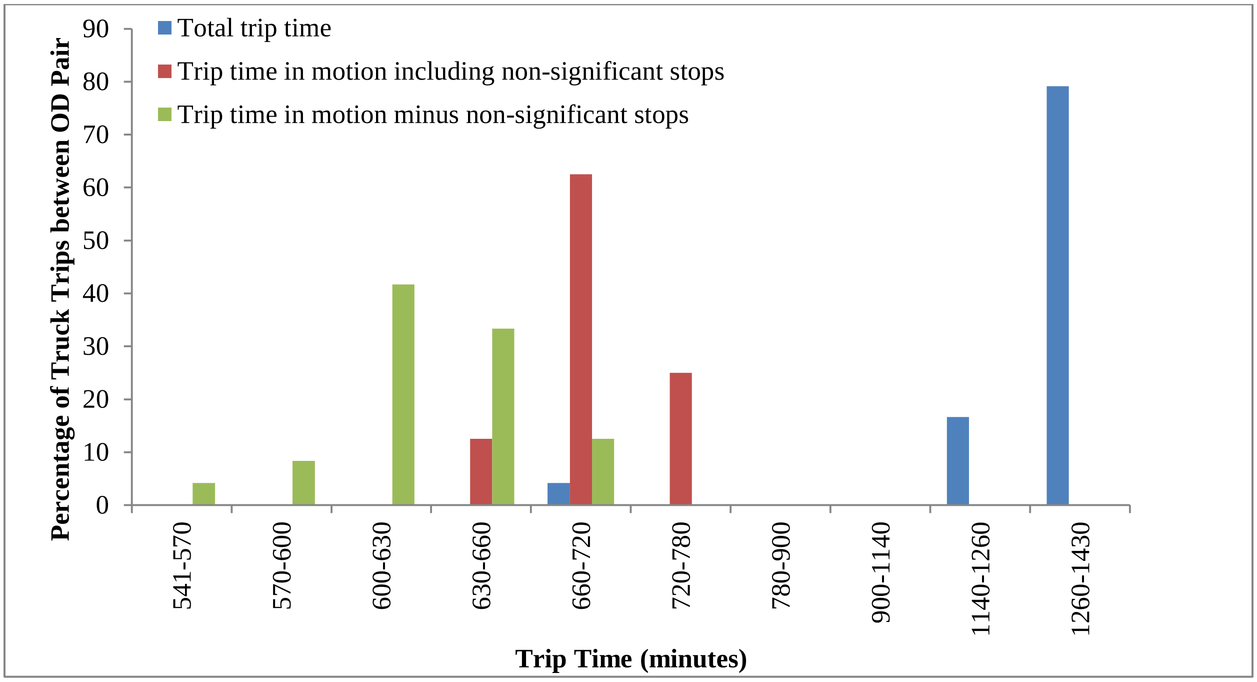


Figure C.35 Night-time Trips between OD Pair "4035-5819" during Weekdays (24 Trips)

Origin TAZ: 5073, Destination TAZ: 6117

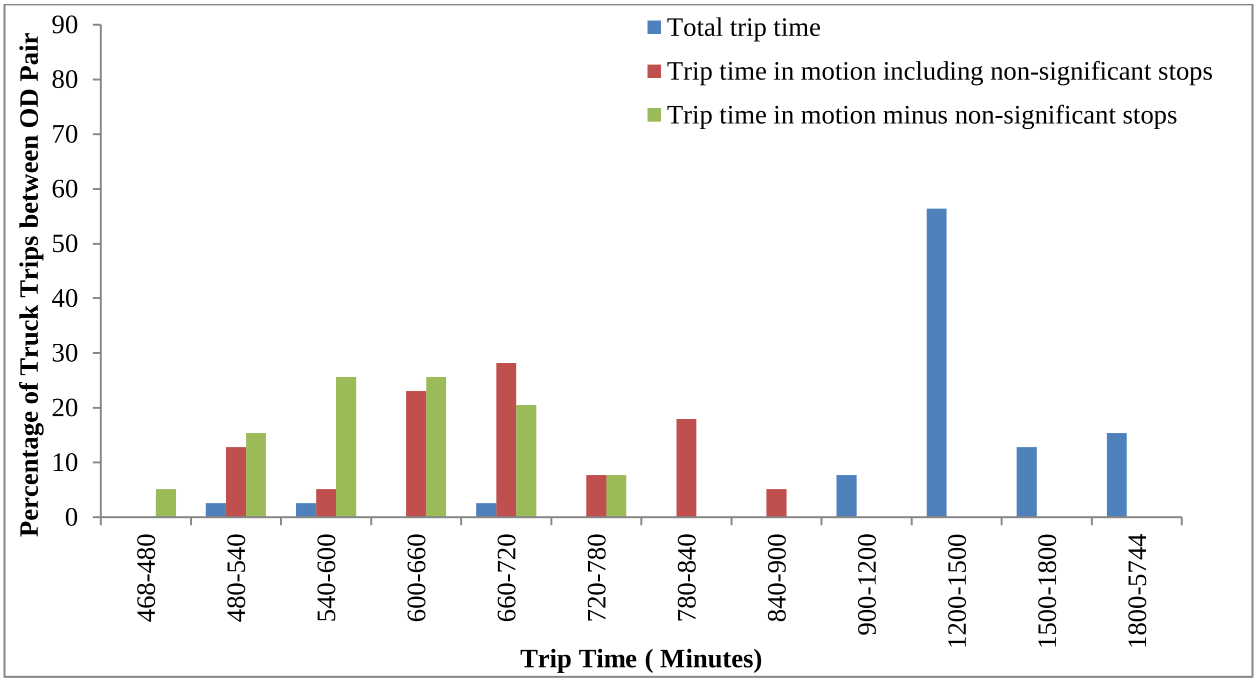


Figure C.36 Travel Time Distribution for Trips between OD Pair "5073-6117" (39 Trips)

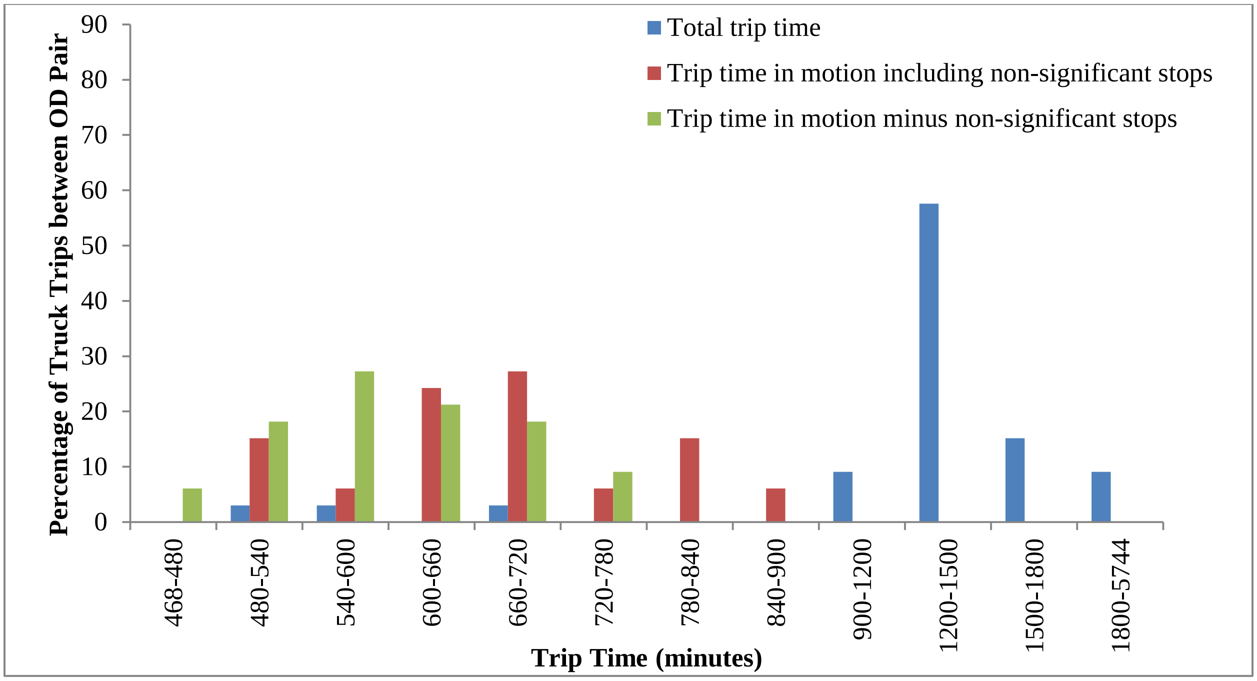


Figure C.37 Trips between OD Pair "5073-6117" during Weekdays (33 Trips)

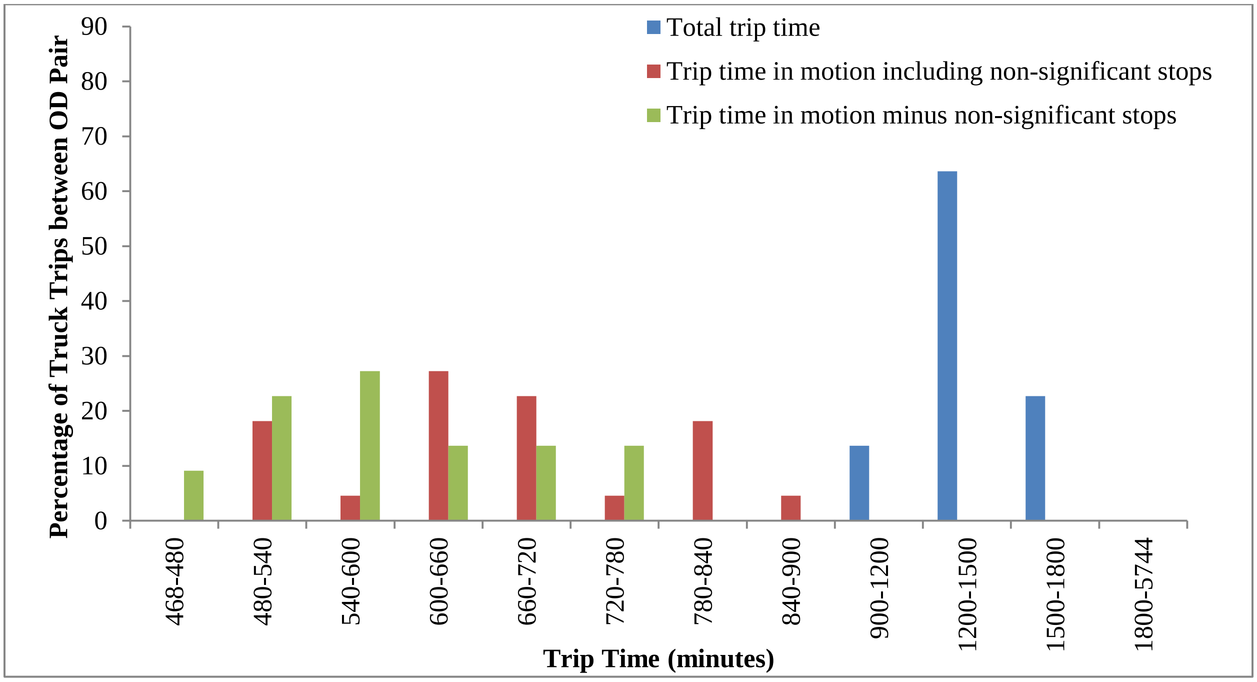


Figure C.38 Night-time Trips between OD Pair "5073-6117" during Weekdays (22 Trips)

Origin TAZ: 413, Destination TAZ: 6086

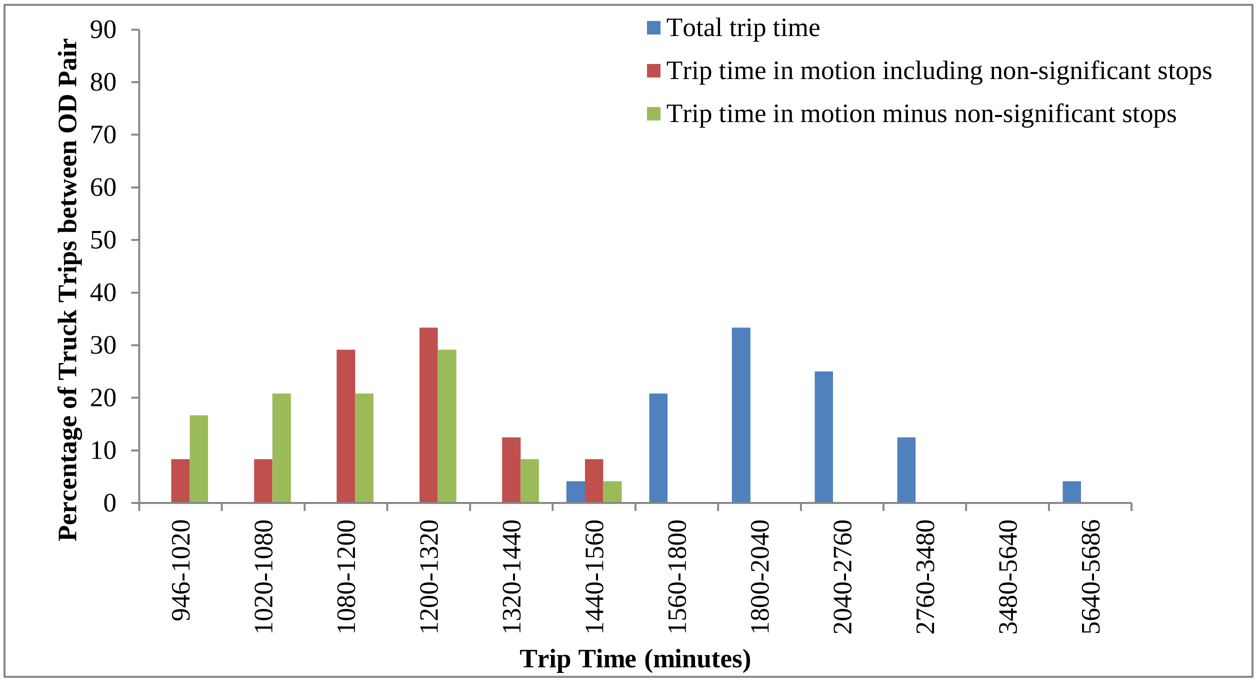


Figure C.39 Travel Time Distribution for Trips between OD Pair "413-6086" during Weekdays (24 Trips)

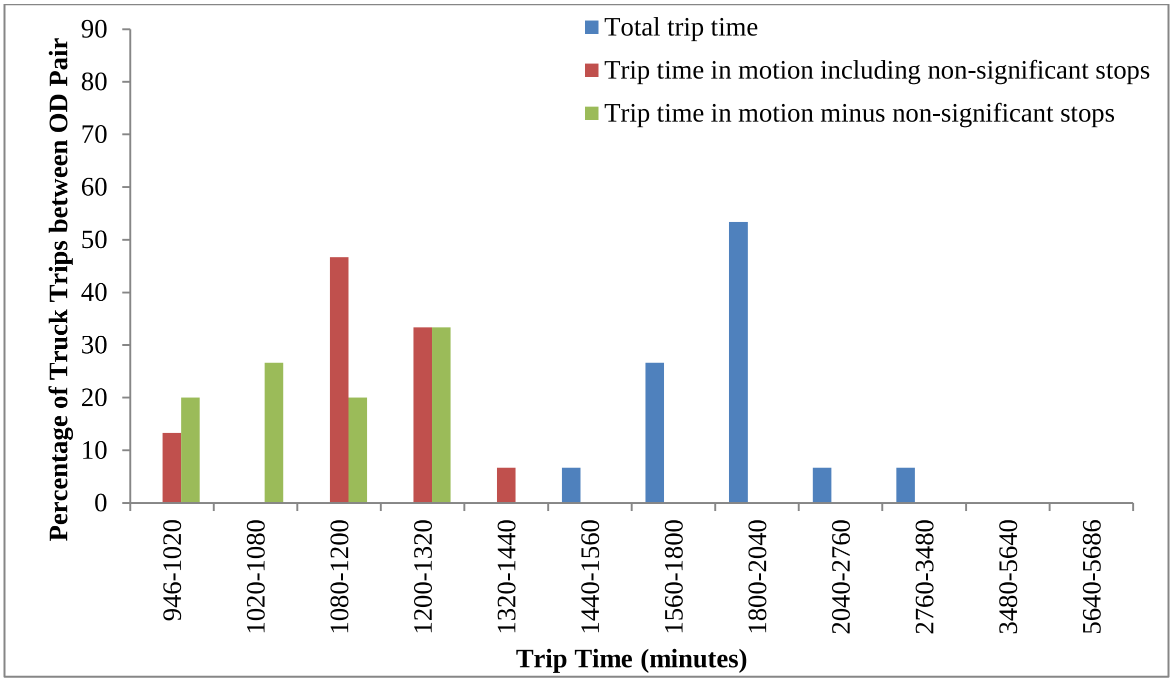


Figure C.40 Night-time Trips between OD Pair "413-6086" during Weekdays (15 Trips)

Origin TAZ: 2355, Destination TAZ: 6176

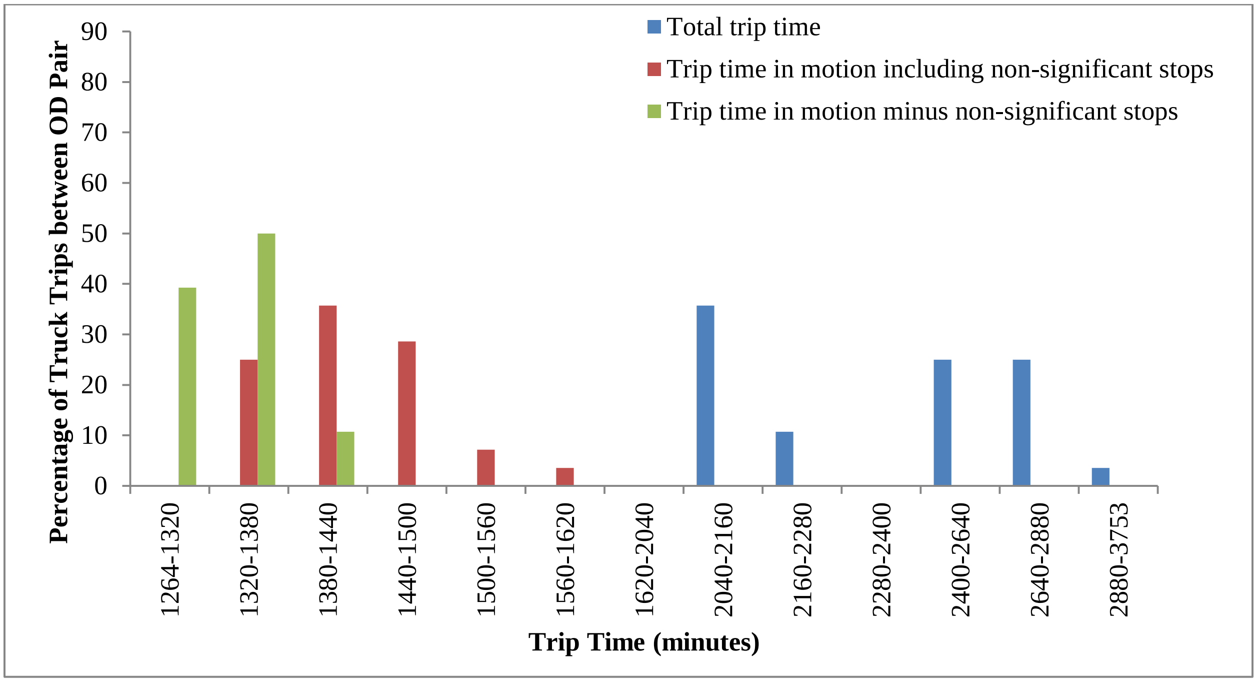


Figure C.41 Travel Time Distribution for Trips between OD Pair "2355-6176" during Weekday (28 Trips)

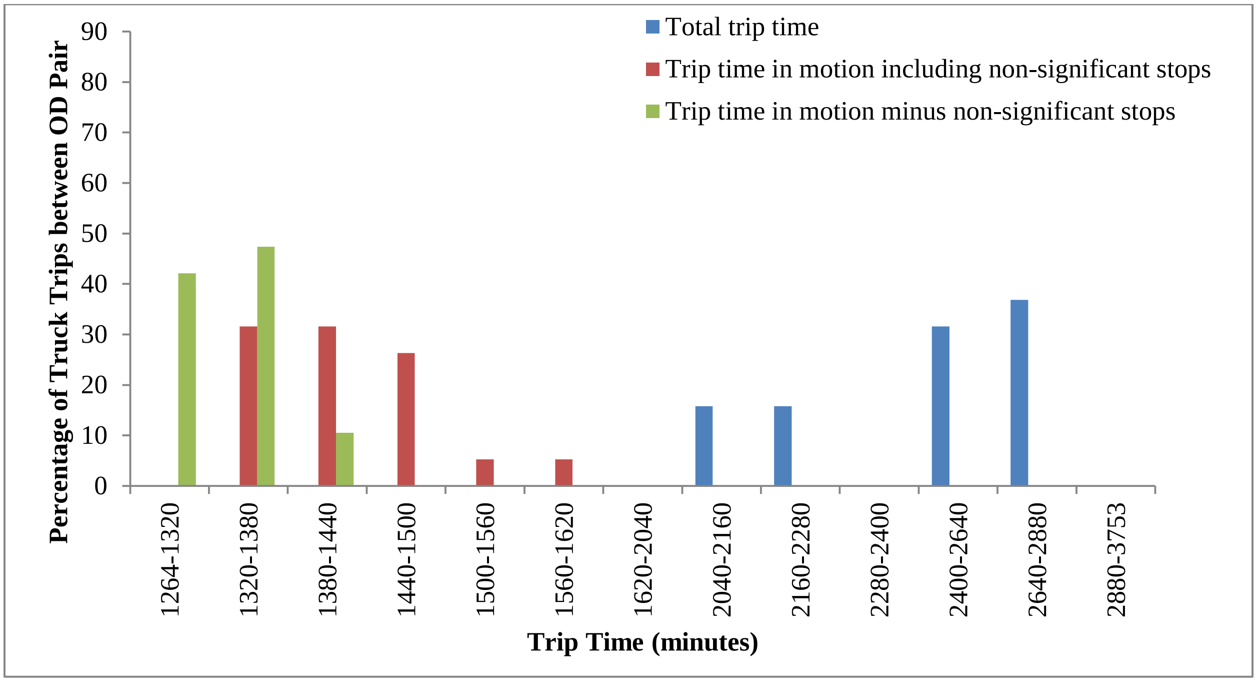


Figure C.42 Mid-day Trips between OD Pair "2355-6176" during Weekdays (19 Trips)

APPENDIX D: SEASONALITY ANALYSIS

As mentioned in Chapter 2 of this report, since ATRI data consist of tractor-trailer trucks of classes 8 and above, seasonality analysis was performed for tractor-trailer trucks and single-unit trucks separately. The tables and charts in this appendix represent the analysis of truck counts during different months of year 2010 as well as the aggregated counts for different seasons based on Table D.1, which shows the dates forming each season. Also, analysis was conducted for different facility types as well as area types during different time periods. The truck counts were obtained from Florida Department of Transportation for 252 locations across Florida.

Table D.1 Dates Forming Each Season

Season	Starting Date	Ending Date
Summer	21-Jun	22-Sep
Autumn	23-Sep	20-Dec
Winter	21-Dec	20-Mar
Spring	21-Mar	20-Jun

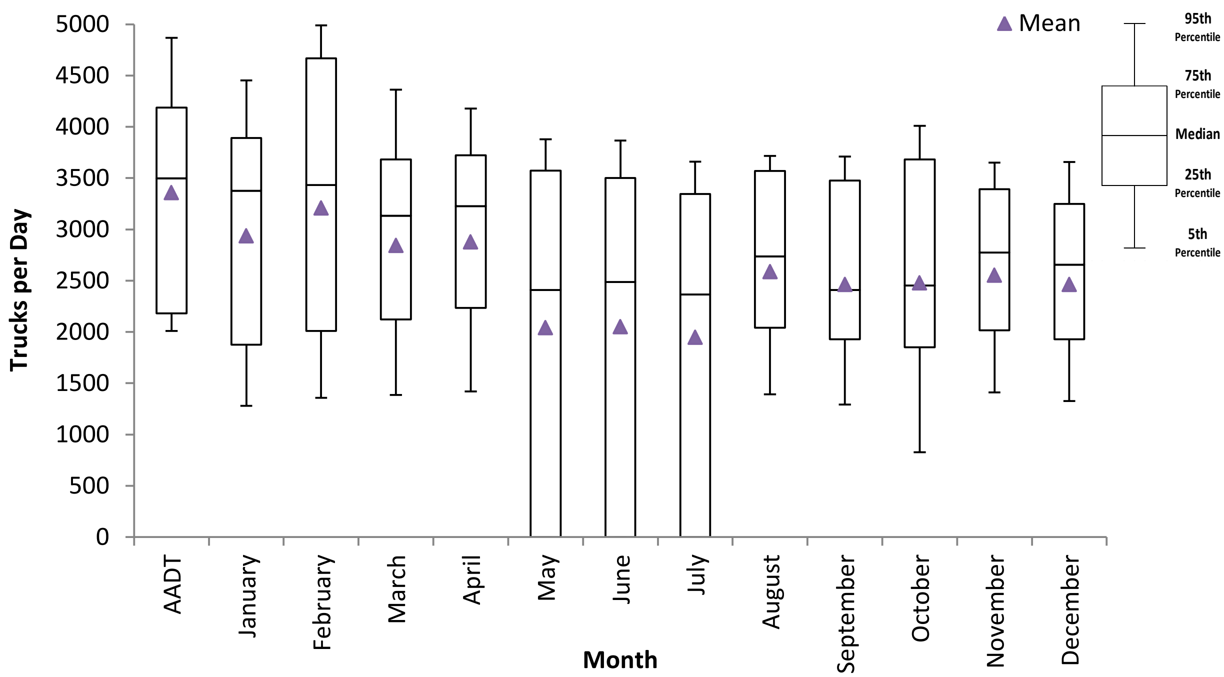
D.1 Single-Unit Trucks

Table D.2 Seasonality Analysis of Single-Unit Trucks by Facility Type

FTYPE	Total Sites	AADT	Summer	Autumn	Winter	Spring	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
11	8	3359	2895	2985	3527	3240	3359	3667	3252	3288	3270	3285	3120	2958	2815	2833	2918	2816
12	40	2066	2004	2032	1989	2089	1790	1980	2145	2007	1965	2091	2011	1975	1958	2102	1981	1893
16	2	2939	2885	2941	2903	2957	2438	3081	3013	3006	2913	3007	2902	2888	2868	3036	2823	2747
21	85	849	833	871	865	893	833	860	890	914	874	861	815	848	864	908	854	821
23	5	891	882	836	1030	880	861	1049	1049	909	840	893	887	870	889	844	812	810
24	1	619	637	678	575	592	552	568	592	582	583	631	641	645	649	692	642	674
31	77	313	302	309	333	337	323	340	340	335	337	326	286	295	299	310	299	297
33	1	345	336	357	348	351	327	377	342	367	347	337	337	317	363	329	369	324
41	2	364	341	366	406	368	395	406	395	402	356	323	295	371	372	375	341	349
46	7	334	327	325	343	352	329	348	365	352	340	354	334	322	323	335	312	304
83	4	4894	4871	4945	4751	4920	4618	4832	4771	4244	4121	4996	4828	4996	4738	5550	4892	5045
91	9	2697	2637	2749	2541	2785	2383	2627	2648	2829	2338	2855	2658	2565	2550	2667	2566	2563
92	10	1306	1280	1242	1409	1343	1353	1390	1338	1448	1342	1349	1293	1283	1240	1330	1274	1194
93	1	1726	1751	1691	1685	1827	1611	1720	1769	1794	1801	1940	1765	1704	1720	1721	1638	1578

Table D.3 Description of Facility Types (FTYPE)

Facility Type	Description	Facility Type	Description
11	Urban Freeway Group 1 (cities of 500,000 or more)	33	Undivided Arterial Class 1b with Turn Bays
12	Other Freeway (not in Group 1)	41	Major Local Divided Roadway
16	Controlled Access Expressway	46	Other Local Undivided Roadway without Turn Bays
21	Divided Arterial Unsignalized (55 mph)	83	Freeway Group 1 HOV Lane (Non-Separated)
23	Divided Arterial Class 1a	91	Freeway Group 1 Toll Facility
24	Divided Arterial Class 1b	92	Other Freeway Toll Facility
31	Undivided Arterial Unsignalized with Turn Bays	93	Expressway/Parkway Toll Facility



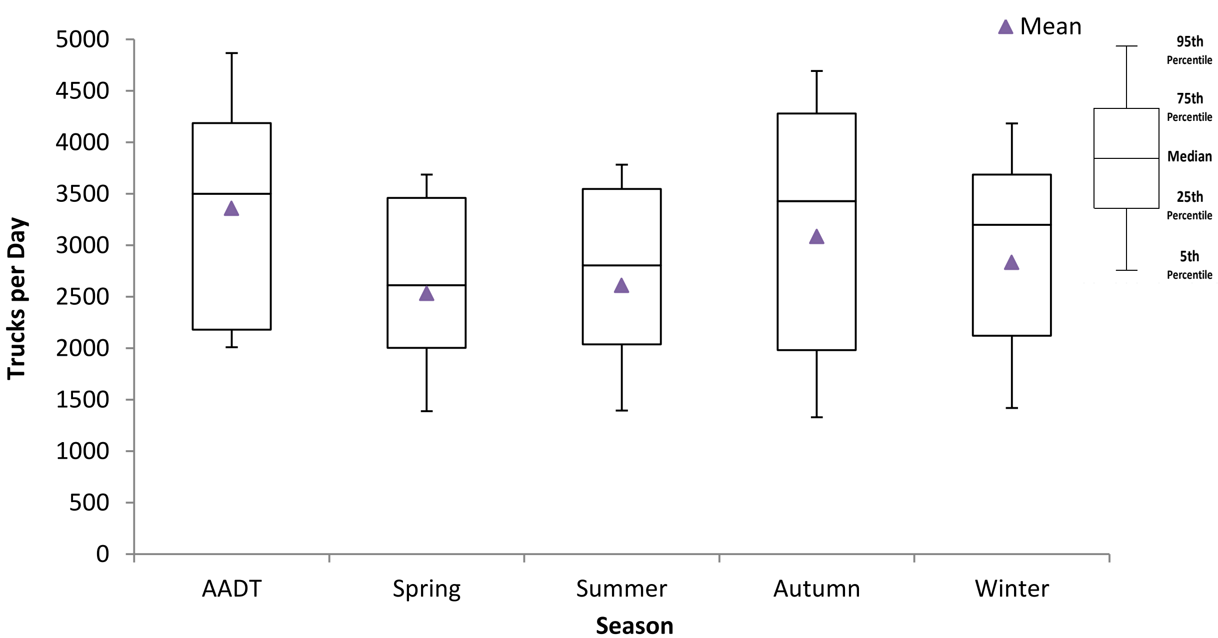
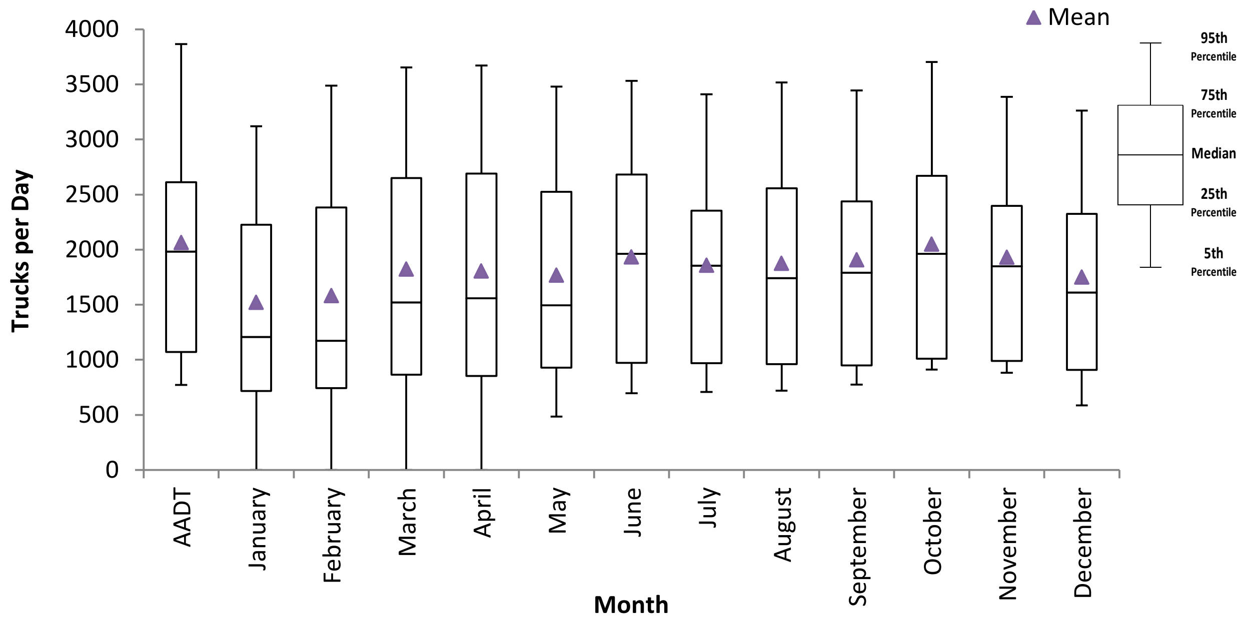


Figure D.1 Florida Truck Flows (Counts for Single-Unit Trucks) for Facility Type: Urban Freeway



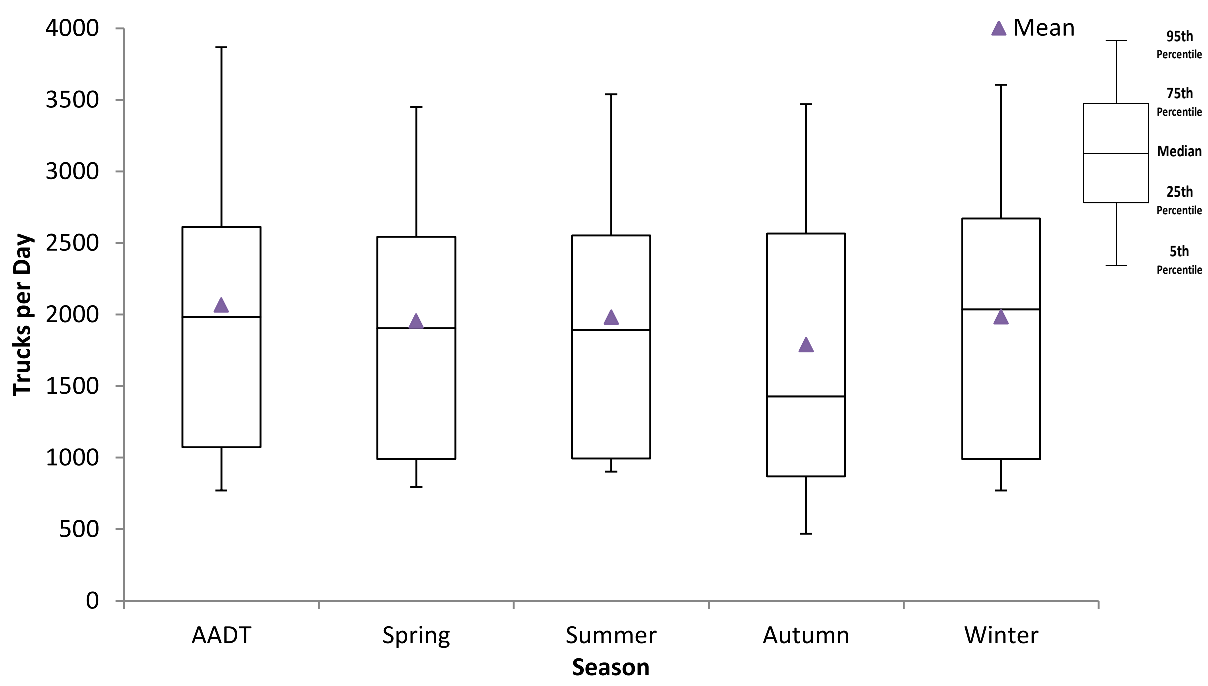
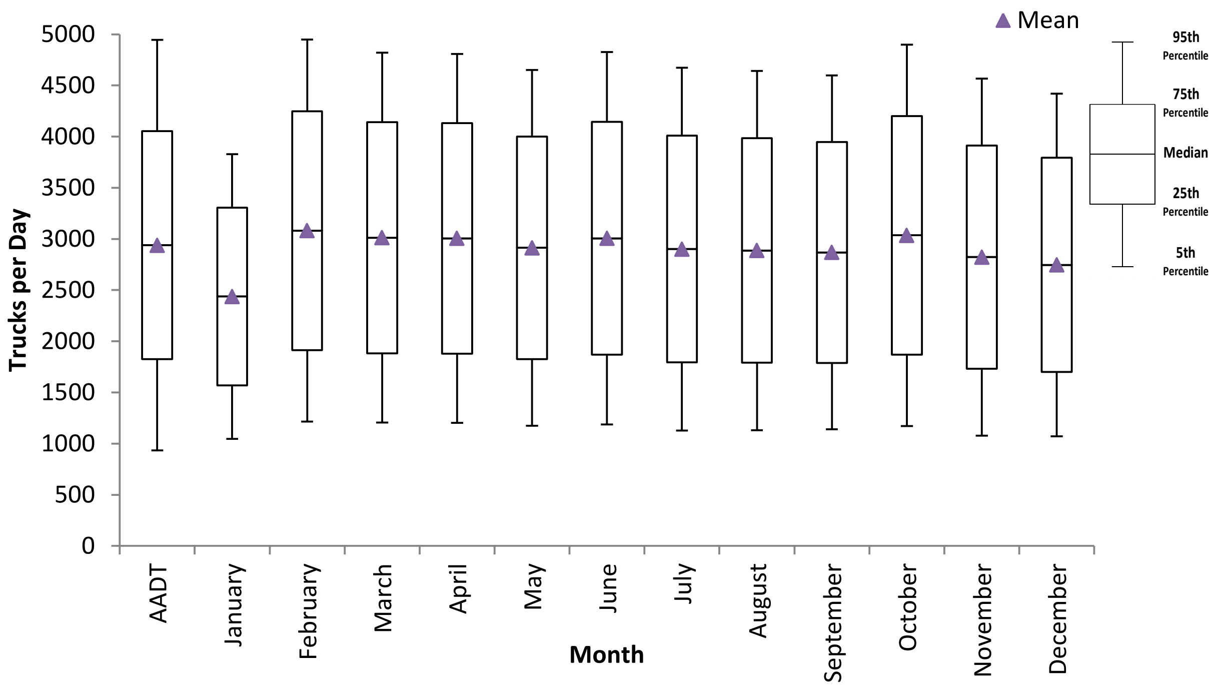


Figure D.2 Florida Truck Flows (Counts for Single-Unit Trucks) for Facility Type: Other Freeway



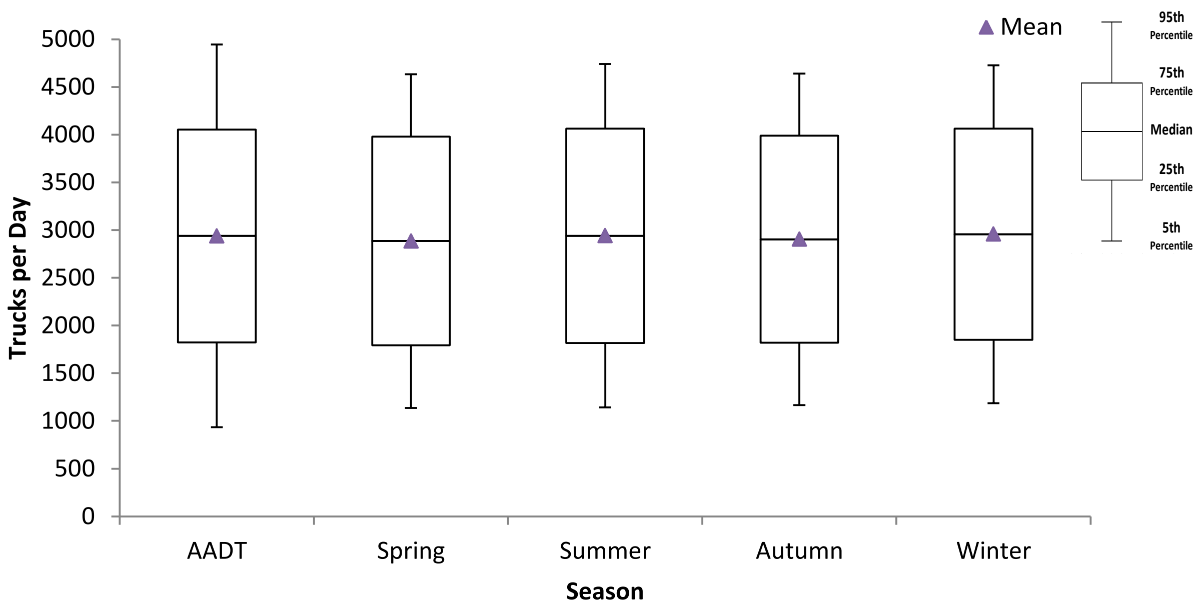
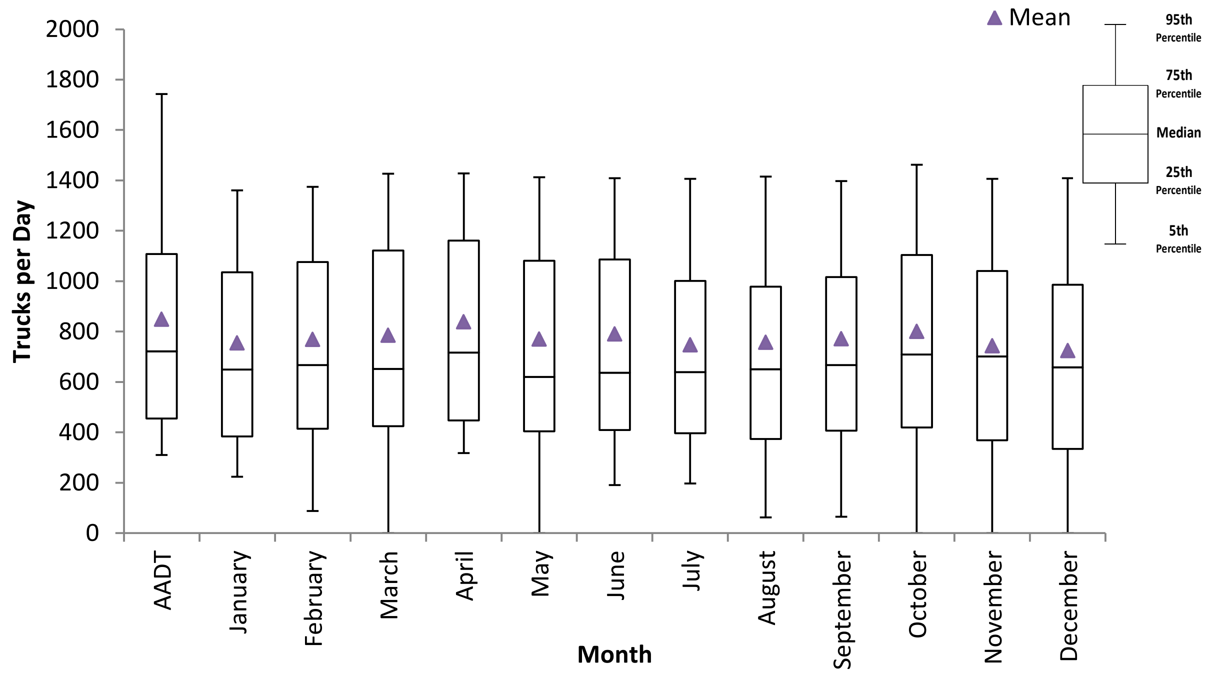


Figure D.3 Florida Truck Flows (Counts for Single-Unit Trucks) for Facility Type: Controlled-Access Expressway



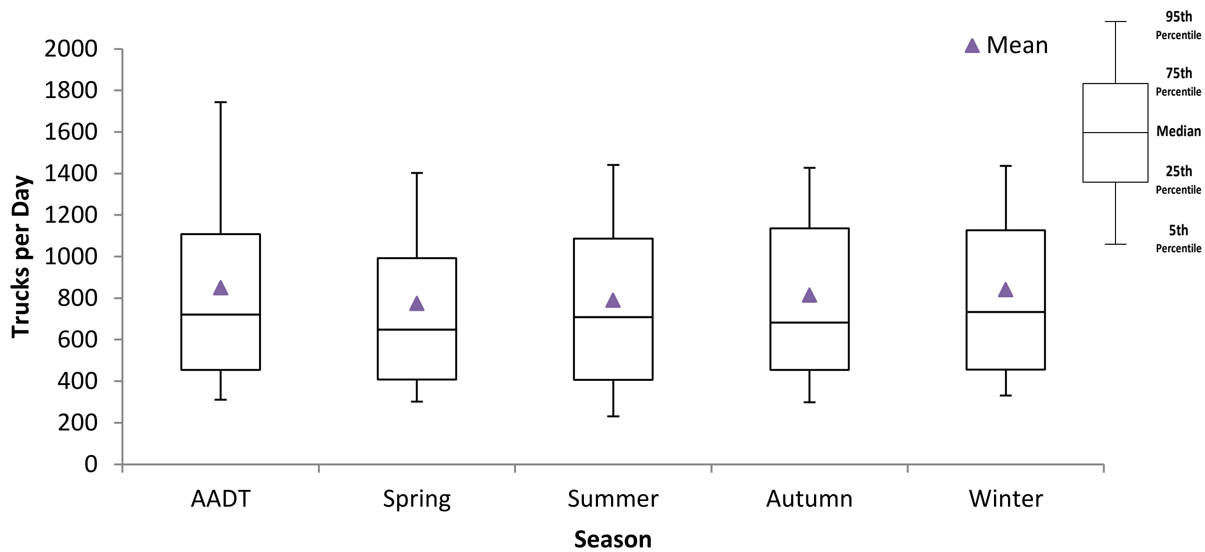
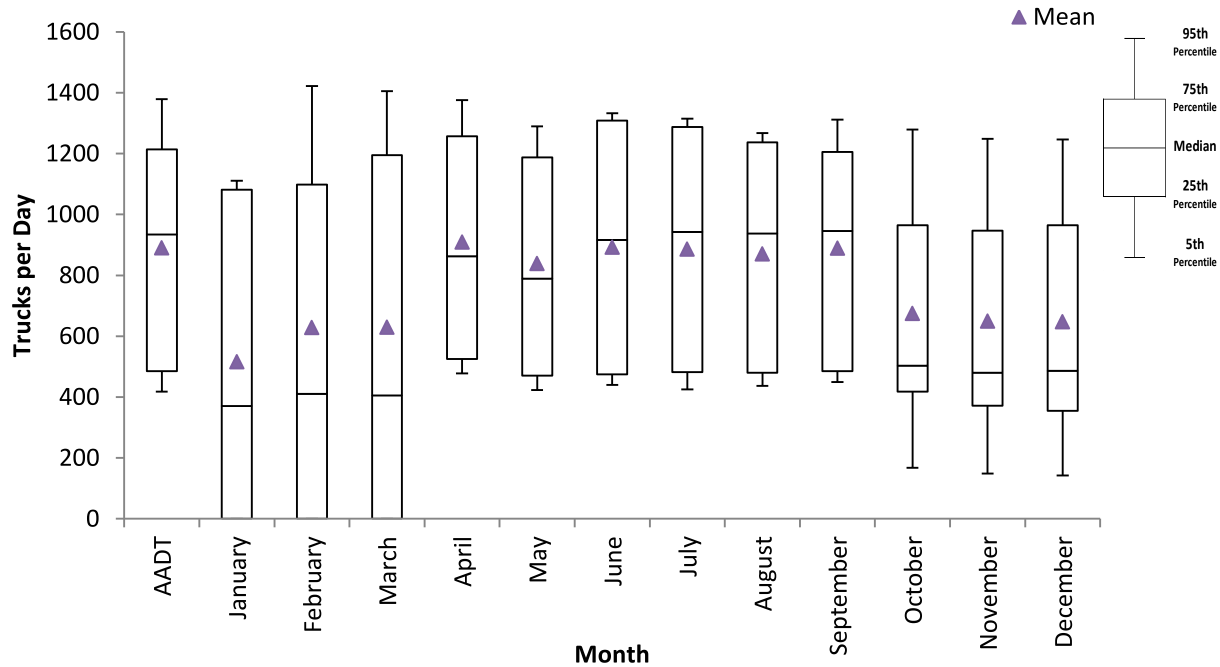


Figure D.4 Florida Truck Flows (Counts for Single-Unit Trucks) for Facility Type: Divided Arterial Unsignalized



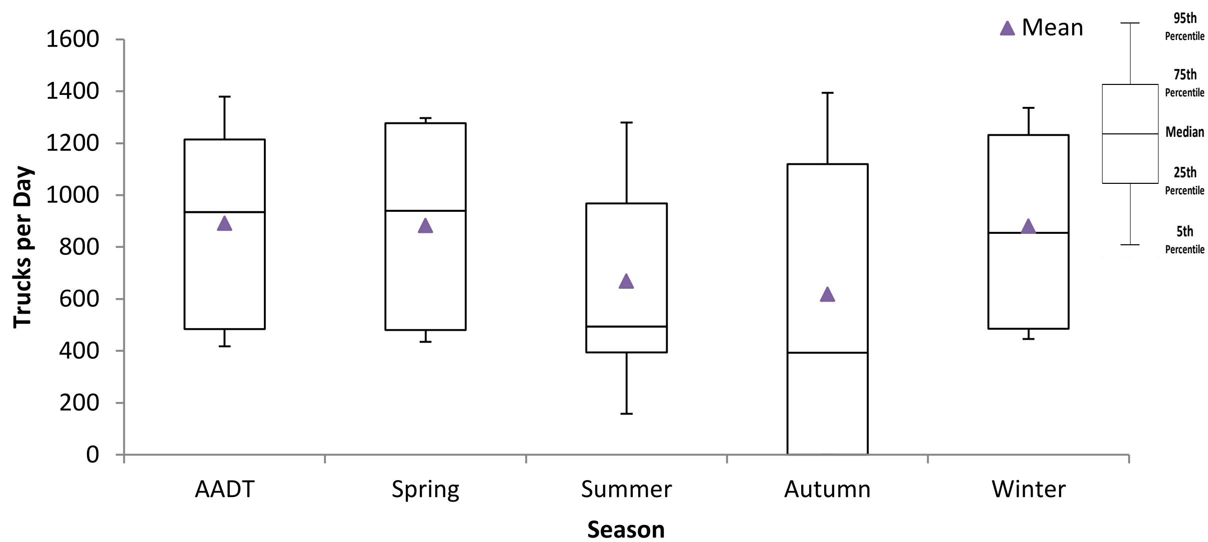
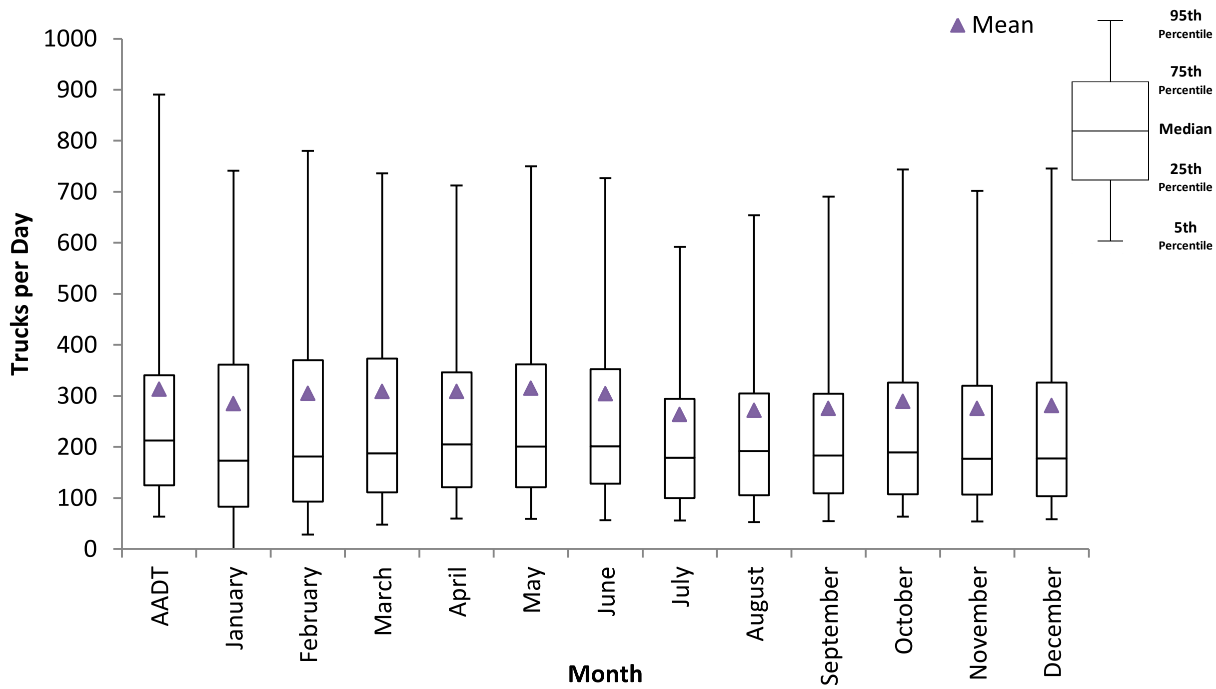


Figure D.5 Florida Truck Flows (Counts for Single-Unit Trucks) for Facility Type: Divided Arterial Class 1a



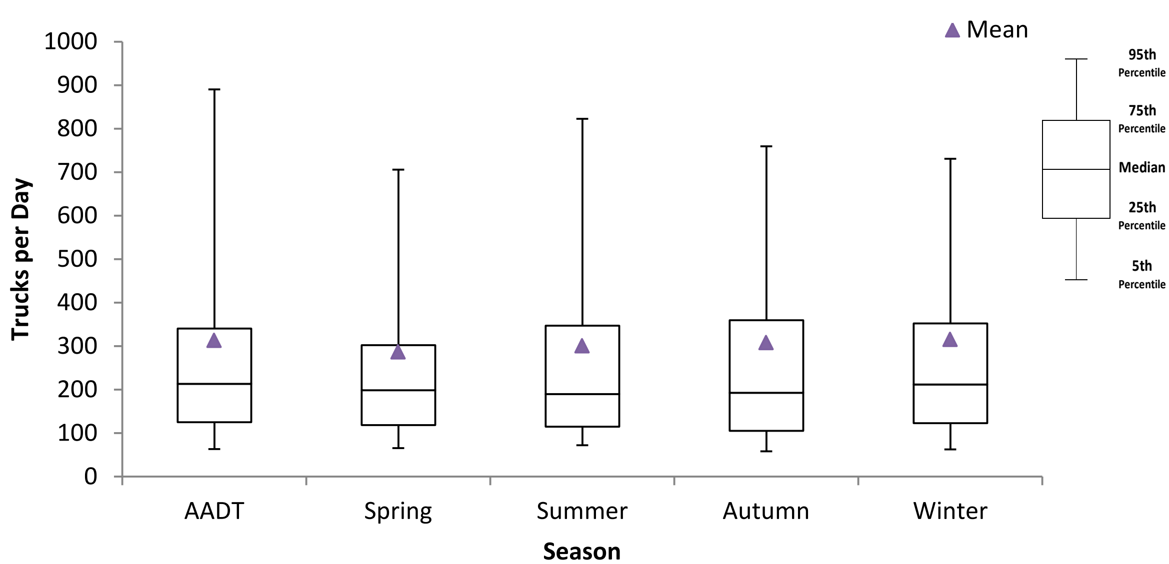
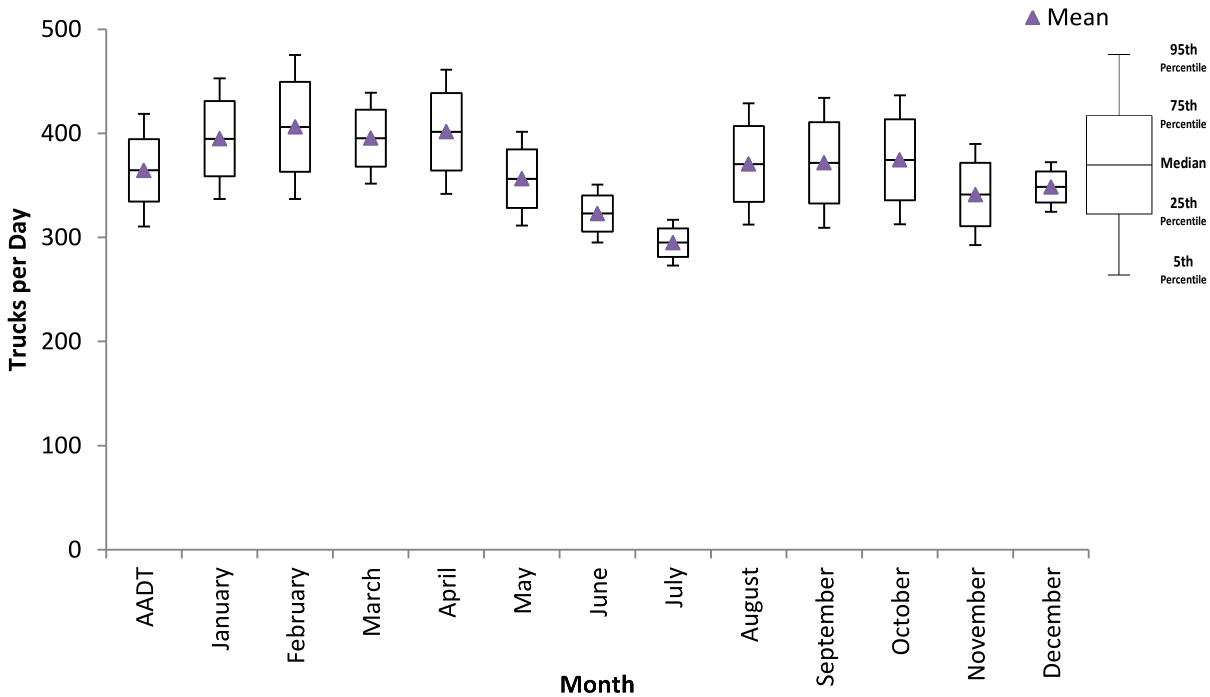


Figure D.6 Florida Truck Flows (Counts for Single-Unit Trucks) for Facility Type: Undivided Arterial Unsignalized with Turn Bays



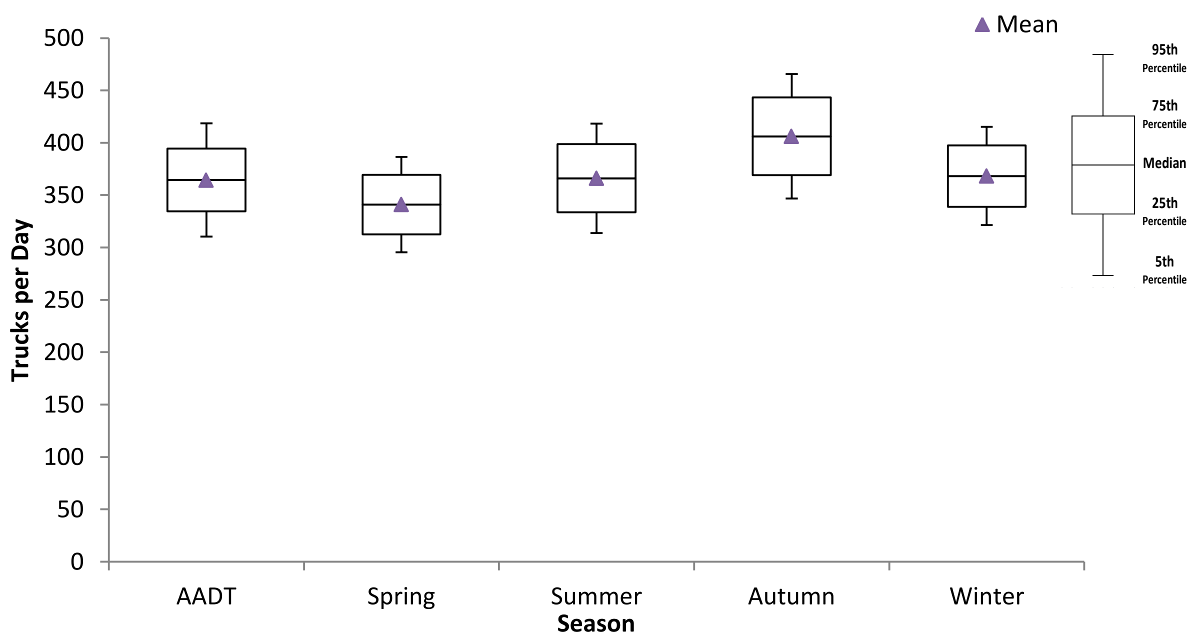
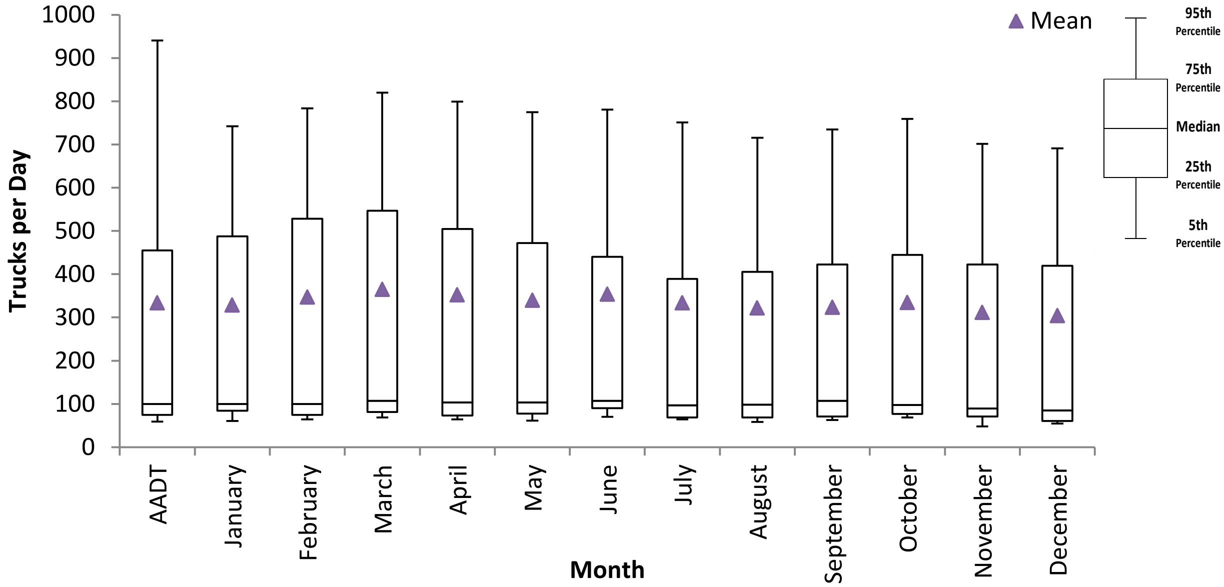


Figure D.7 Florida Truck Flows (Counts for Single-Unit Trucks) for Facility Type: Major Local Divided Roadway



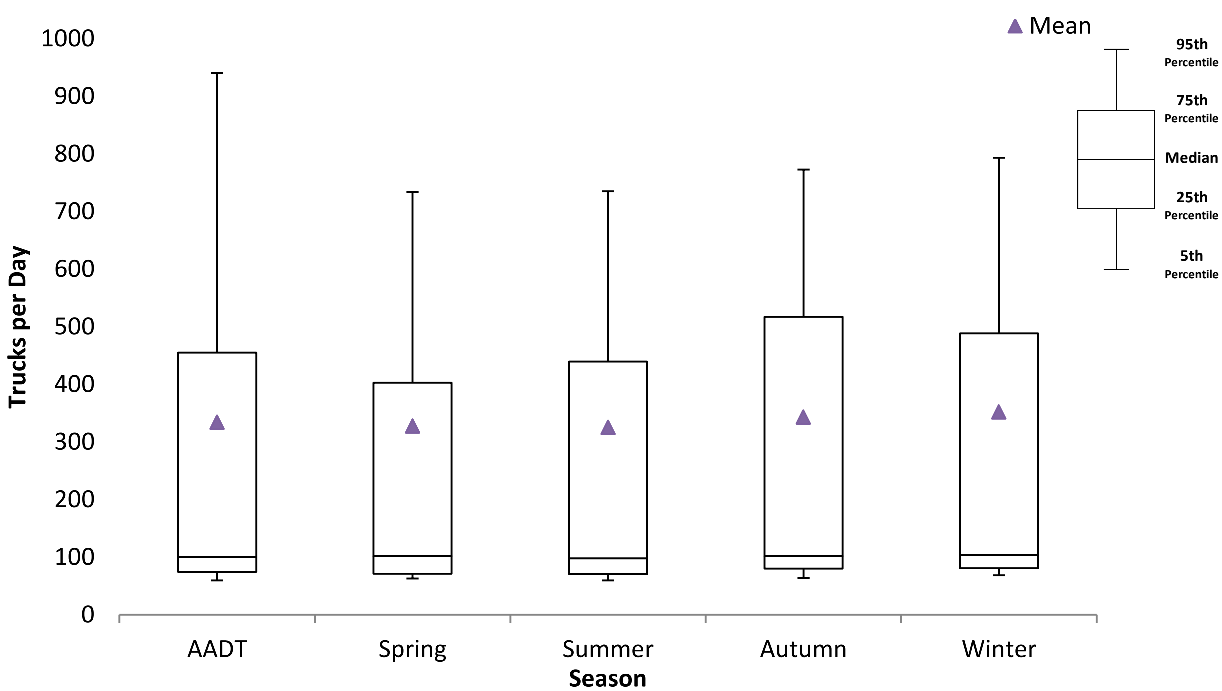
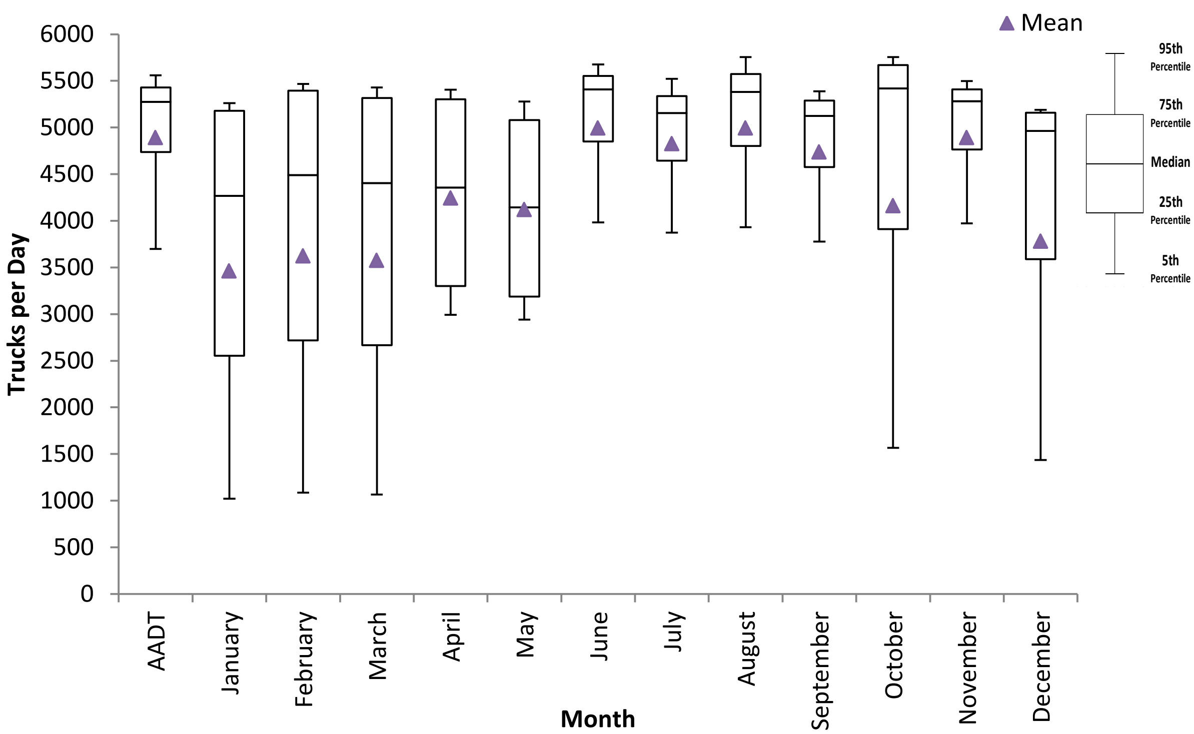


Figure D.8 Florida Truck Flows (Counts for Single-Unit Trucks) for Facility Type: Other Local Undivided Roadway without Turn Bays



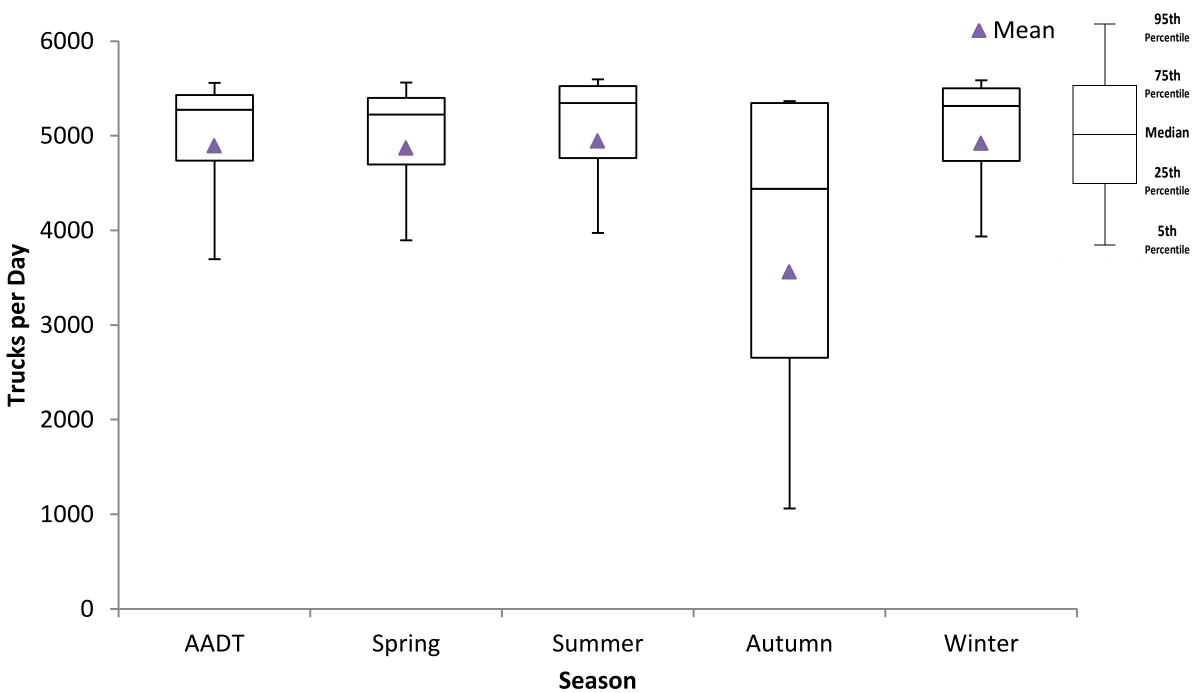
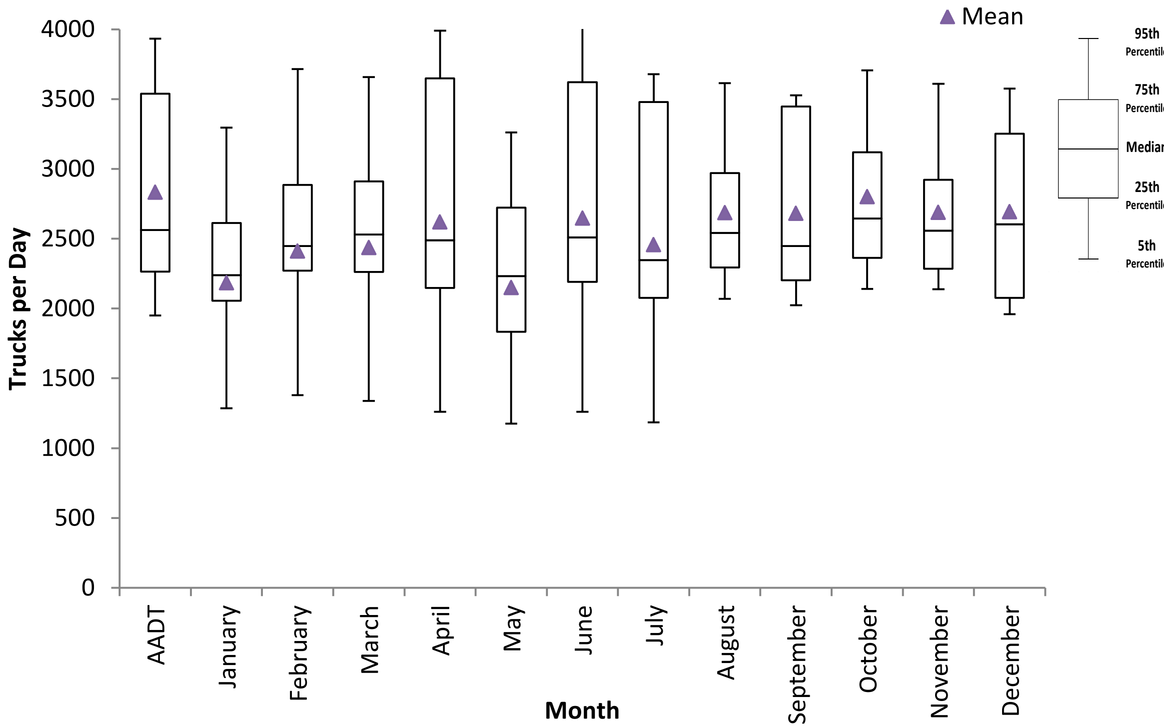


Figure D.9 Florida Truck Flows (Counts for Single-Unit Trucks) for Facility Type: Freeway Group 1 HOV Lane (Non-Separated)



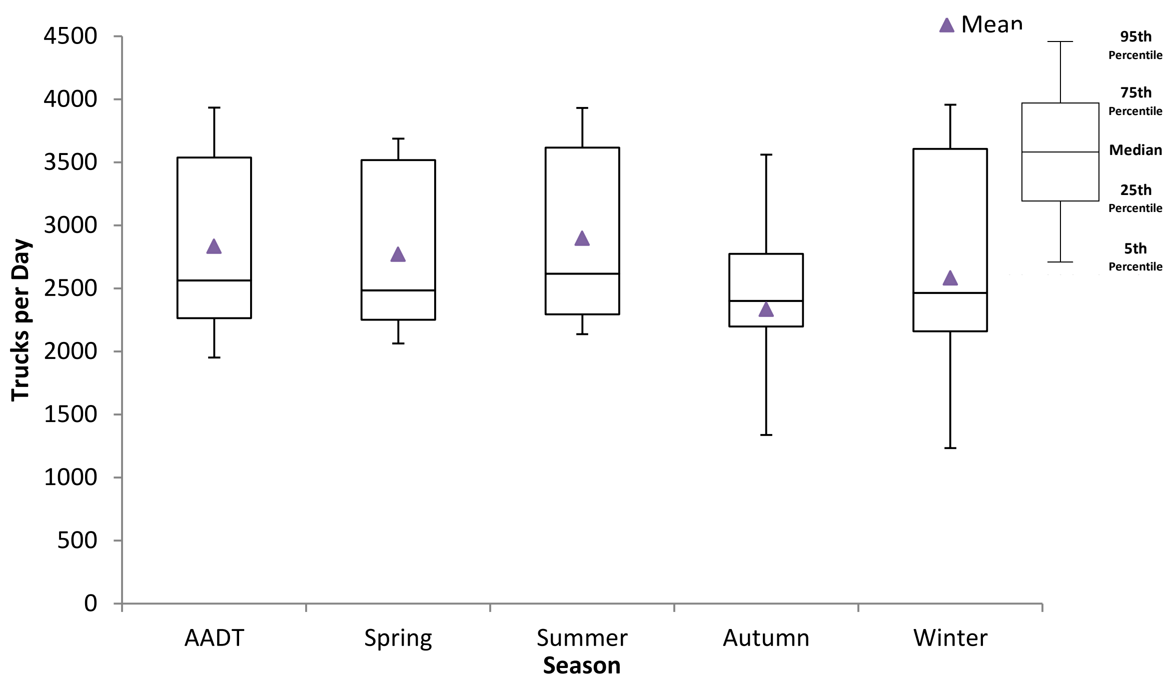
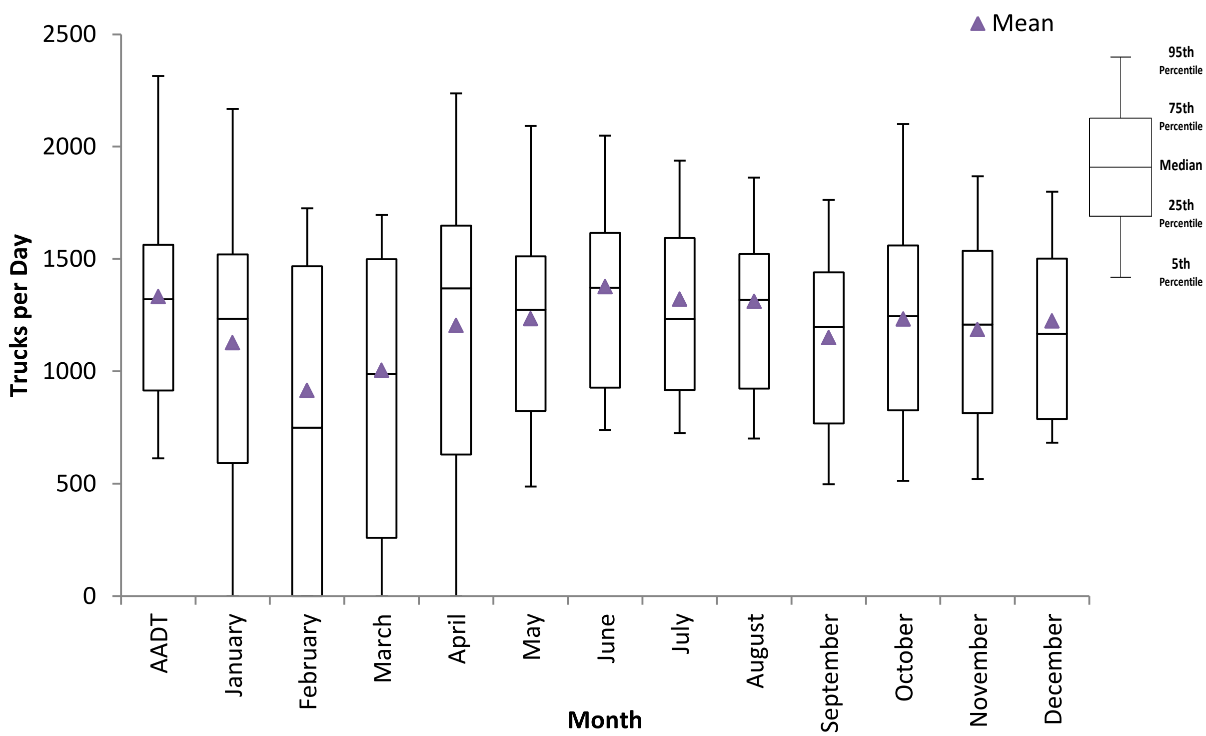


Figure D.10 Florida Truck Flows (Counts for Single-Unit Trucks) for Facility Type: Freeway Group 1 Toll Facility



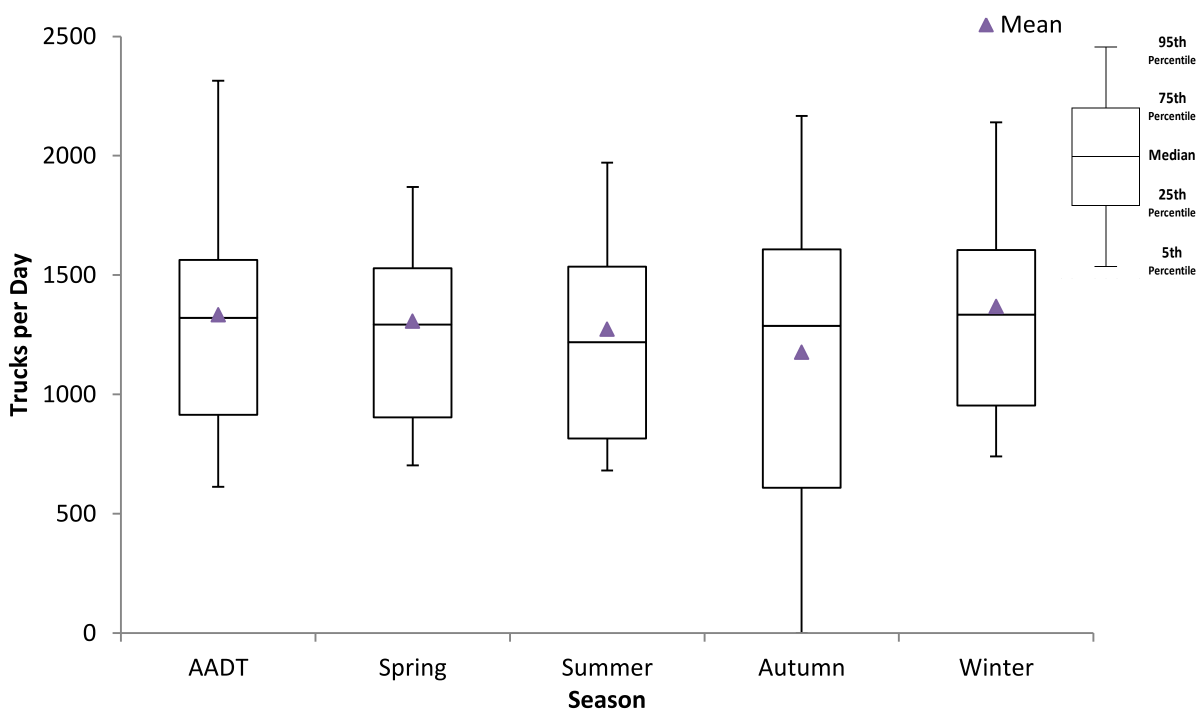


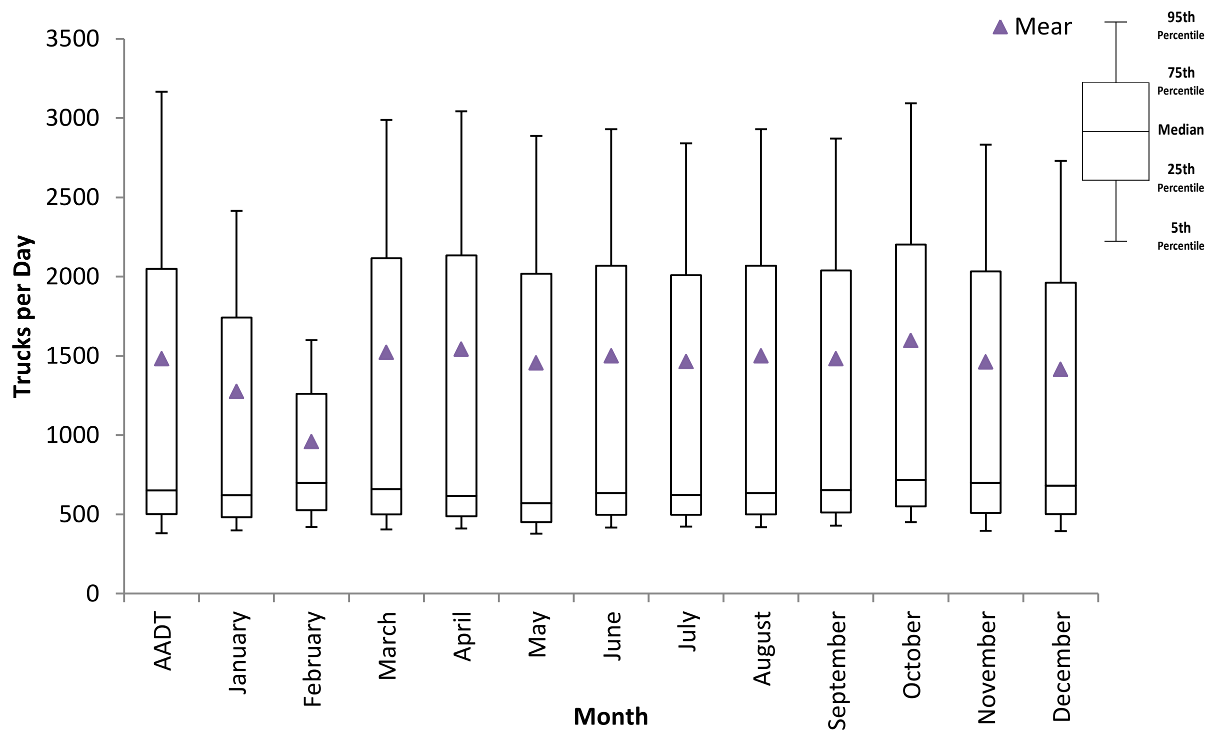
Figure D.11 Florida Truck Flows (Counts for Single Unit-Trucks) for Facility Type: Other Freeway Toll Facility

Table D.4 Seasonality Analysis of Single-Unit Trucks by Area Type

ATYPE	Total Sites	AADT	Summer	Autumn	Winter	Spring	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
12	1	243	262	228	234	253	224	240	235	239	263	282	274	256	249	227	222	209
14	1	619	637	678	575	592	552	568	592	582	583	631	641	645	649	692	642	674
21	3	1483	1478	1526	1327	1512	1275	958	1523	1542	1456	1500	1464	1501	1483	1597	1462	1415
31	53	1513	1478	1537	1482	1554	1329	1399	1524	1597	1497	1546	1458	1466	1491	1580	1461	1435
32	6	1692	1683	1671	1686	1820	1583	1709	1819	1835	1766	1839	1750	1675	1640	1684	1631	1581
33	23	1377	1283	1331	1382	1244	1277	1420	1434	1297	1249	1246	1192	1205	1368	1435	1337	1293
34	1	262	0	284	255	0	253	262	0	0	0	0	0	0	0	0	0	262
41	1	1214	1277	0	1120	1231	1081	1098	1195	1257	1188	1309	1333	1237	1206	0	0	0
42	36	1840	1728	1830	1746	1810	1687	1836	1740	1742	1645	1756	1674	1763	1757	1772	1922	1782
43	1	197	215	153	184	237	165	179	242	238	214	264	256	193	181	164	137	139
51	17	1099	1070	1108	1128	1113	1068	1164	1155	1140	1077	1108	1066	1075	1055	1127	1093	1046
52	109	595	598	596	598	648	571	600	609	623	577	626	595	598	578	618	593	554

Table D.5 Description of Area Types (ATYPE)

Area Type	Description
12	Urbanized Area (under 500,000) Primary City Central Business District
14	Non-Urbanized Area Small City Downtown
21	All Central Business District
31	Residential Area of Urbanized Areas
32	Undeveloped Portions of Urbanized Areas
33	Transitioning Areas/Urban Areas over 5,000 Population
34	Beach Residential (per SERPM)
41	High Density Outlying Business District
42	Other Outlying Business District
43	Beach OBD (per SERPM)
51	Developed Rural Areas/Small Cities under 5,000 Population
52	Undeveloped Rural Areas



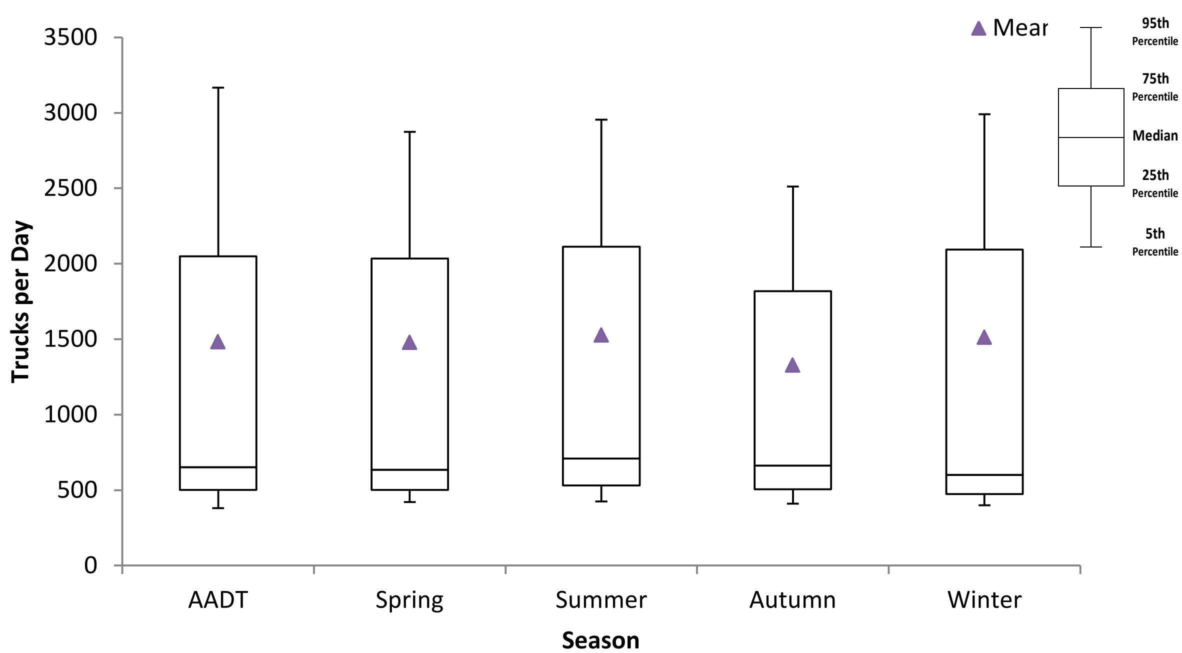
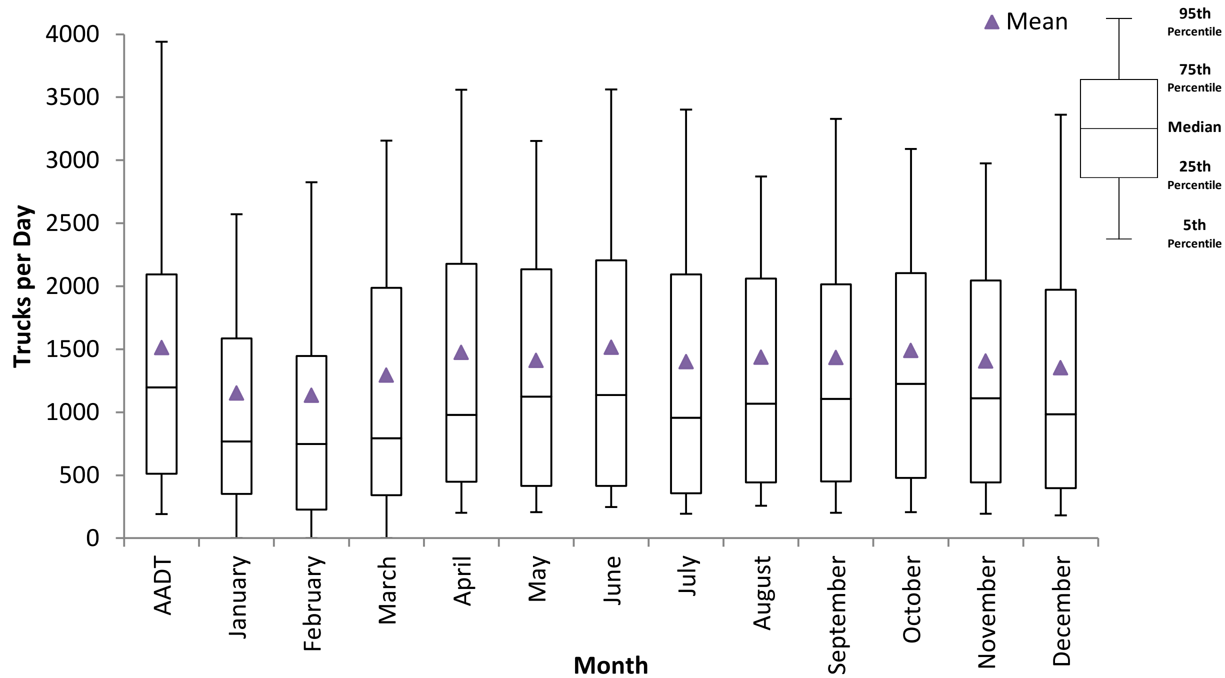


Figure D.12 Florida Truck Flows (Counts for Single-Unit Trucks) for Area Type: Central Business District



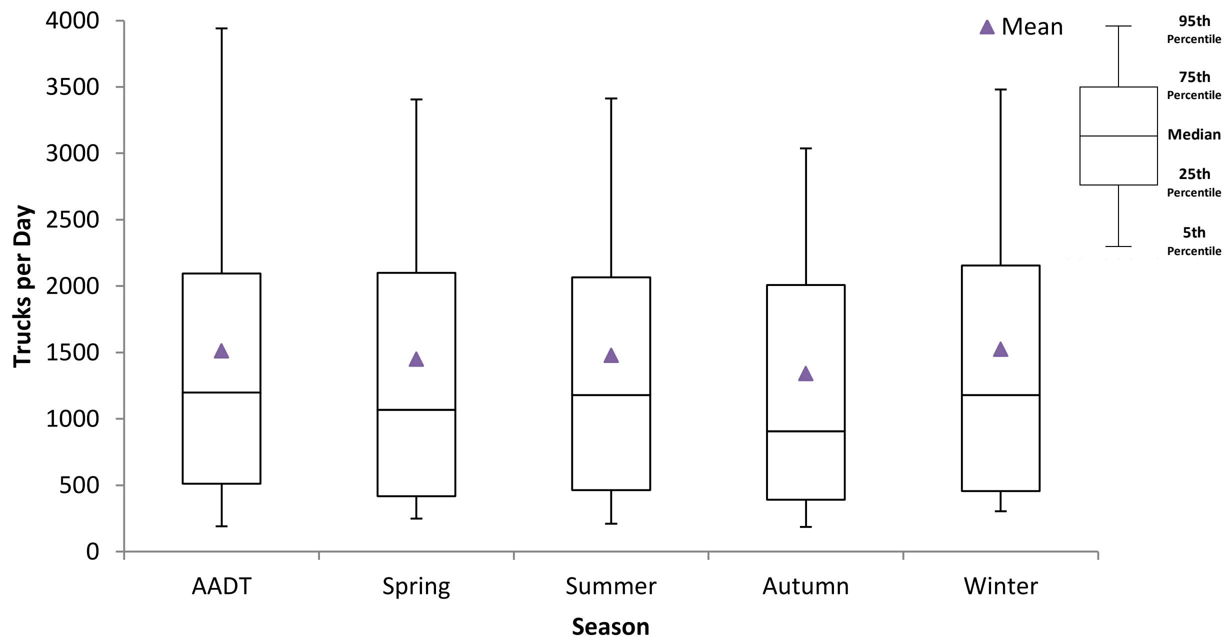
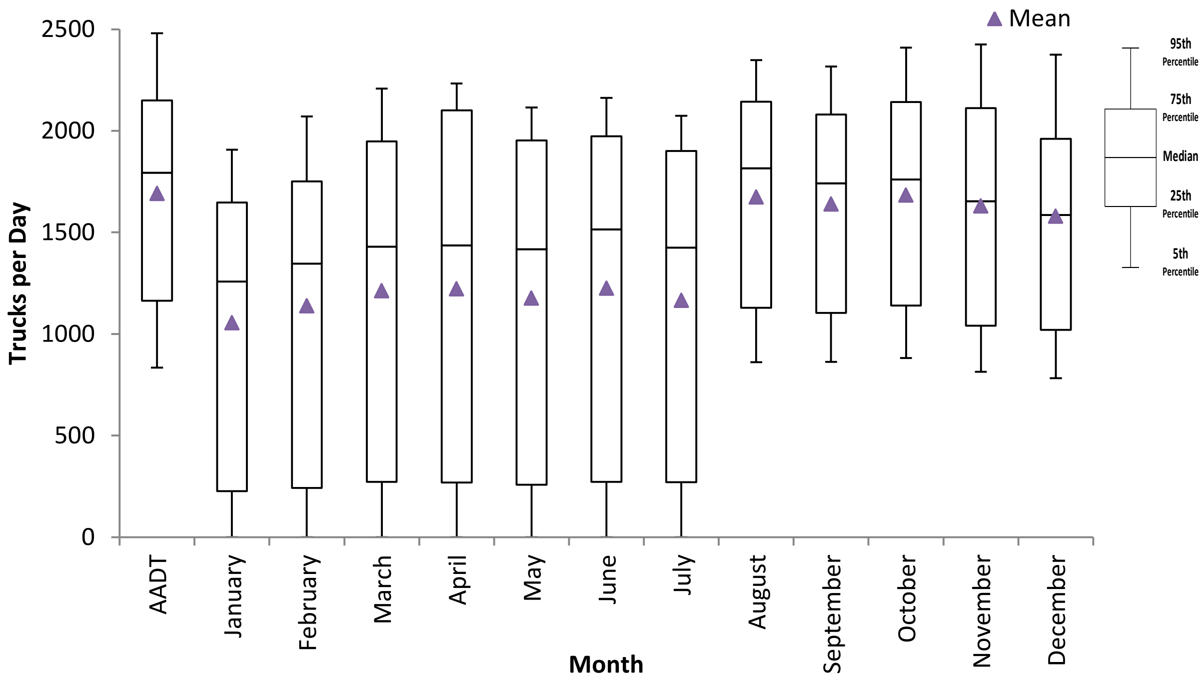


Figure D.13 Florida Truck Flows (Counts for Single-Unit Trucks) for Area Type: Residential Area of Urbanized Areas



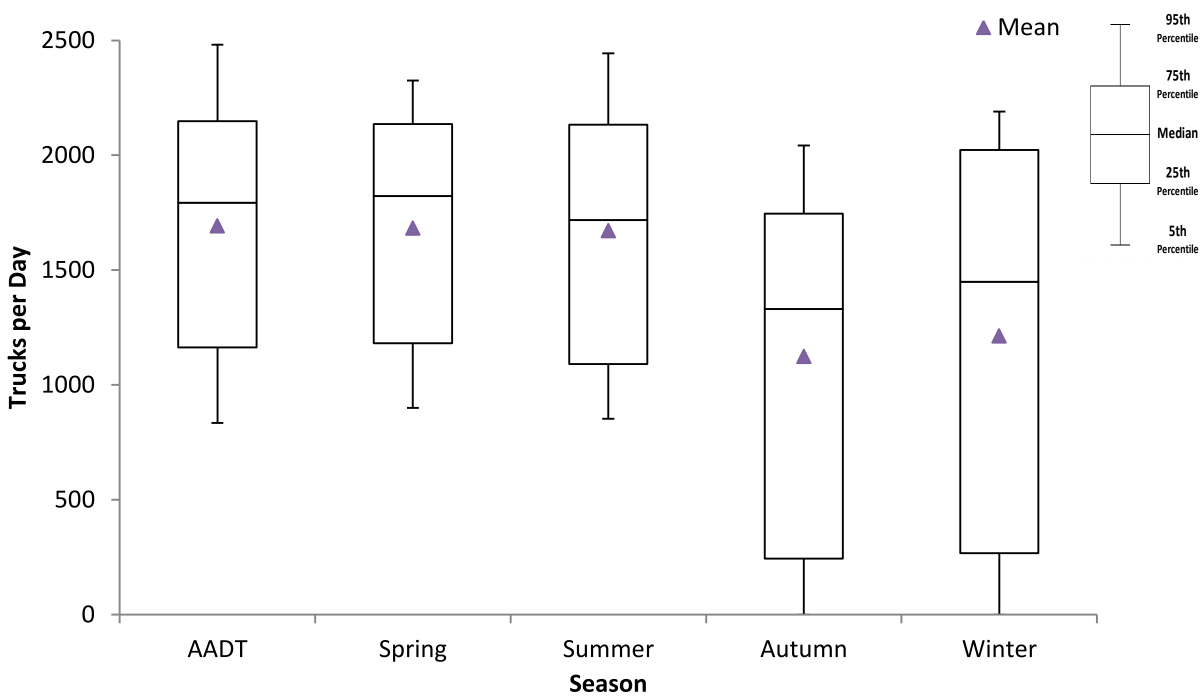
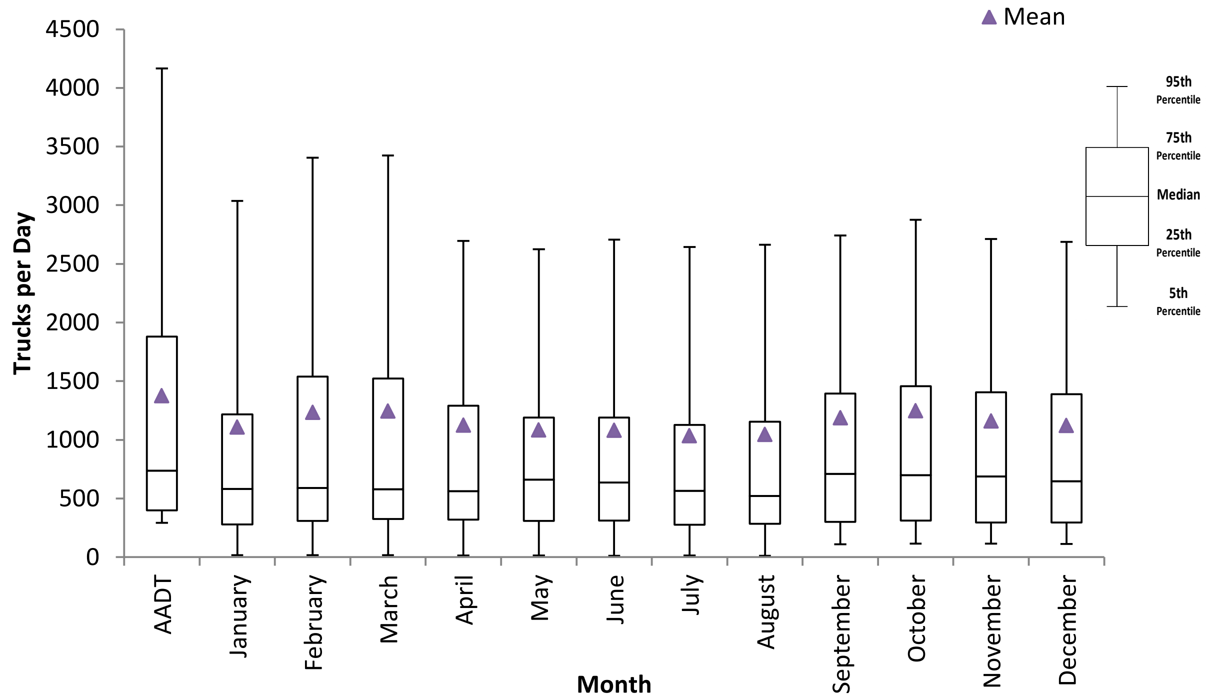


Figure D.14 Florida Truck Flows (Counts for Single-Unit Trucks) for Area Type: Undeveloped Portions of Urbanized Areas



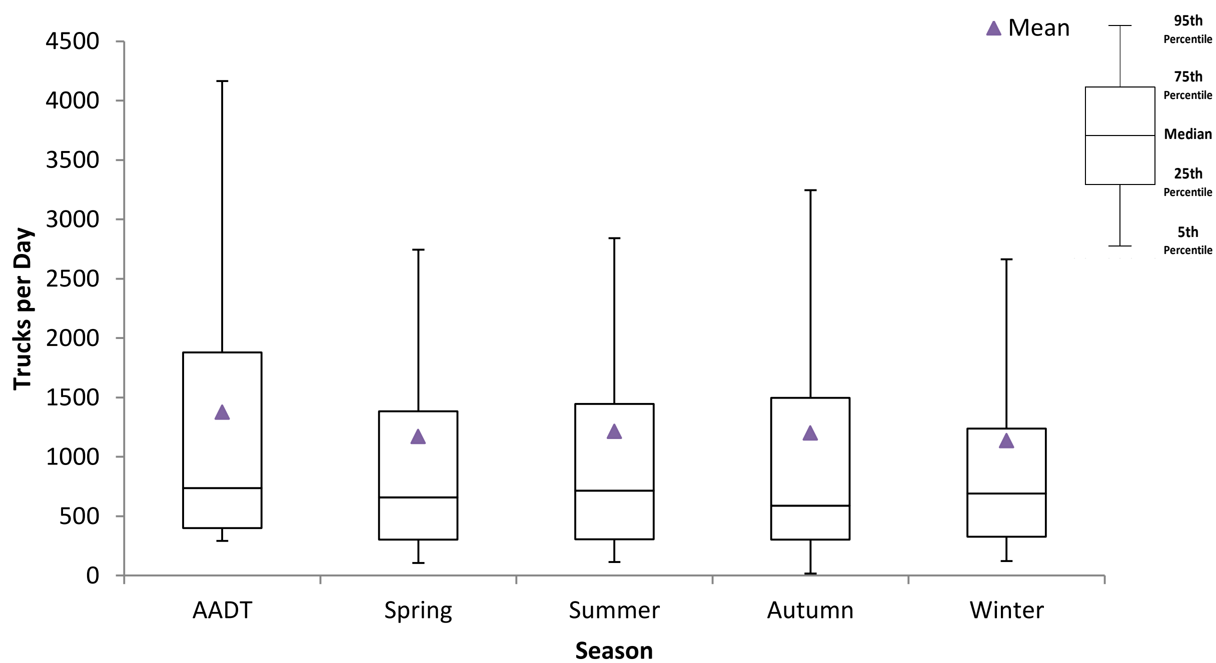


Figure D.15 Florida Truck Flows (Counts for Single-Unit Trucks) for Area Type: Transitioning Areas/Urban Areas over 5,000 Population

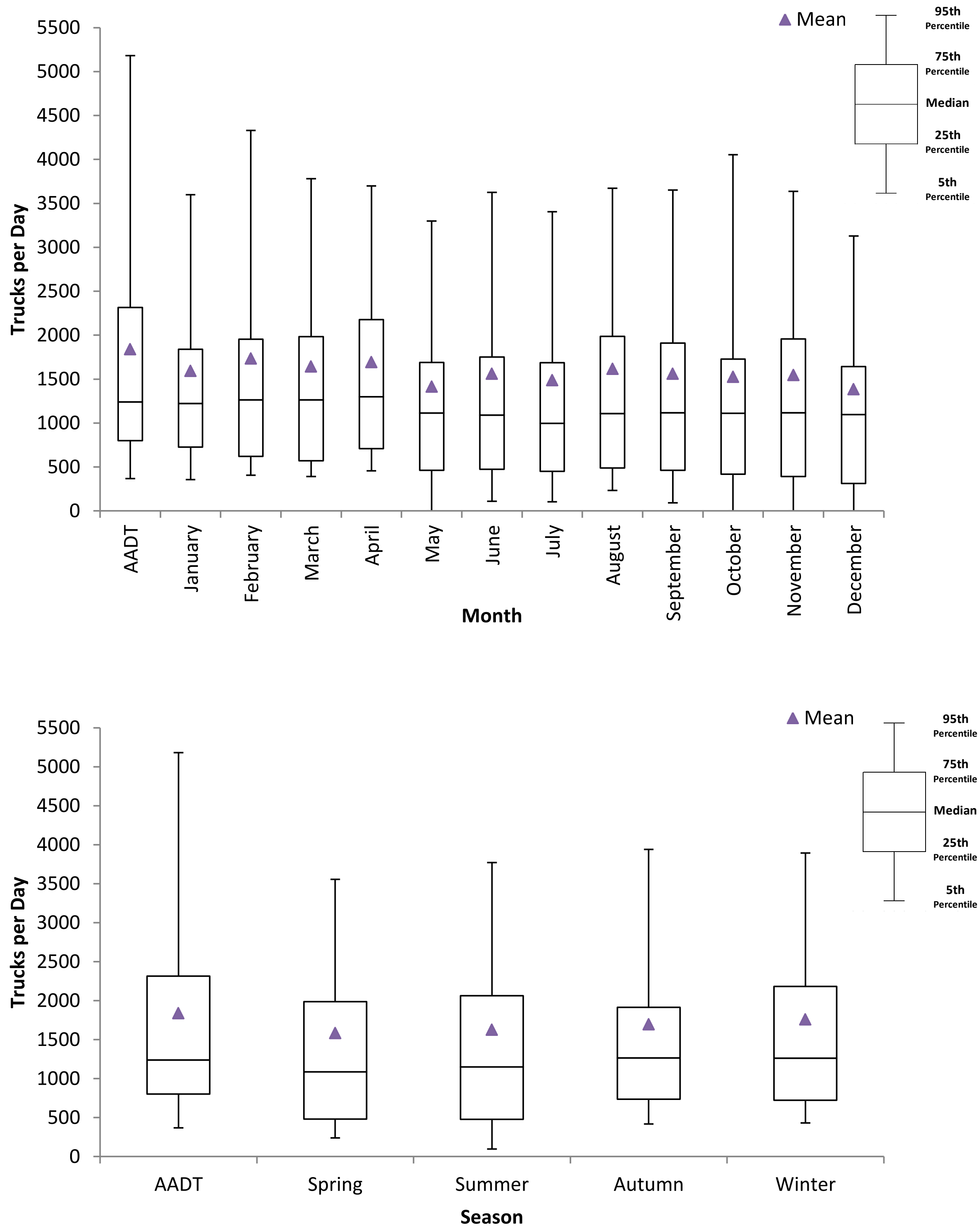
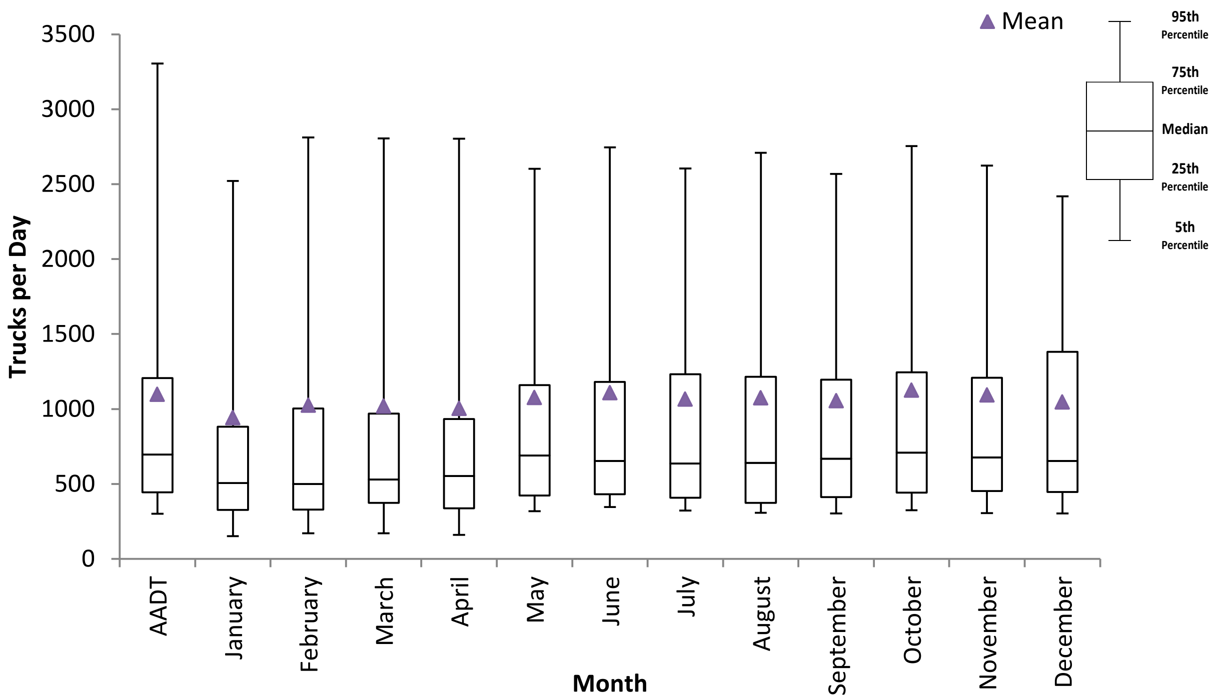


Figure D.16 Florida Truck Flows (Counts for Single-Unit Trucks) for Area Type: Other Outlying Business District



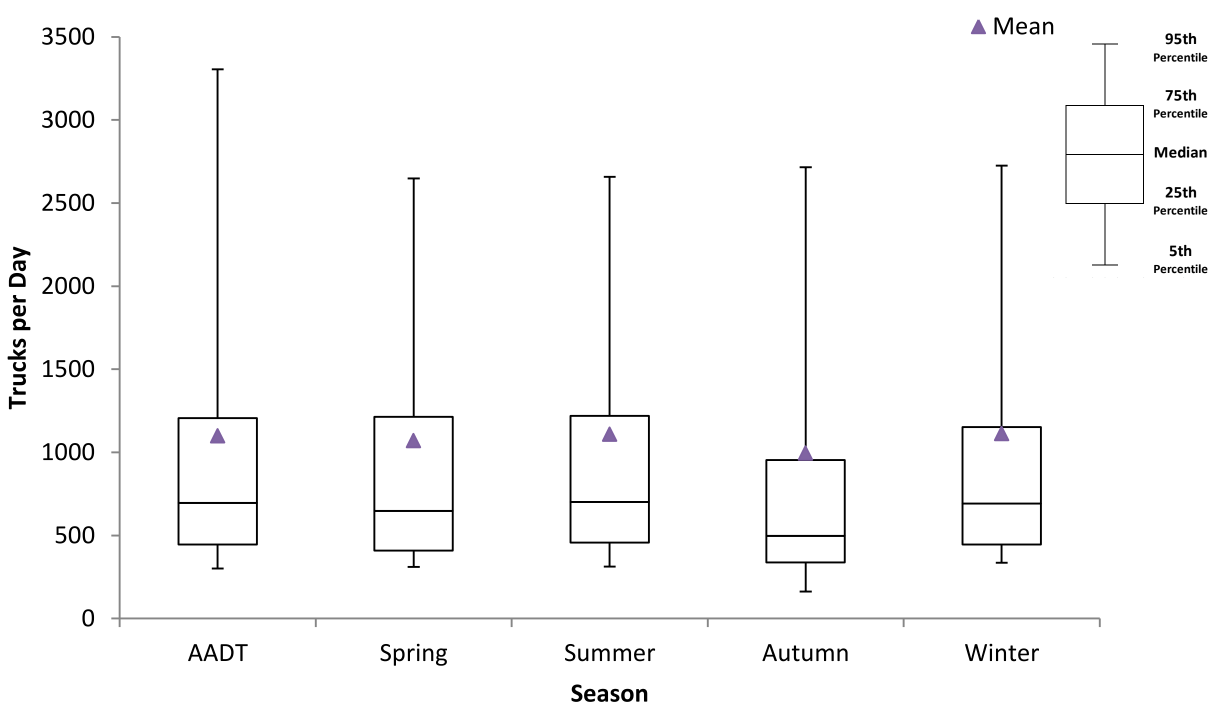
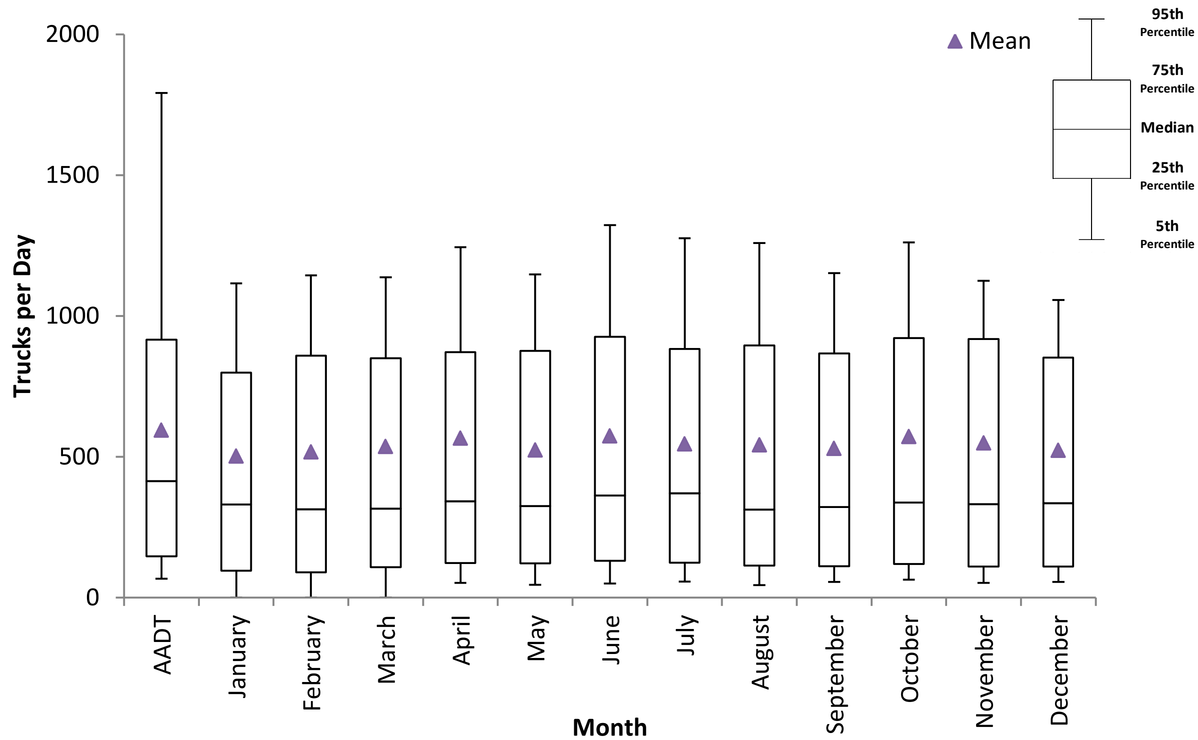


Figure D.17 Florida Truck Flows (Counts for Single-Unit Trucks) for Area Type: Developed Rural Areas/Small Cities under 5,000 Population



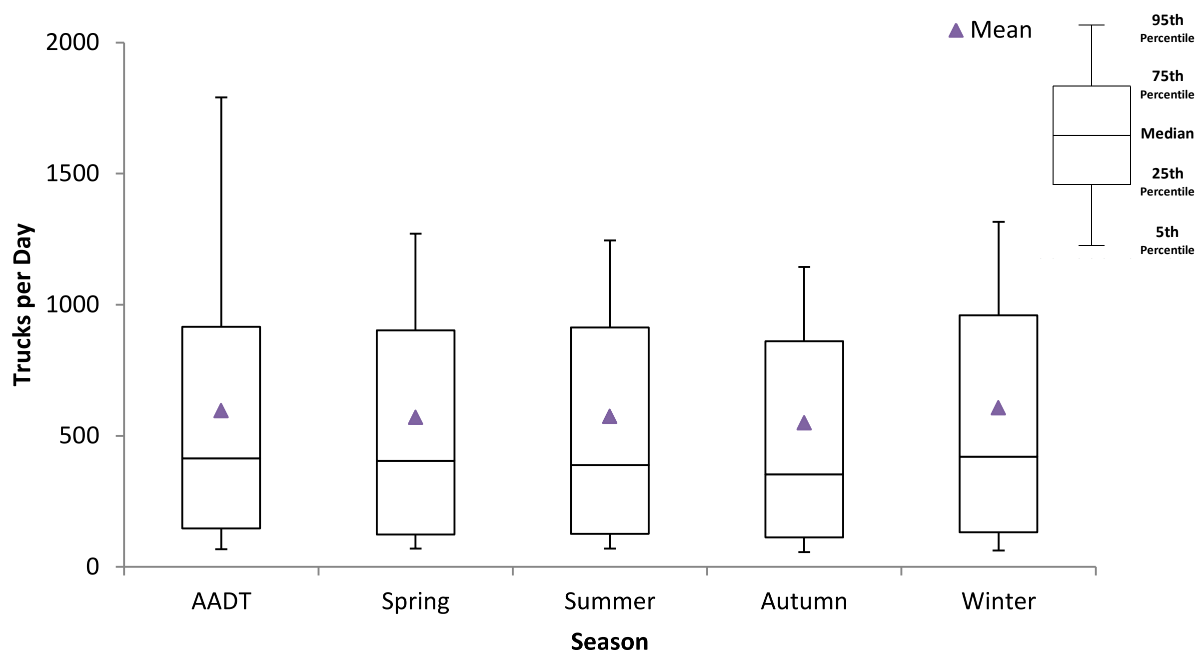
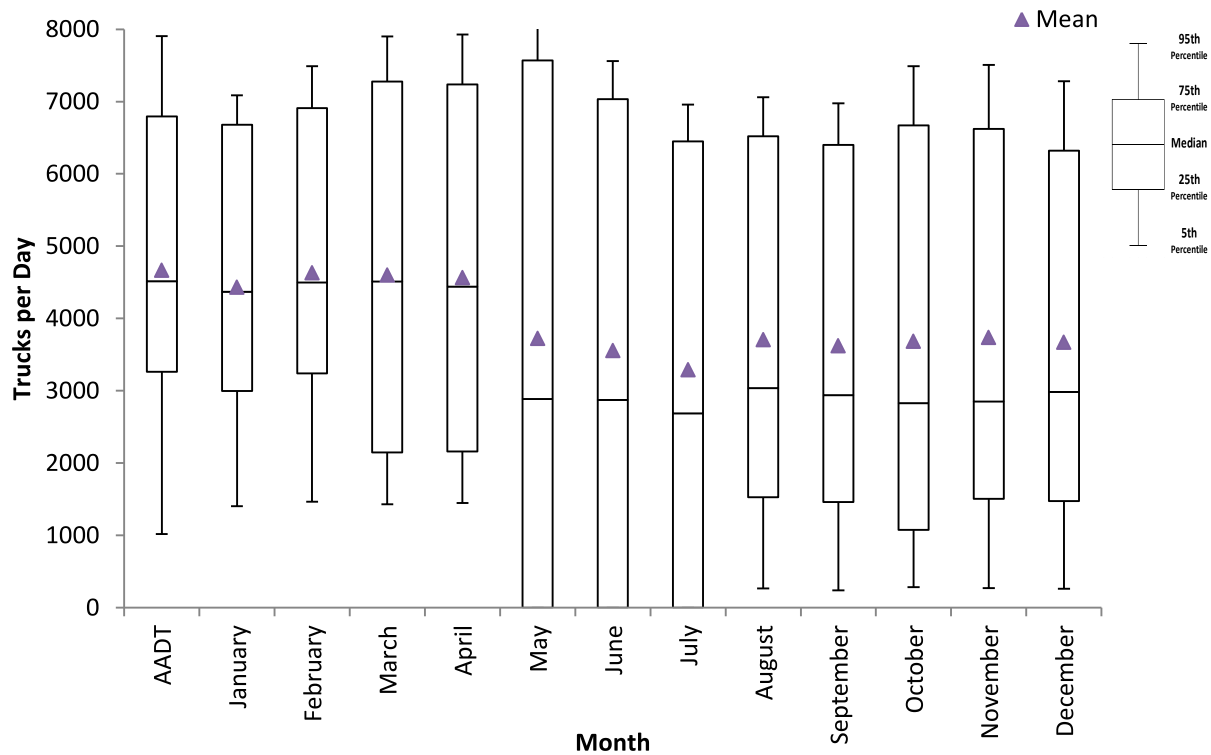


Figure D.18 Florida Truck Flows (Counts for Single-Unit Trucks) for Area Type: Undeveloped Rural Areas

D.2 Tractor-Trailer Trucks

Table D.6 Seasonality Analysis of Tractor-Trailer Trucks by Facility Type

FTYPE	Total Sites	AADT	Summer	Autumn	Winter	Spring	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
11	8	4670	4194	4360	5262	5237	5065	5294	5258	5217	5958	5691	5265	4238	4144	4213	4272	4195
12	40	6129	5957	6147	5929	6288	5762	6224	6390	6281	5995	6138	5824	5965	5906	6214	5860	5646
16	2	2477	2474	2565	2318	2453	1883	2465	2502	2482	2390	2545	2502	2506	2417	2587	2524	2395
21	85	748	752	741	756	831	730	767	817	860	833	757	757	747	766	793	754	713
23	5	1000	969	1032	1349	1086	1081	1354	1425	1123	1080	1033	971	969	945	842	1017	945
24	1	374	406	362	320	423	301	318	368	440	404	432	413	398	399	388	348	317
31	77	319	307	304	299	354	288	294	322	363	359	329	306	302	298	309	302	290
33	1	223	242	214	187	246	176	195	216	247	246	260	256	235	221	228	211	179
41	2	561	576	549	536	591	519	543	558	599	592	603	573	588	544	573	543	500
46	7	782	768	762	784	829	743	781	867	843	818	811	768	766	754	777	737	713
83	4	6883	6690	7039	6848	6886	6704	6941	6964	6104	5779	6865	6624	6746	6632	7929	7023	7594
91	9	2918	2872	2983	2998	3301	2799	3066	3179	3355	3019	3320	3118	2804	2807	2898	2840	2855
92	10	1873	1845	1816	1640	1930	1571	1157	1434	1853	1862	1957	1830	1843	1829	1920	1865	1731
93	1	1255	1217	1239	1227	1368	1176	1246	1315	1392	1350	1320	1225	1197	1217	1256	1215	1170



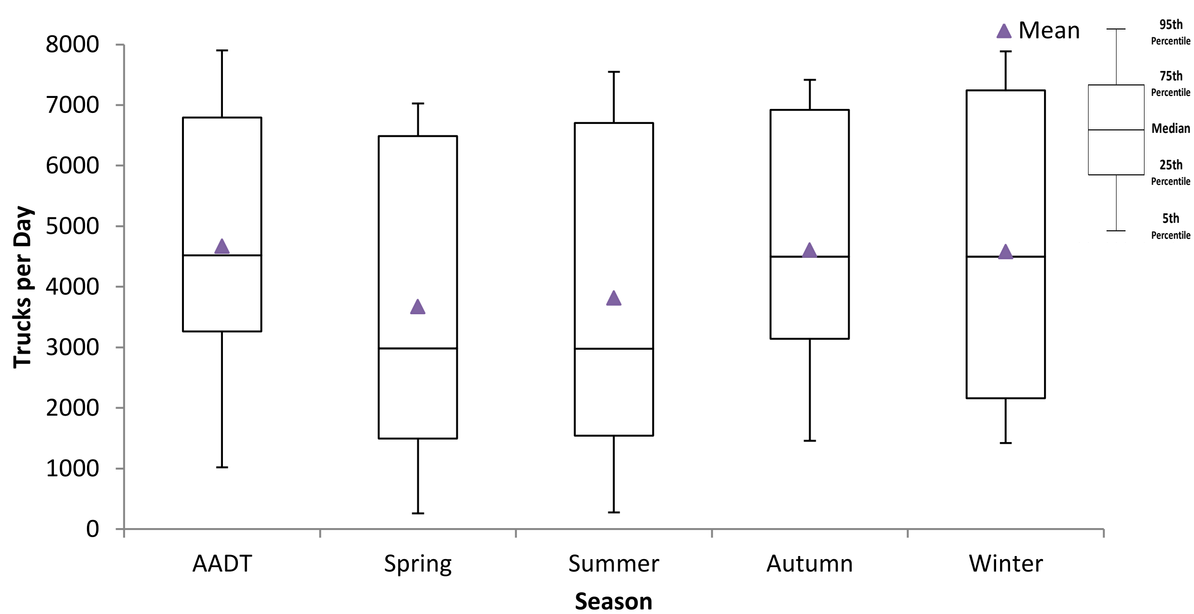
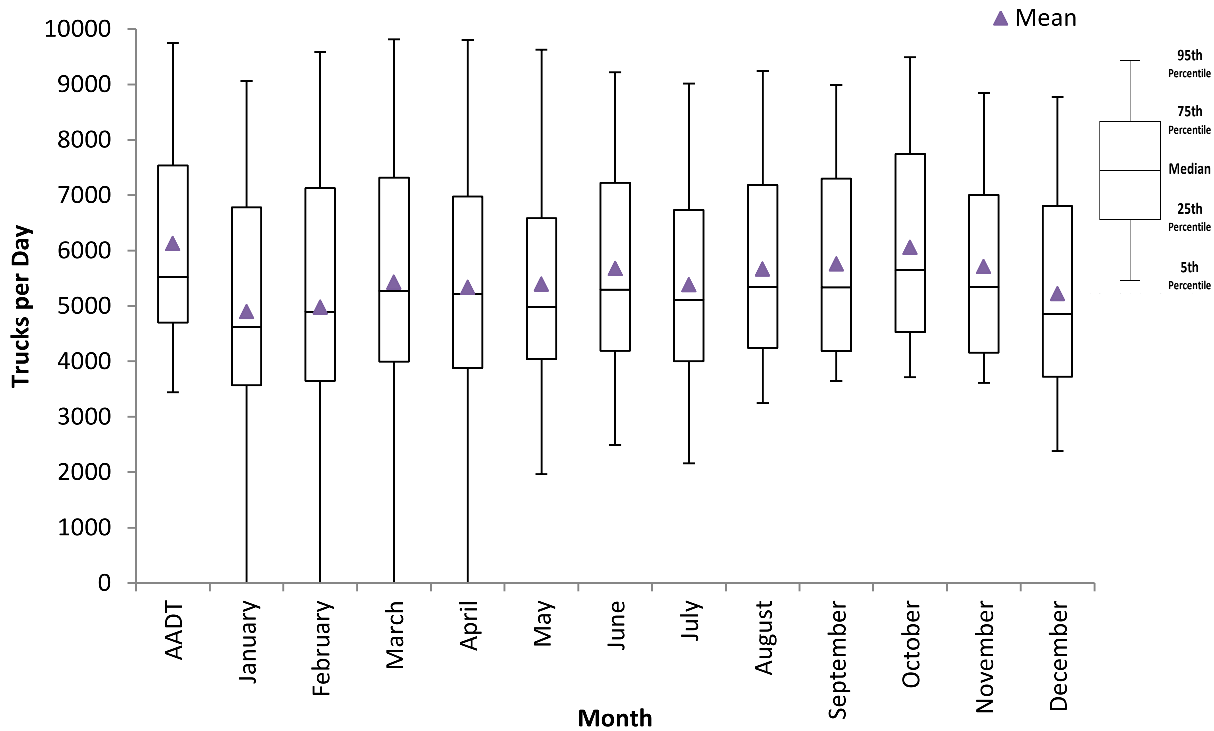


Figure D.19 Florida Truck Flows (Counts for Tractor-Trailer Trucks) for Facility Type: Urban Freeway Group 1



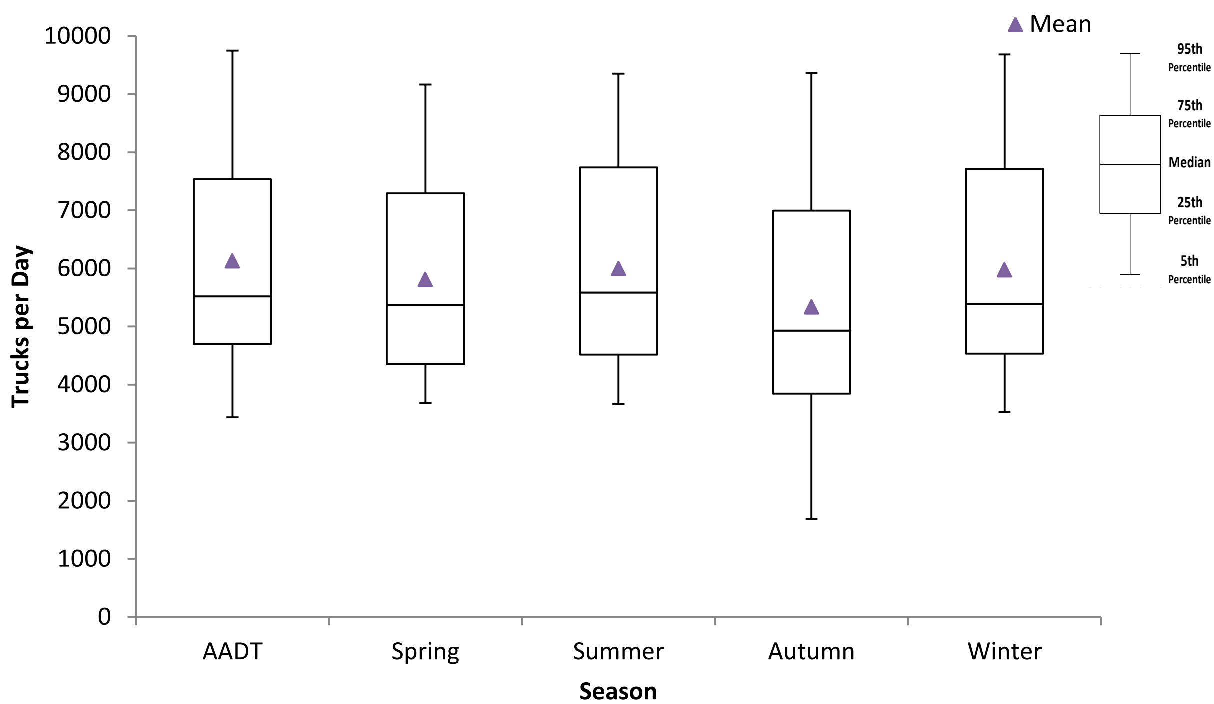
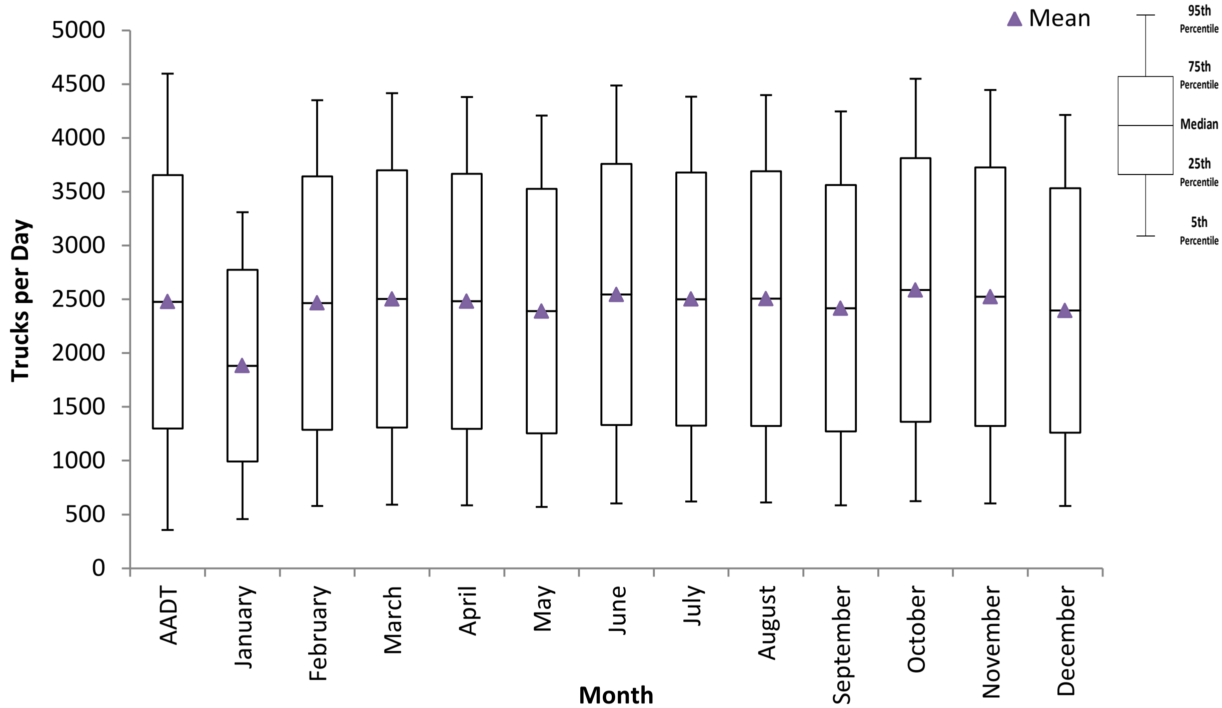


Figure D.20 Florida Truck Flows (Counts for Tractor-Trailer Trucks) for Facility Type: Other Freeway



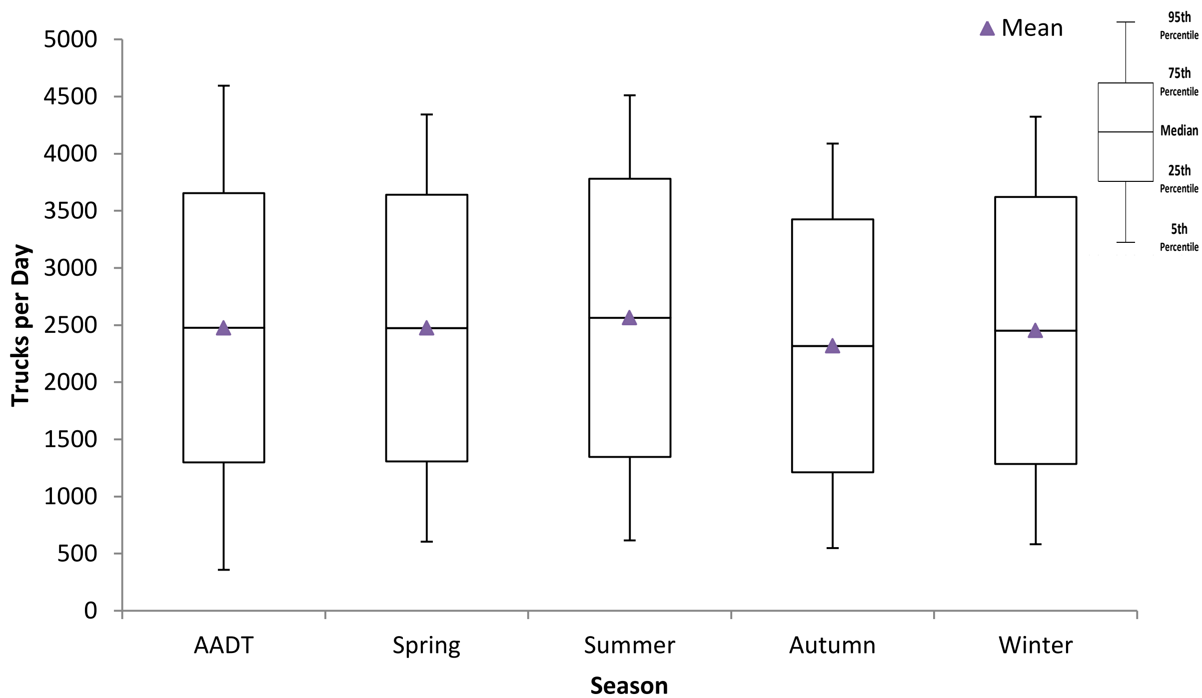
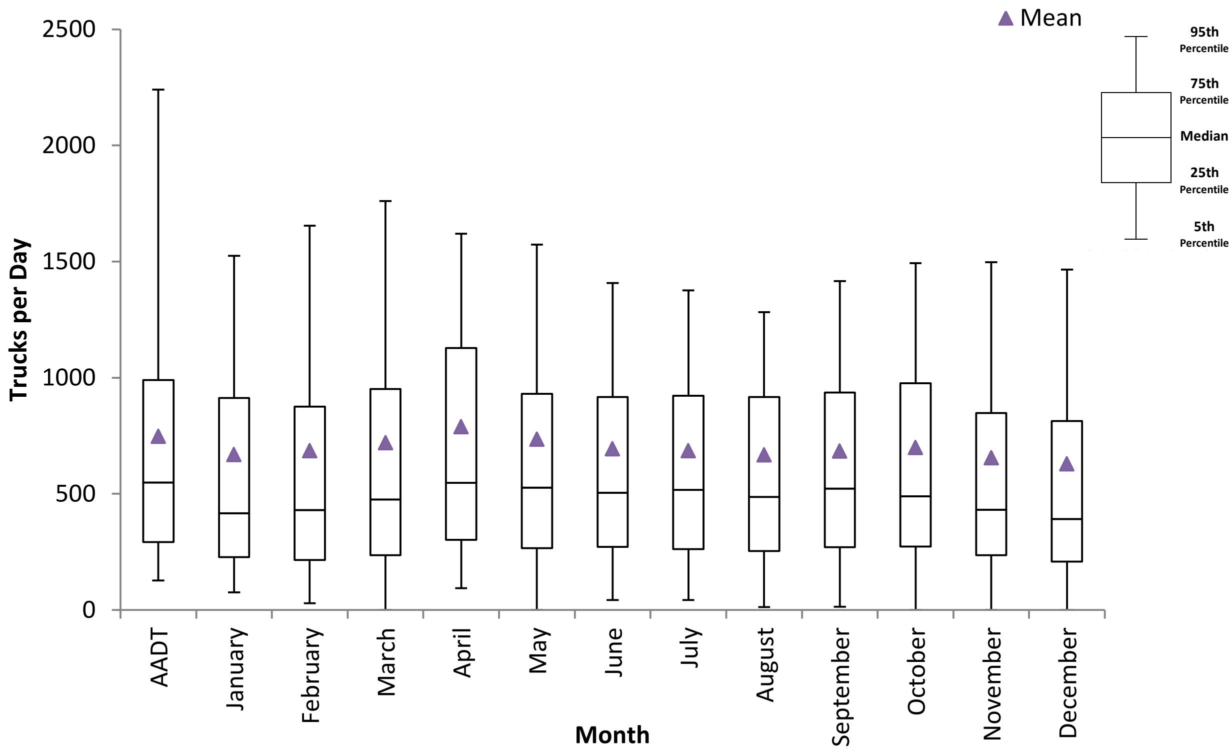


Figure D.21 Florida Truck Flows (Counts for Tractor-Trailer Trucks) for Facility Type: Controlled Access Expressway



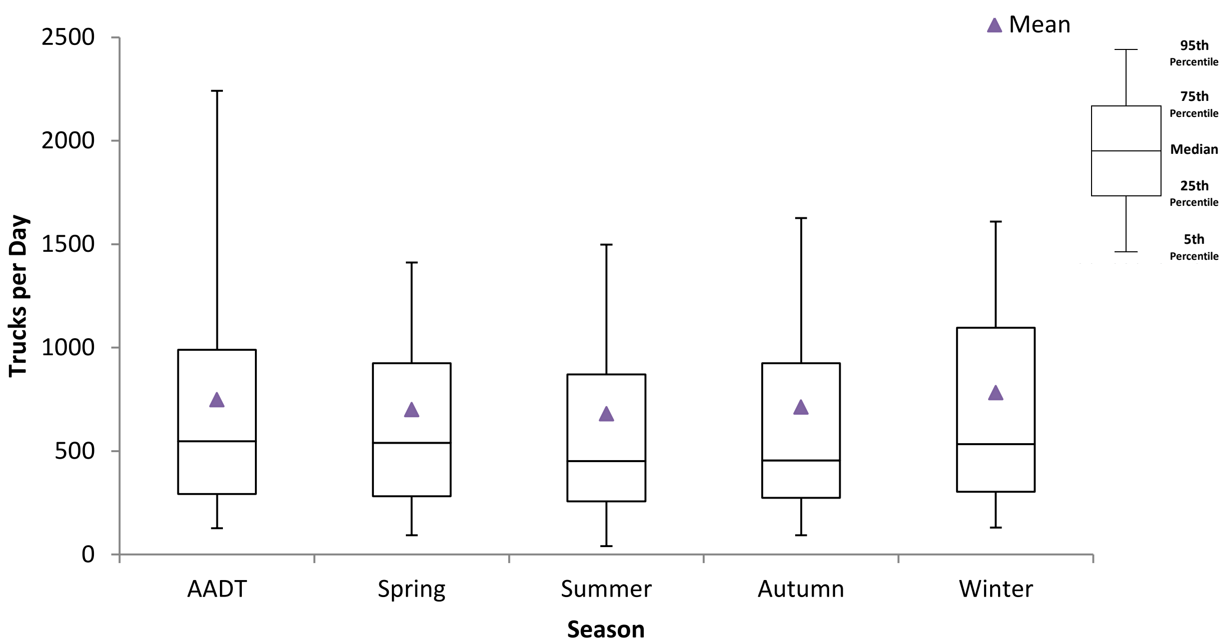
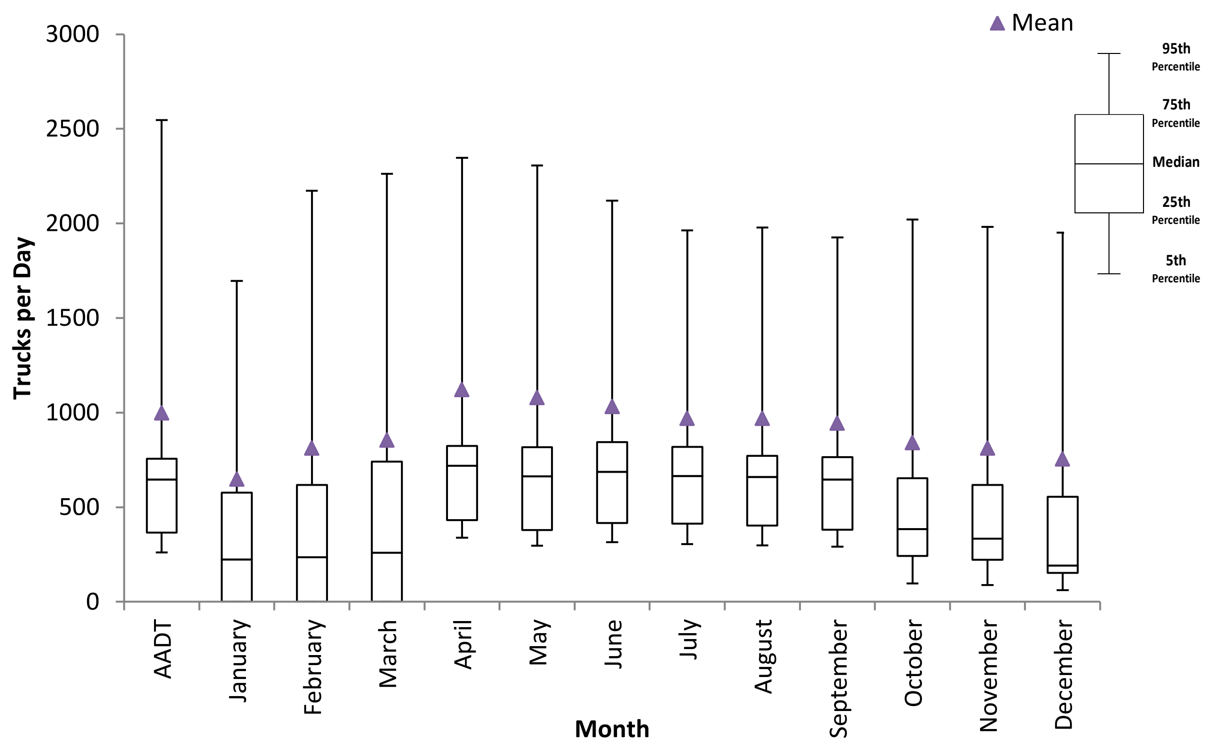


Figure D.22 Florida Truck Flows (Counts for Tractor-Trailer Trucks) for Facility Type: Divided Arterial Unsignalized



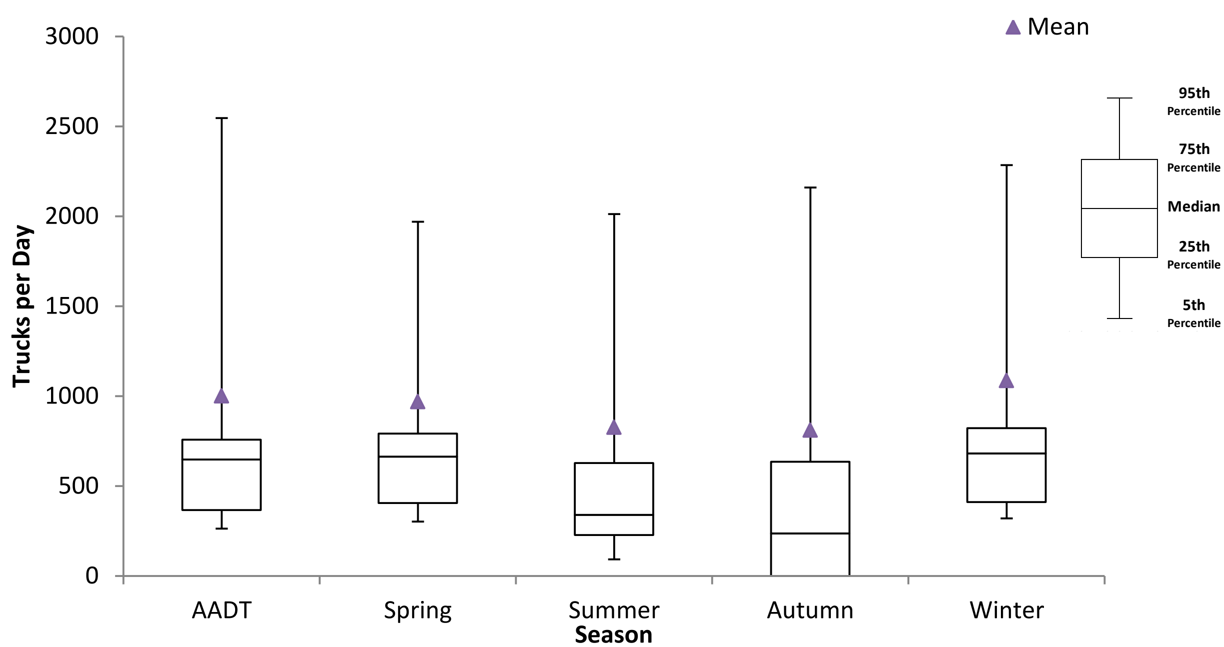
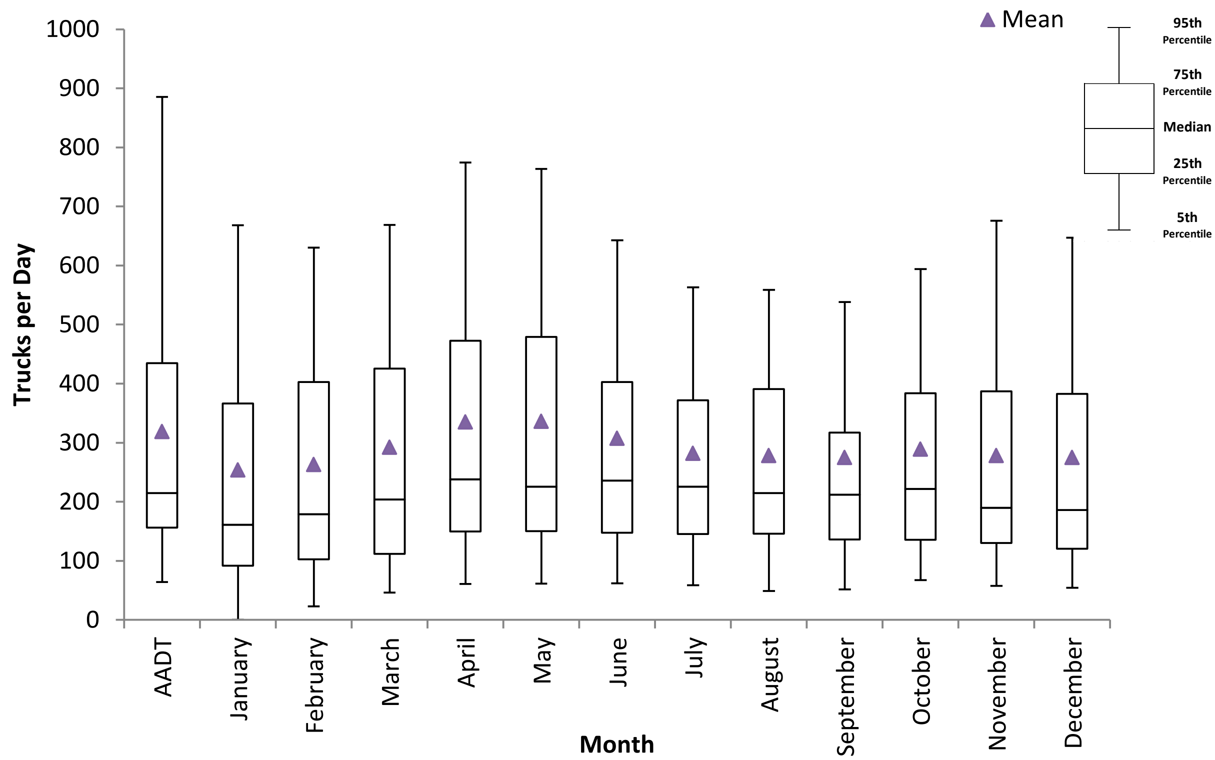


Figure D.23 Florida Truck Flows (Counts for Tractor-Trailer Trucks) for Facility Type: Divided Arterial Class 1a



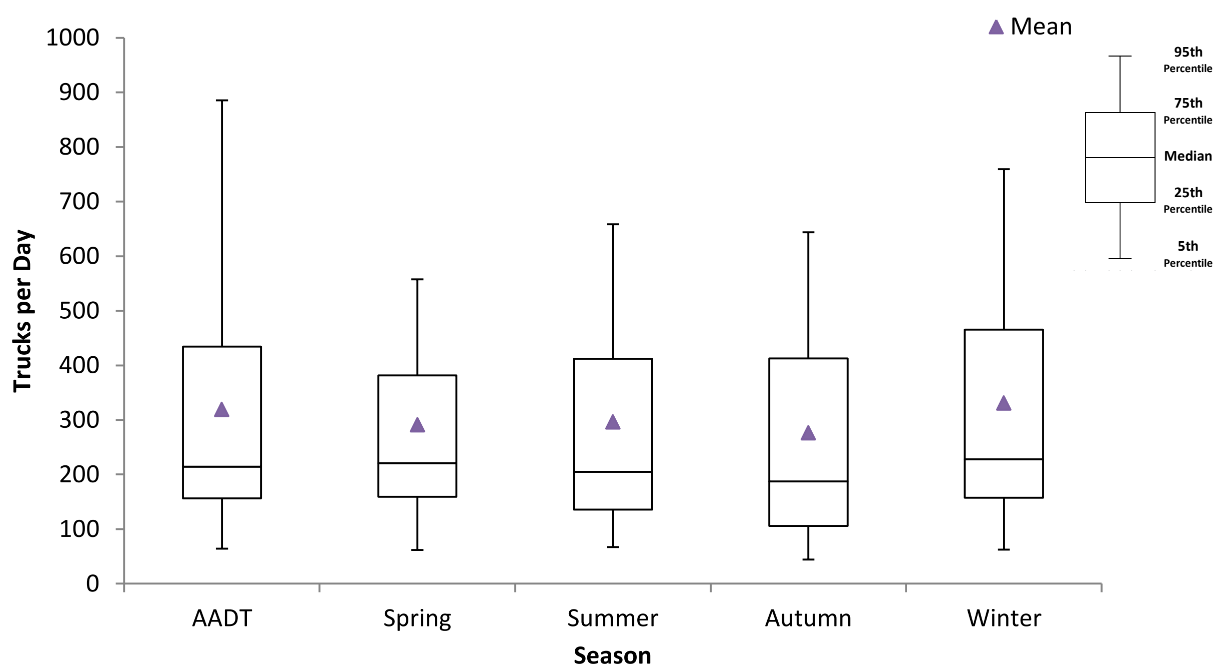
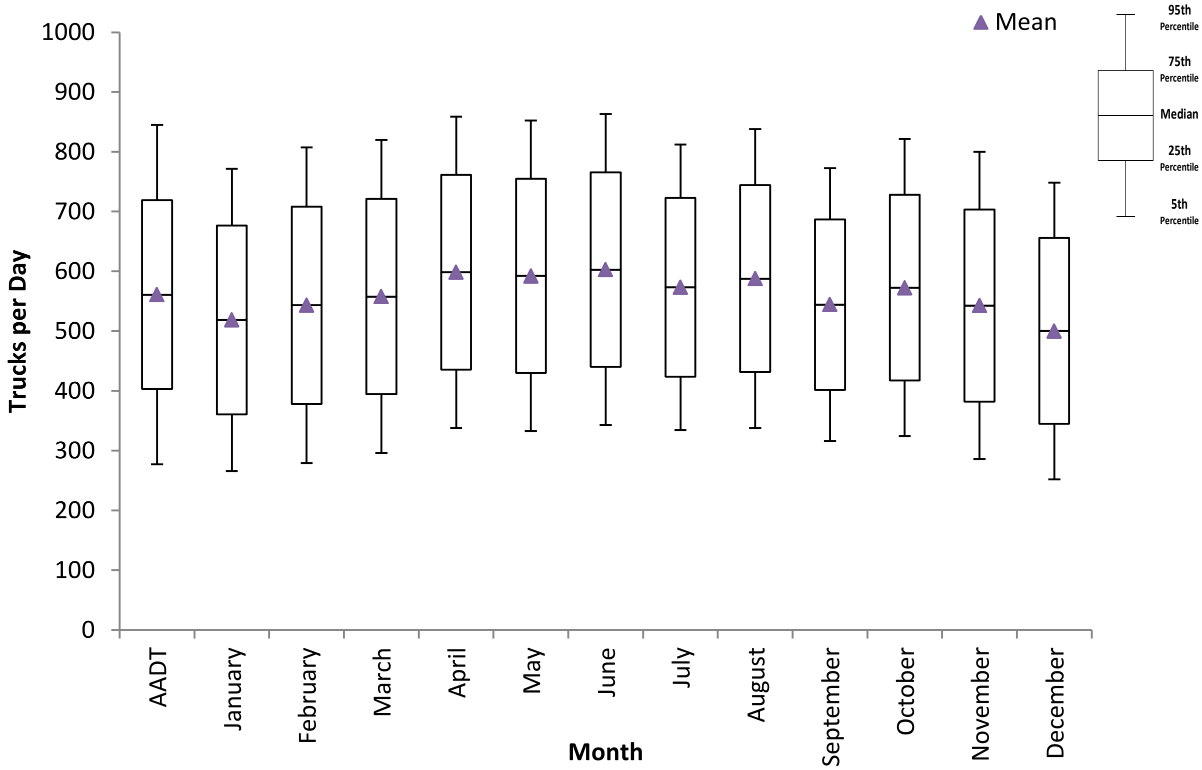


Figure D.24 Florida Truck Flows (Counts for Tractor-Trailer Trucks) for Facility Type: Undivided Arterial Unsignalized with Turn Bays



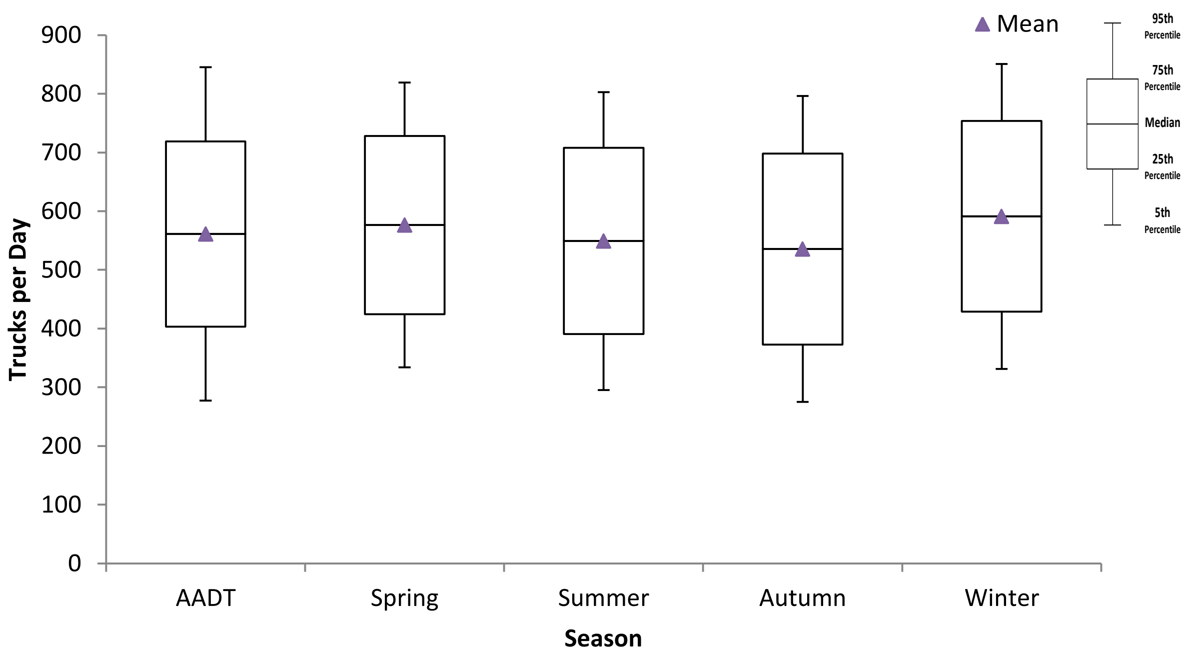
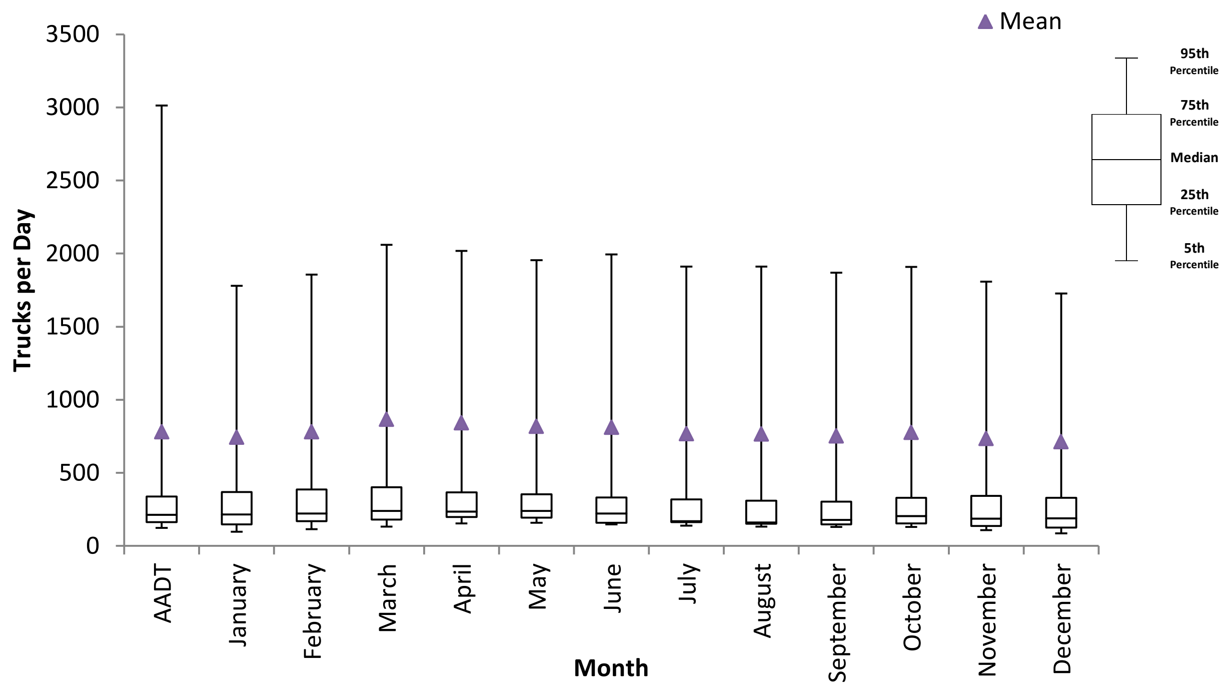


Figure D.25 Florida Truck Flows (Counts for Tractor-Trailer Trucks) for Facility Type: Major Local Divided Roadway



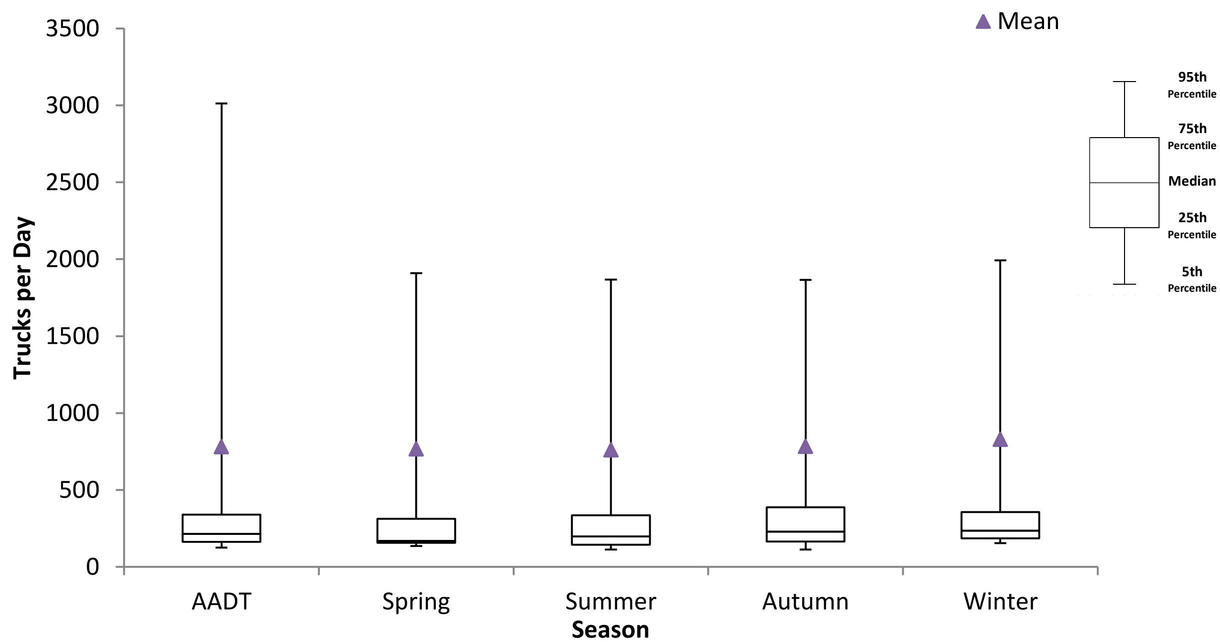
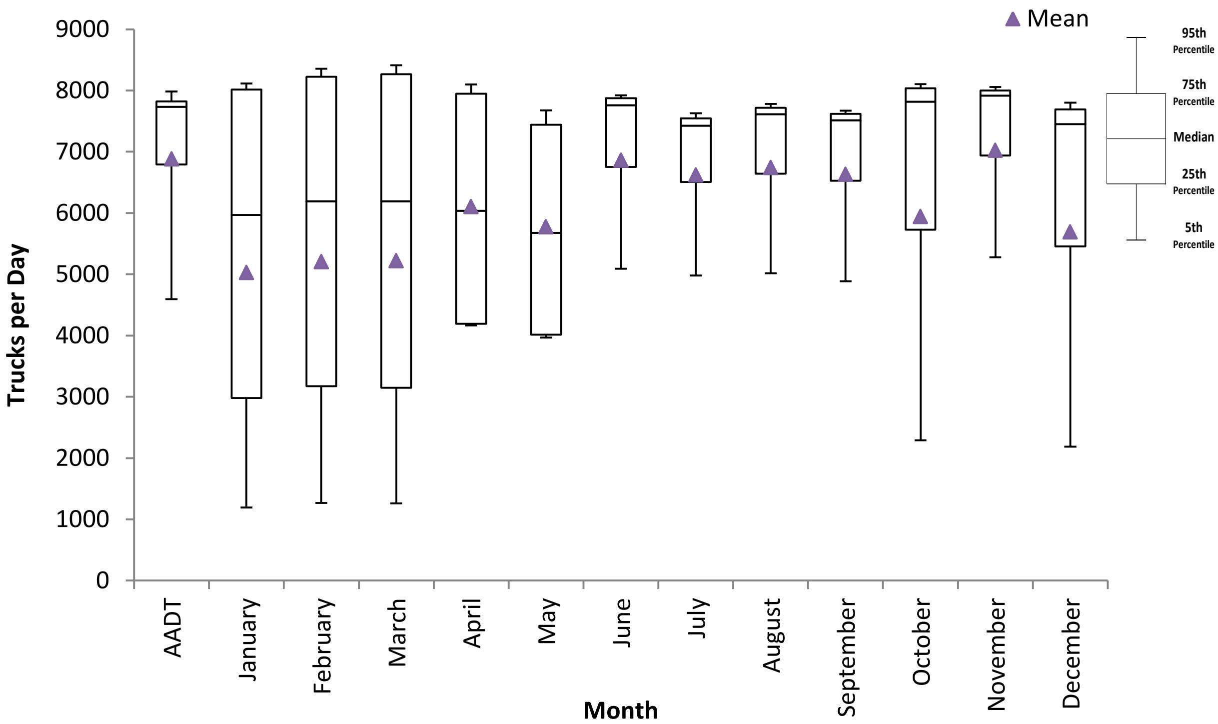


Figure D.26 Florida Truck Flows (Counts for Tractor-Trailer Trucks) for Facility Type: Other Local Undivided Roadway without Turn Bays



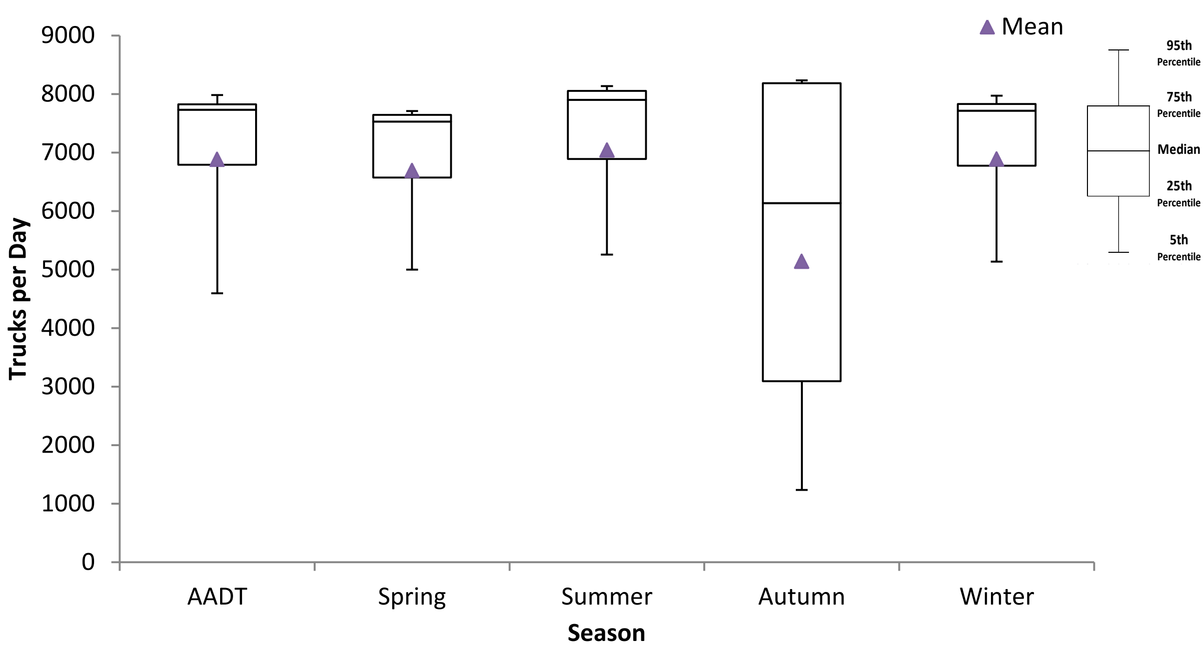
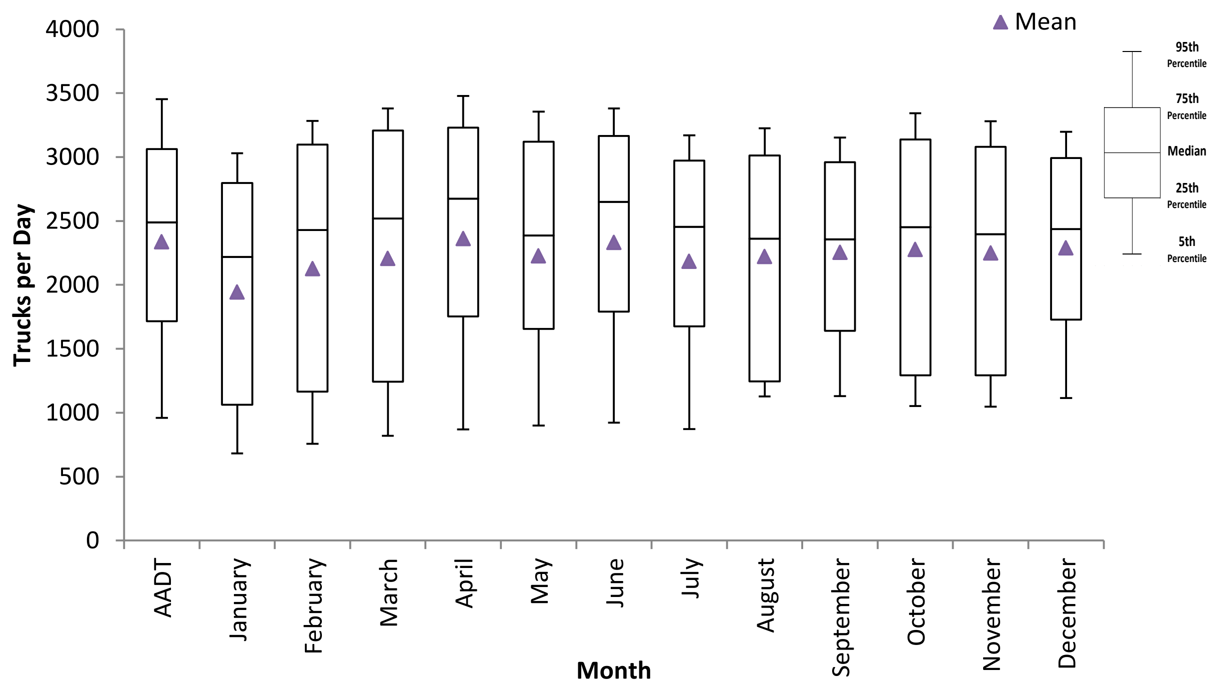


Figure D.27 Florida Truck Flows (Counts for Tractor-Trailer Trucks) for Facility Type: Freeway Group 1 HOV Lane



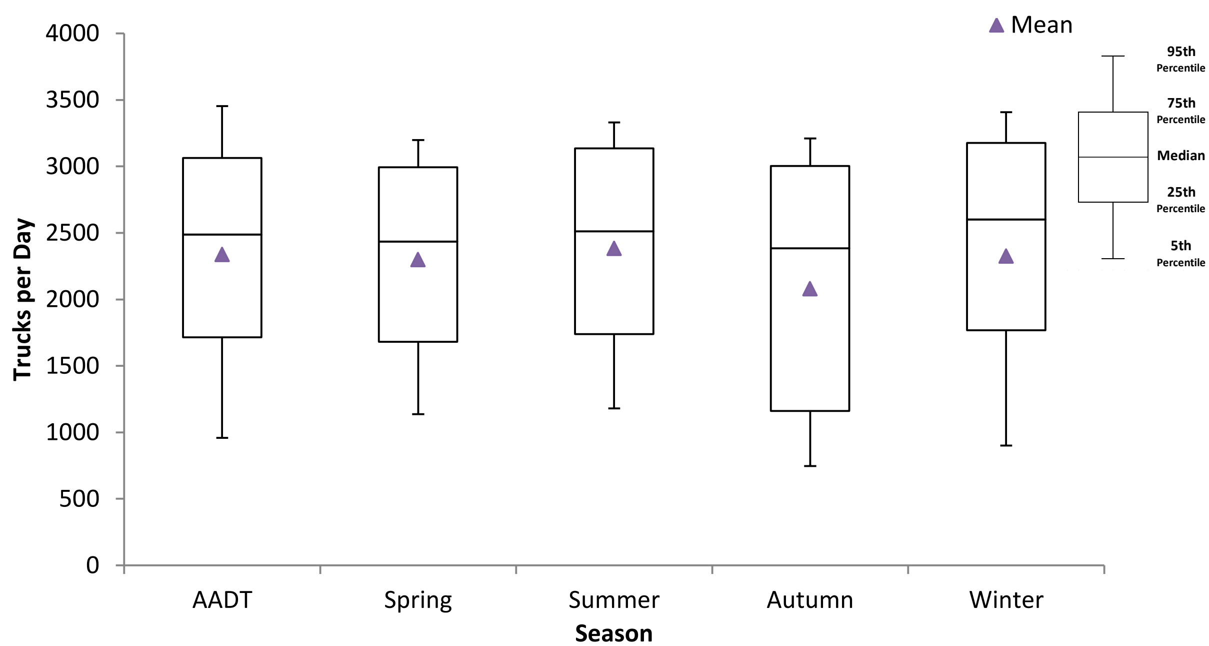
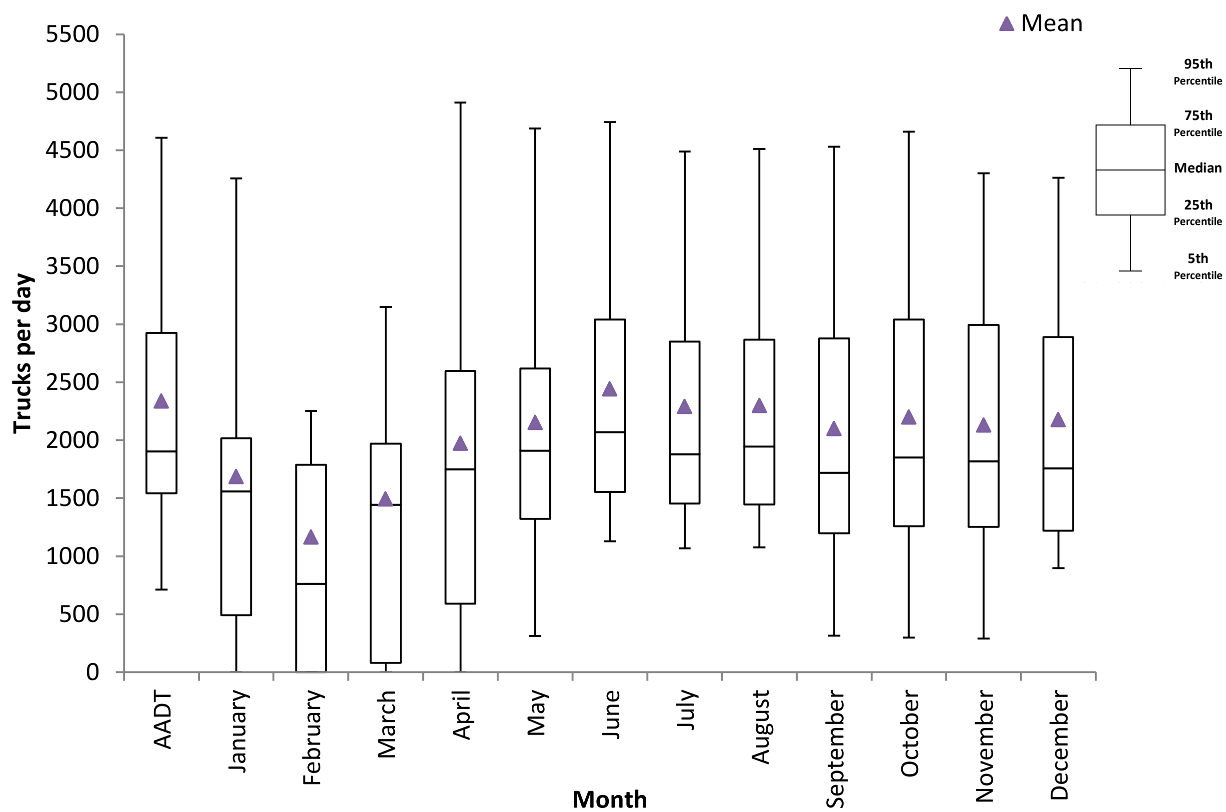


Figure D.28 Florida Truck Flows (Counts for Tractor-Trailer Trucks) for Facility Type: Freeway Group 1 Toll Facility



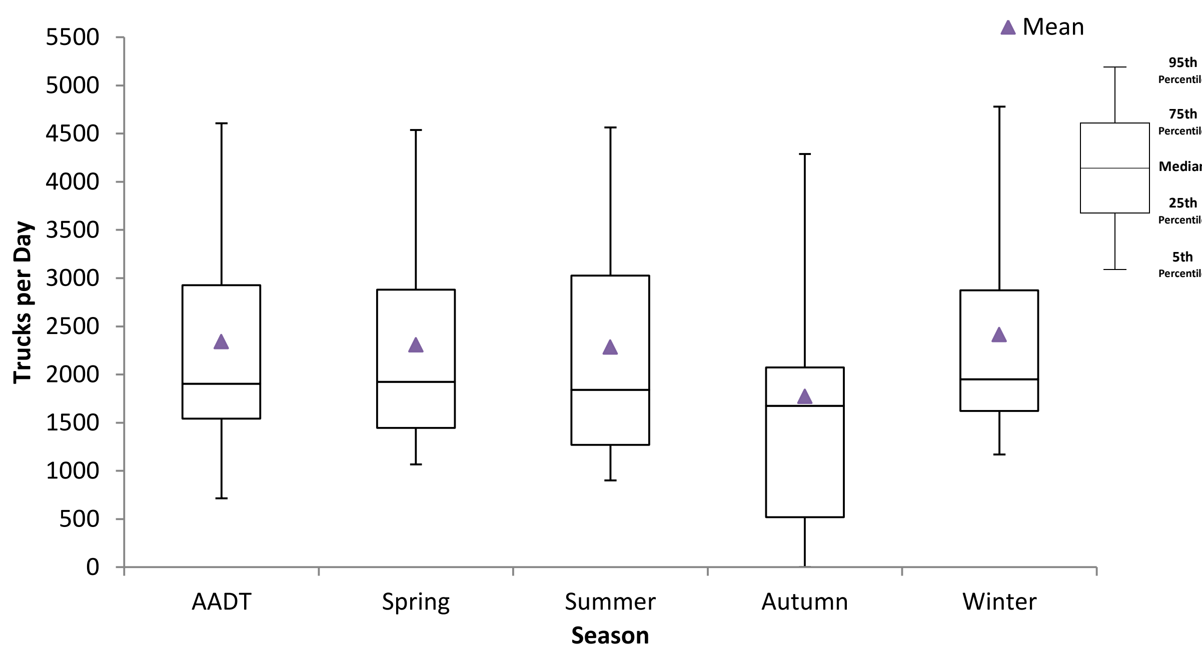


Figure D.29 Florida Truck Flows (Counts for Tractor-Trailer Trucks) for Facility Type: Other Freeway Toll Facility

Table D.7 Seasonality Analysis of Tractor-Trailer Trucks by Area Type

ATYPE	Total Sites	AADT	Summer	Autumn	Winter	Spring	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
12	1	7016	6561	7119	7019	7518	6675	7097	7491	7613	7529	7120	6509	6560	6505	7035	7148	6908
14	1	8384	8117	8553	8355	8751	8023	8405	8857	8664	8805	8586	8012	8226	8073	8547	8337	8150
21	3	2069	2115	2118	1859	1982	1778	1906	1933	1980	1257	1261	1177	2153	2077	1806	2032	2114
31	53	5140	4842	5092	5011	5109	4814	5271	5419	4905	4754	4767	4603	4737	4893	5250	4864	4555
32	6	630	639	584	839	1001	814	606	665	1037	948	977	950	643	613	618	564	525
33	23	522	486	453	535	594	501	473	523	624	533	540	498	507	496	486	453	425
34	1	287	282	283	282	307	275	288	289	303	313	306	283	277	272	292	290	259
41	1	1057	1068	1003	1064	1121	1042	1094	1068	1135	1074	1169	1034	1088	1071	1097	934	897
42	36	872	899	917	875	945	838	900	932	949	1022	874	928	901	912	973	1014	975
43	1	1188	1217	1169	1141	1248	1095	1157	1211	1255	1204	1320	1186	1214	1198	1209	1117	1088
51	17	767	745	676	764	773	683	5647	800	275	736	755	706	582	717	692	661	627
52	109	961	972	985	865	1048	853	853	909	1012	990	1053	991	1007	968	961	982	912

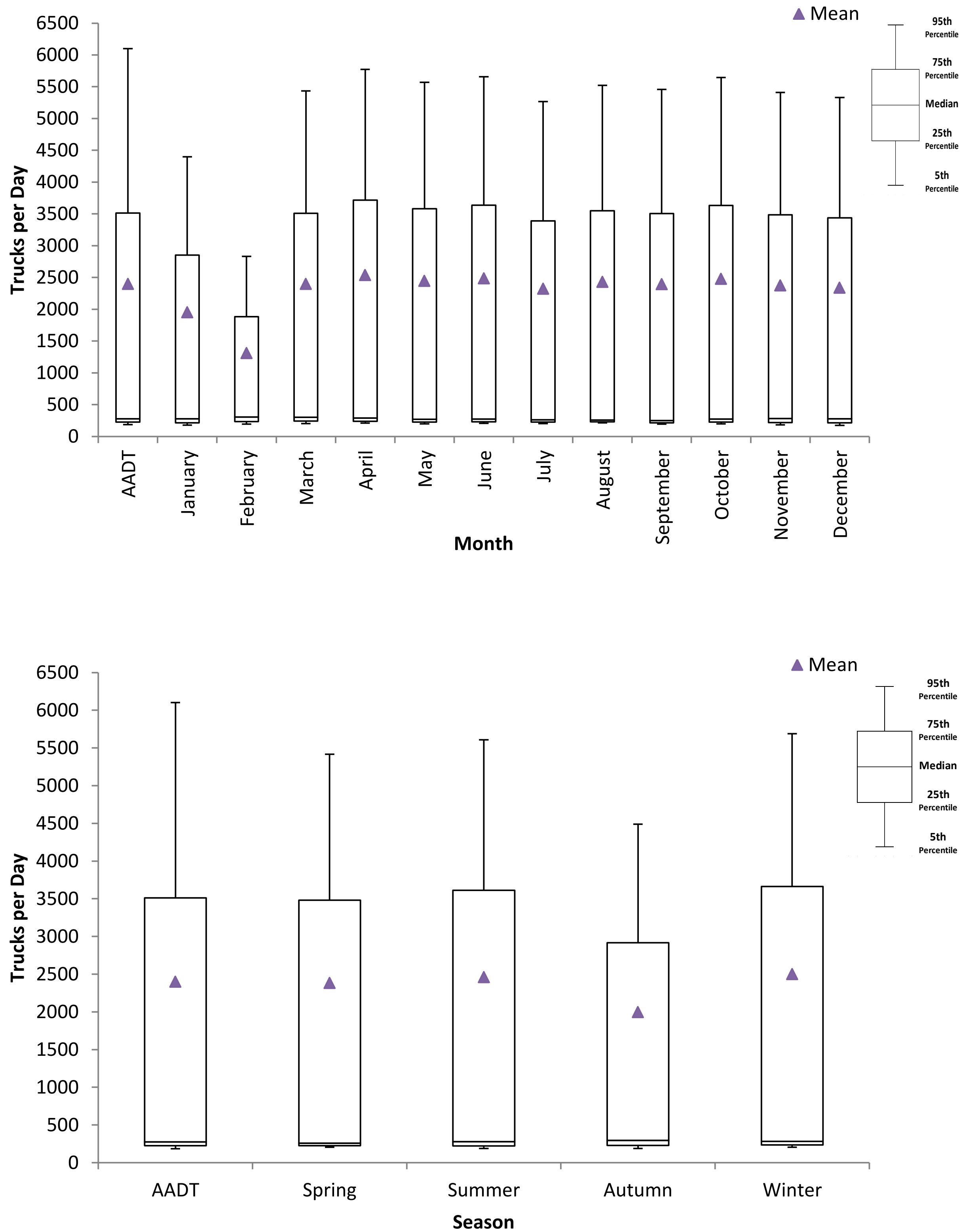
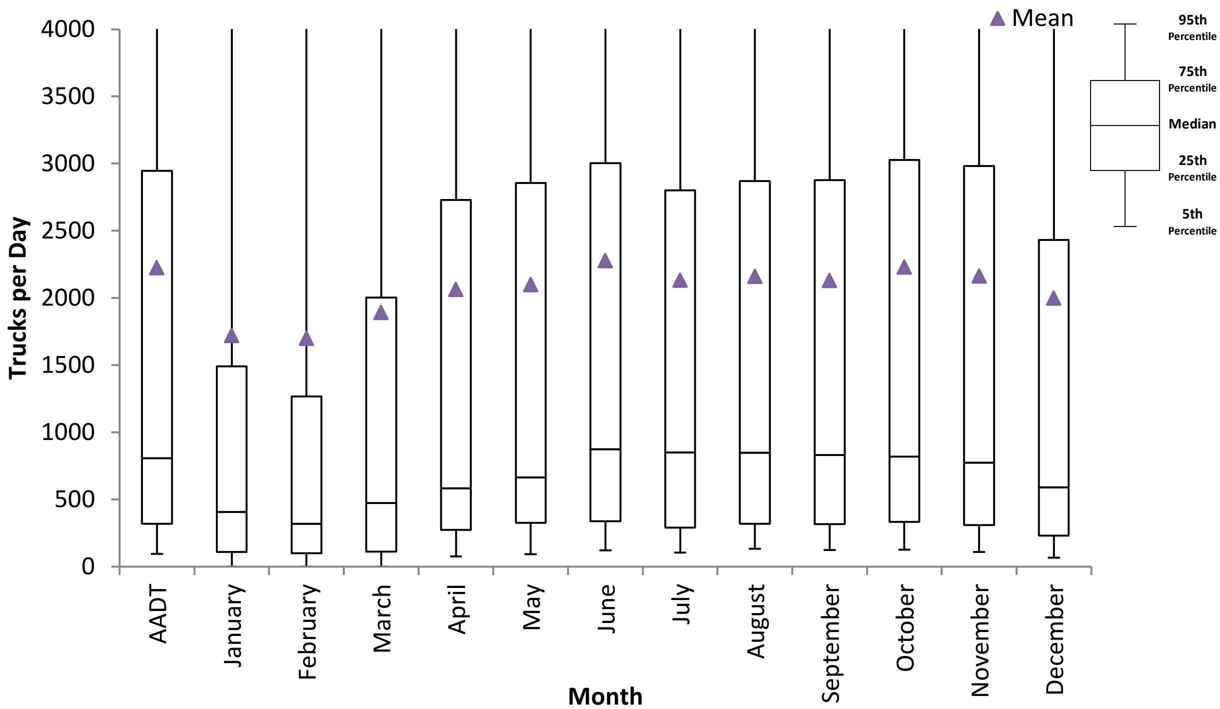


Figure D.30 Florida Truck Flows (Counts for Tractor-Trailer Trucks) for Area Type: Central Business District



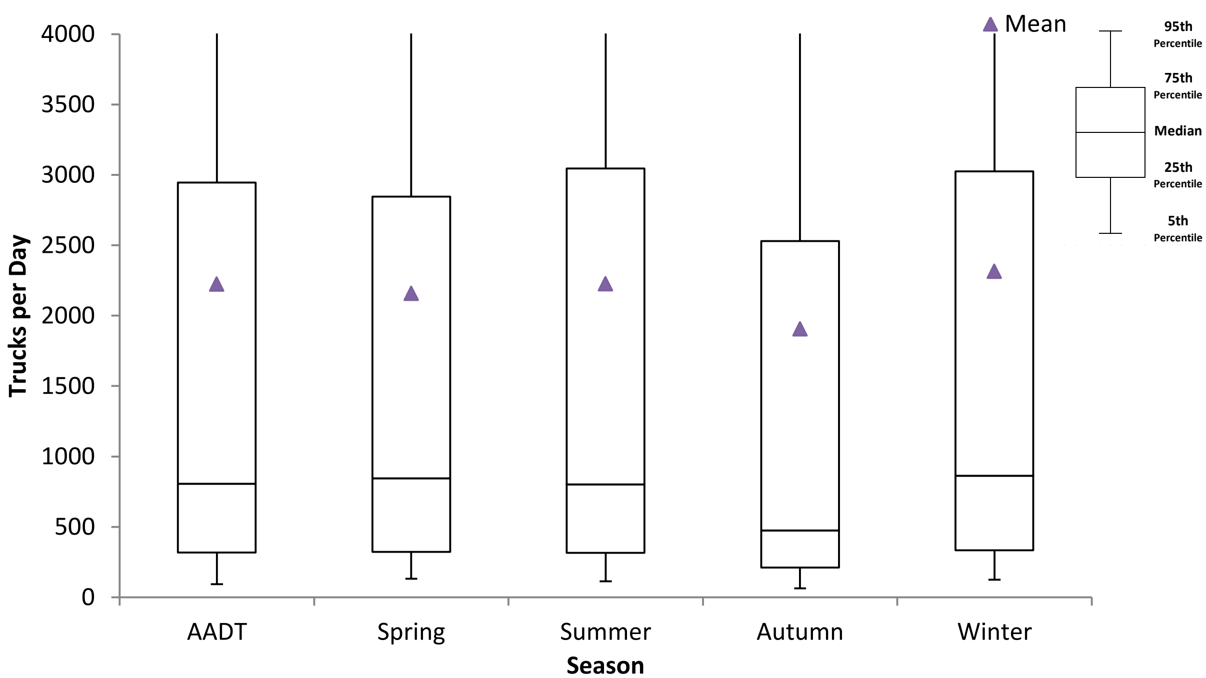
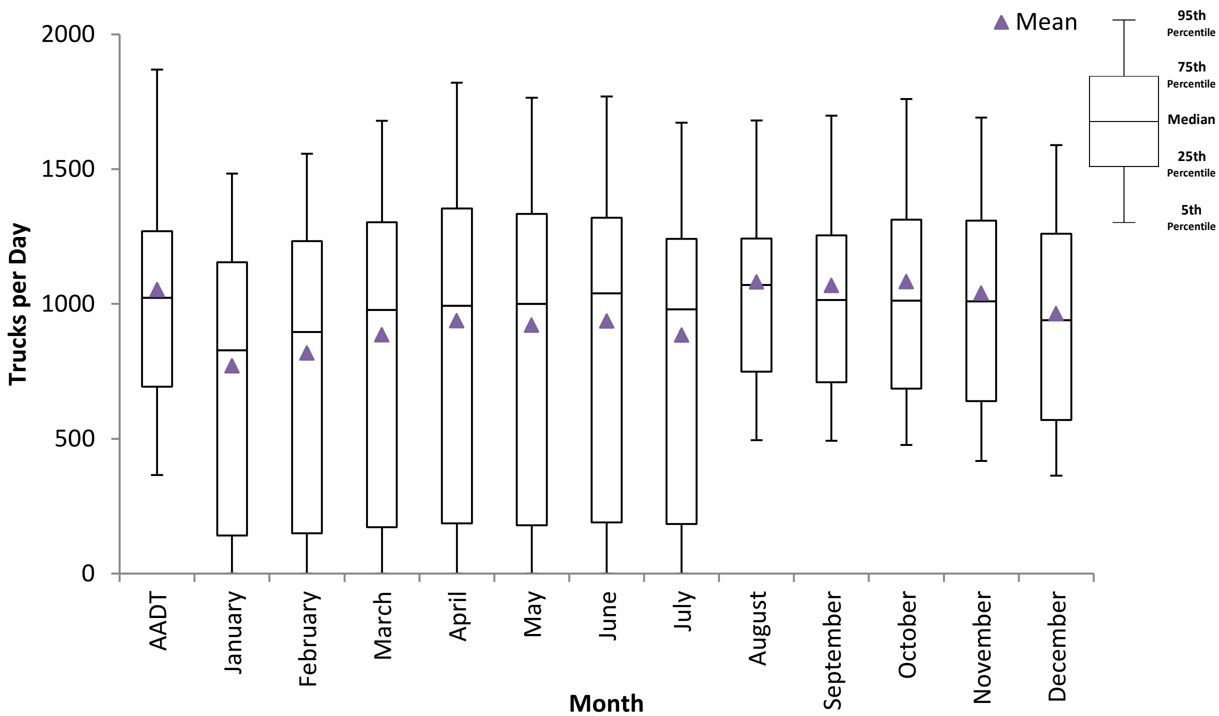


Figure D.31 Florida Truck Flows (Counts for Tractor-Trailer Trucks) for Area Type: Residential Areas of Urbanized Areas



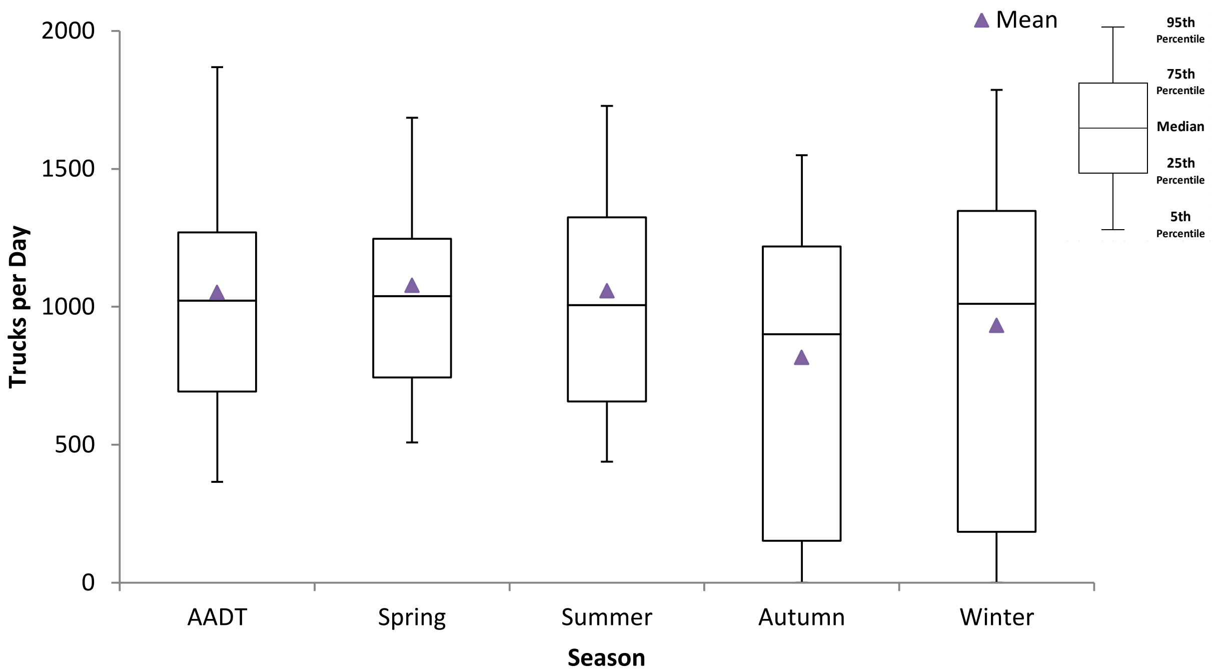
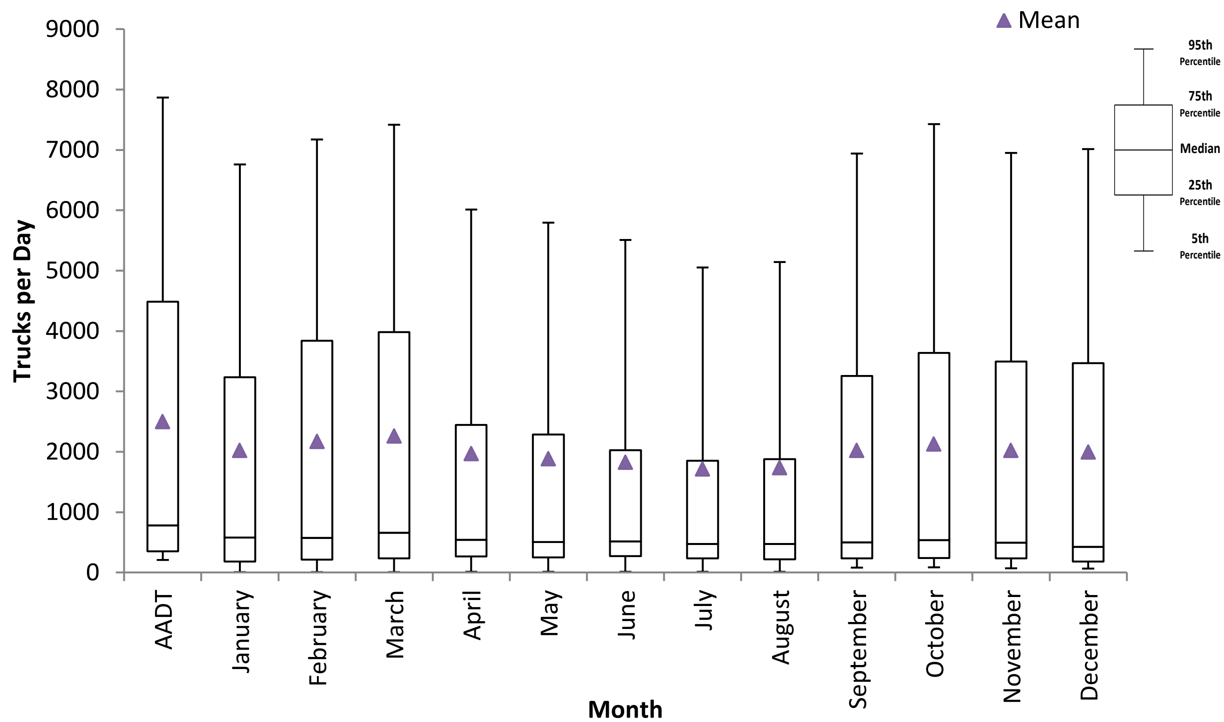


Figure D.32 Florida Truck Flows (Counts for Tractor-Trailer Trucks) for Area Type: Undeveloped Portions of Urbanized Areas



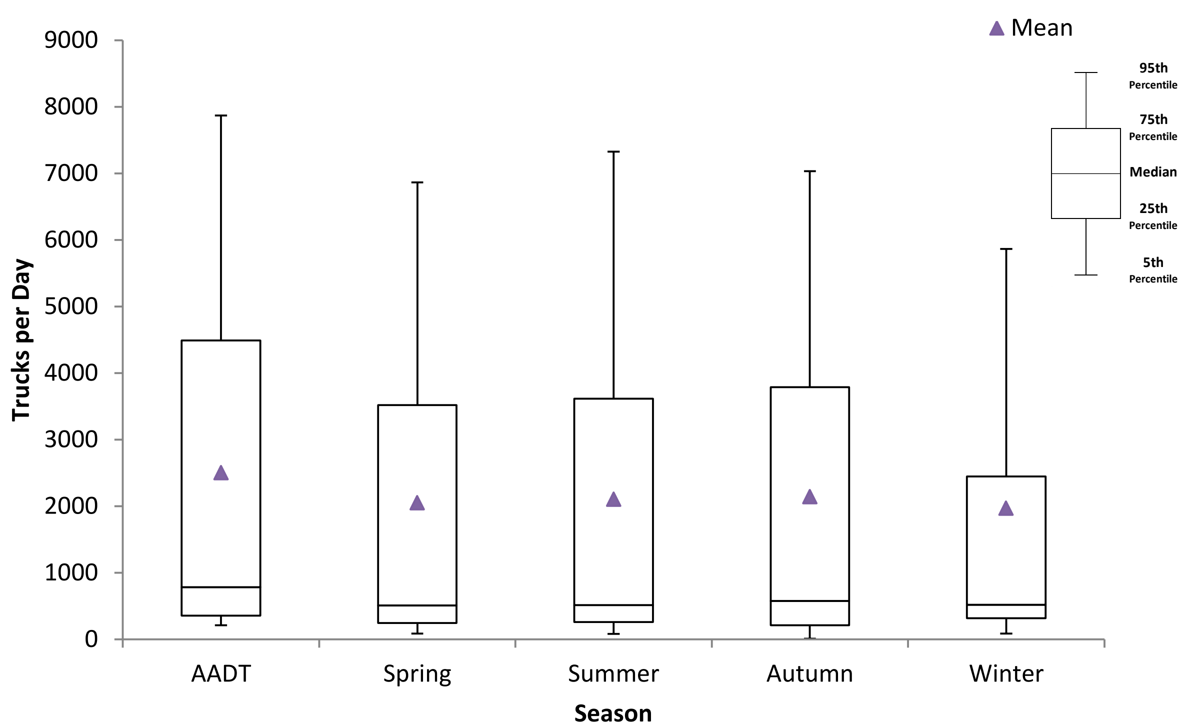
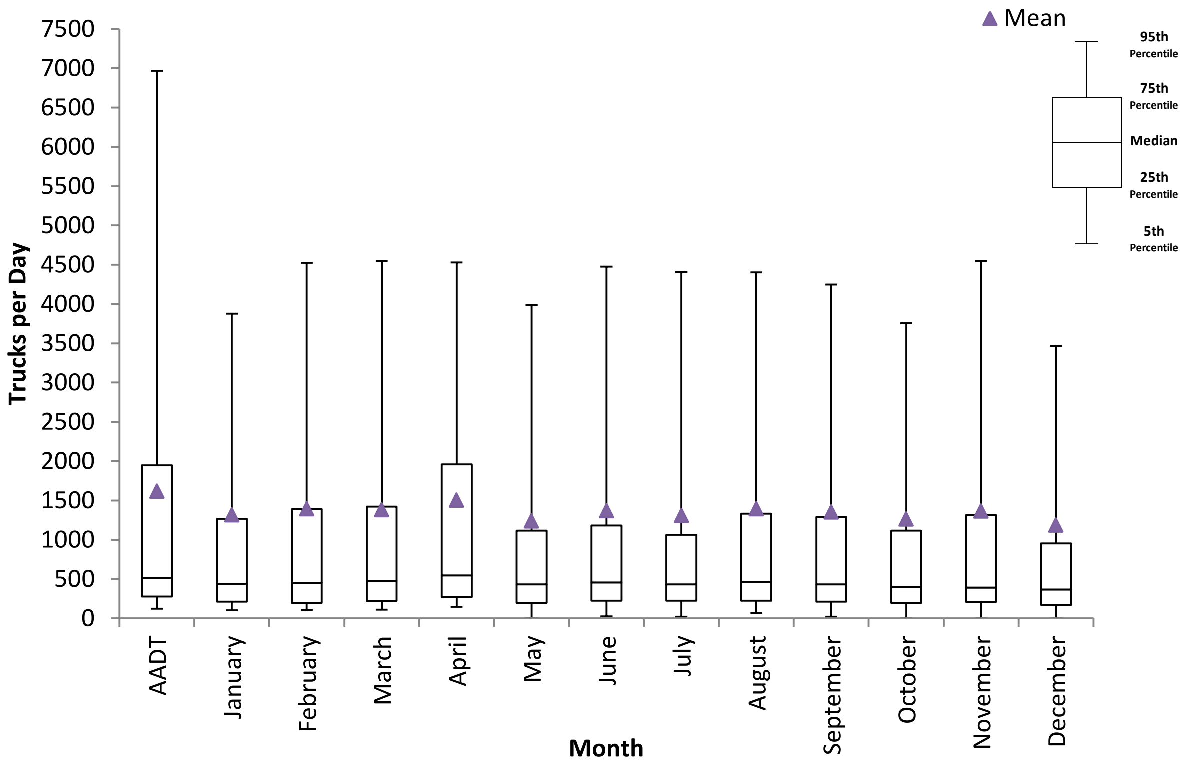


Figure D.33 Florida Truck Flows (Counts for Tractor-Trailer Trucks) for Area Type: Transitioning Areas/Urban Areas over 5,000 Population



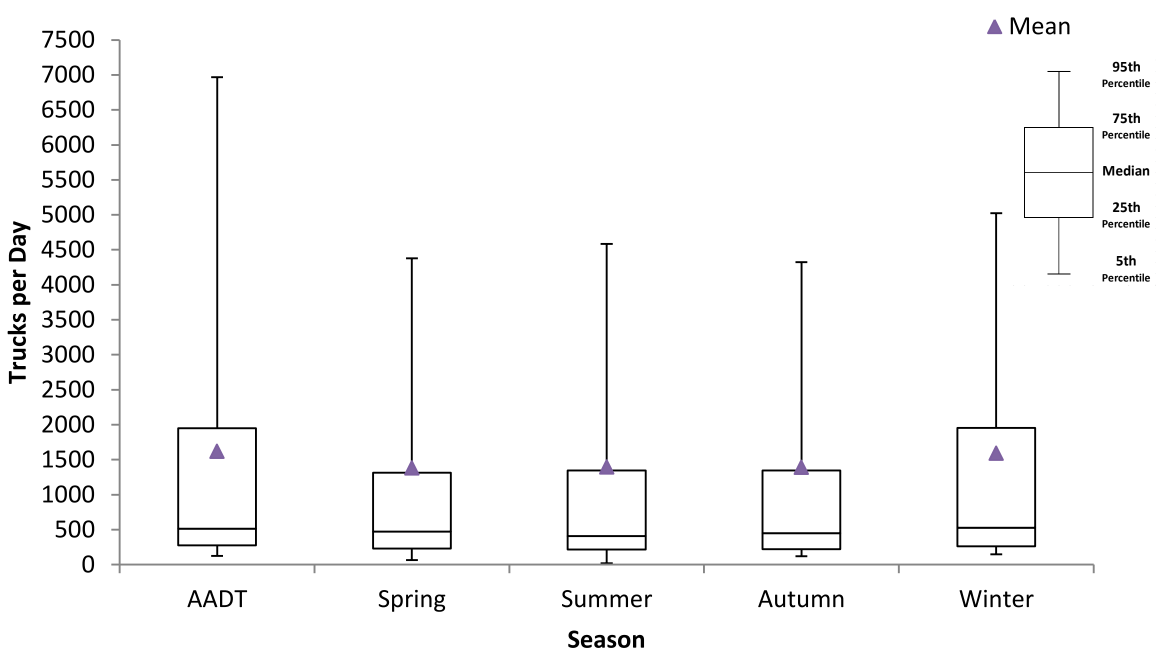
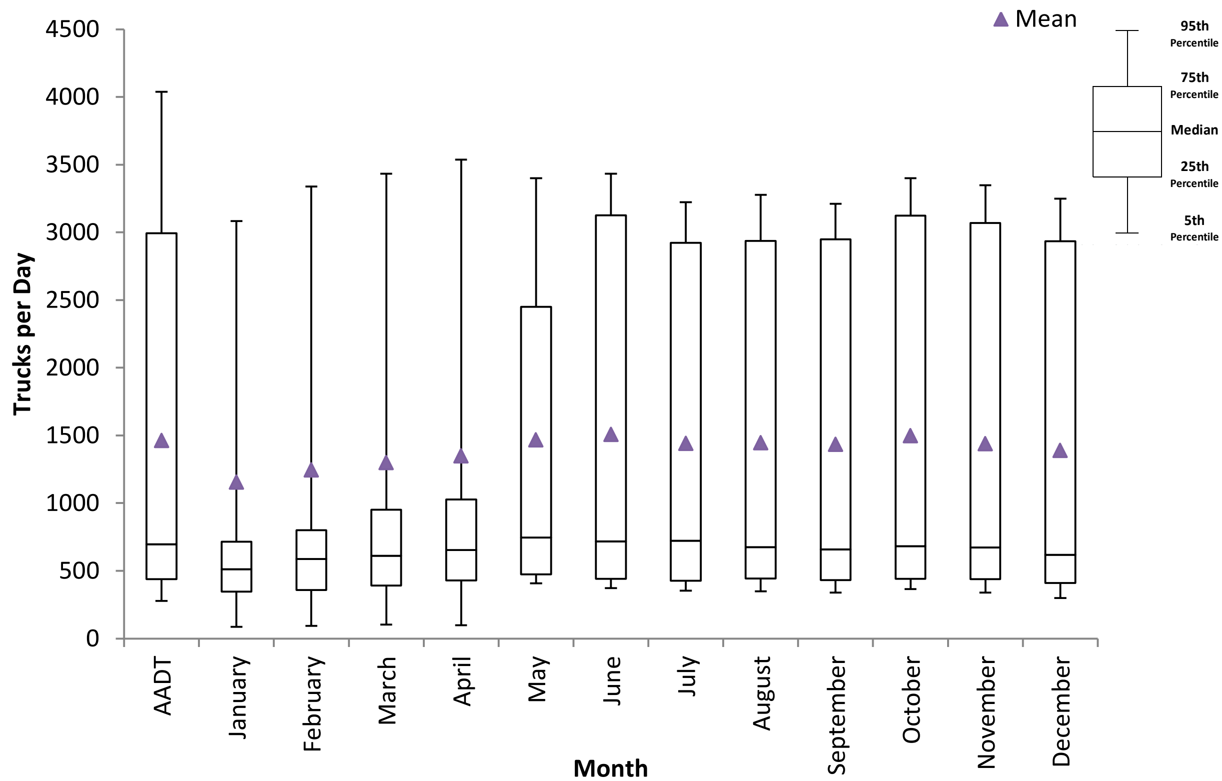


Figure D.34 Florida Truck Flows (Counts for Tractor-Trailer Trucks) for Area Type: Other Outlying Business District



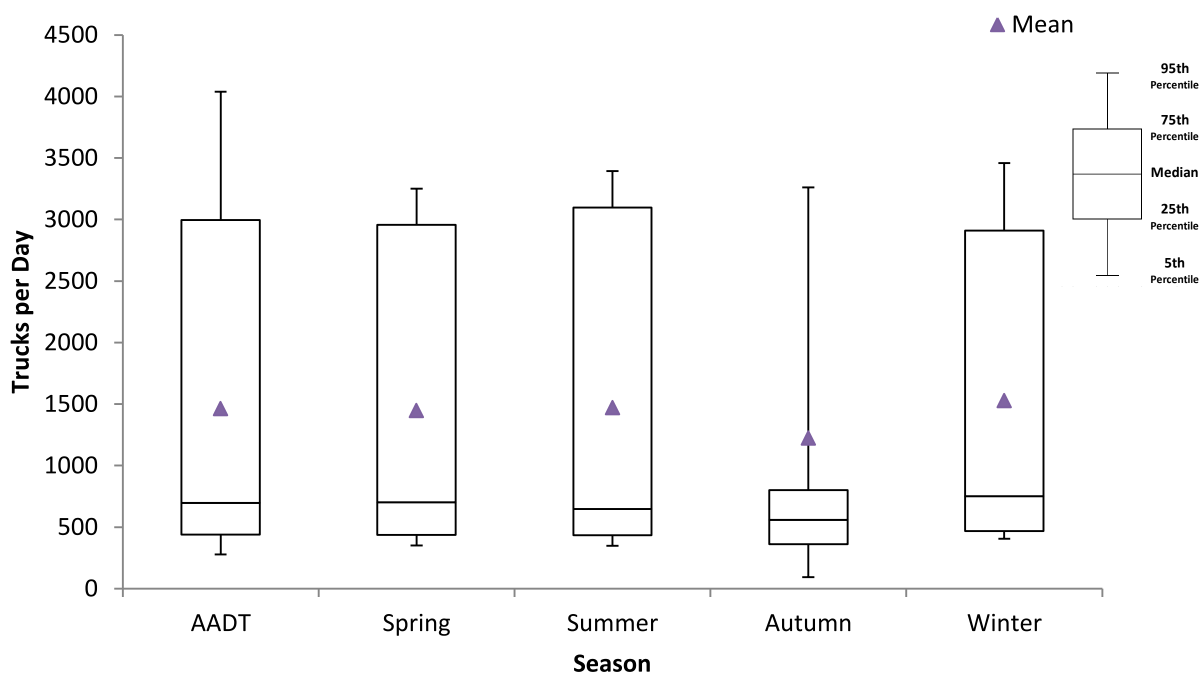
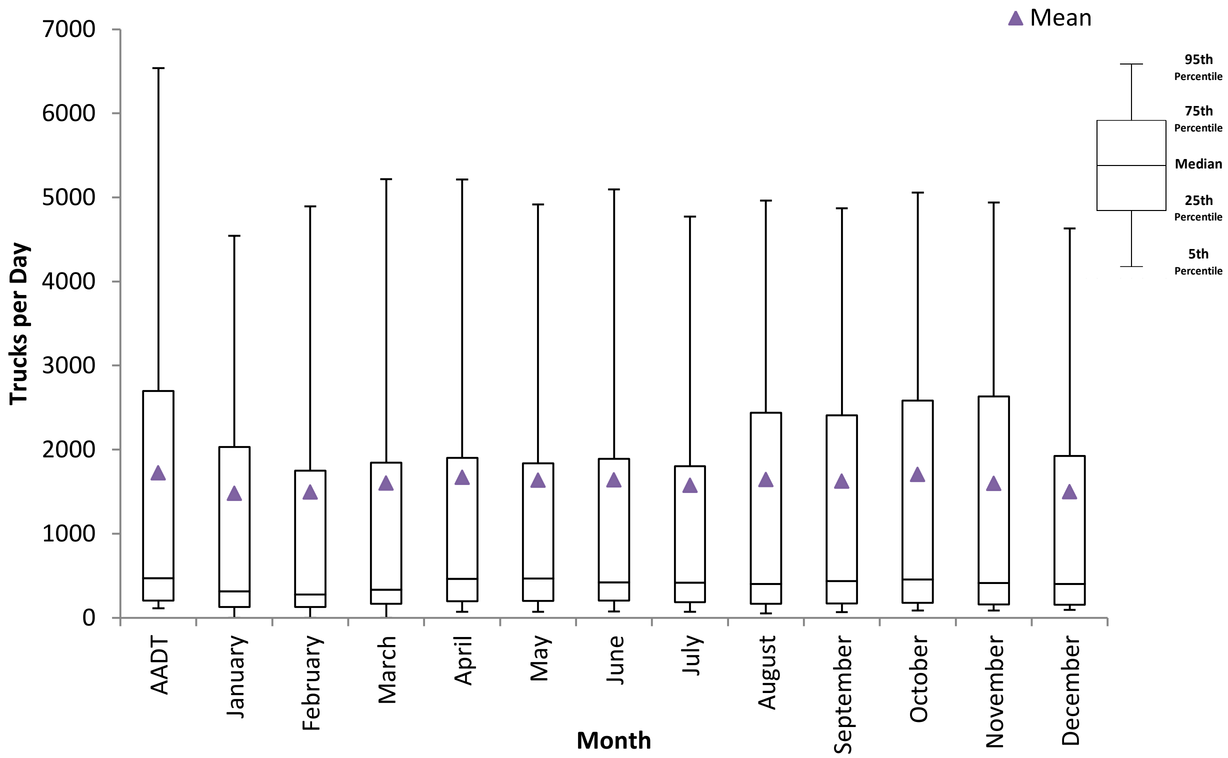


Figure D. 35 Florida Truck Flows (Counts for Tractor-Trailer Trucks) for Area Type: Developed Rural Areas/Small Cities



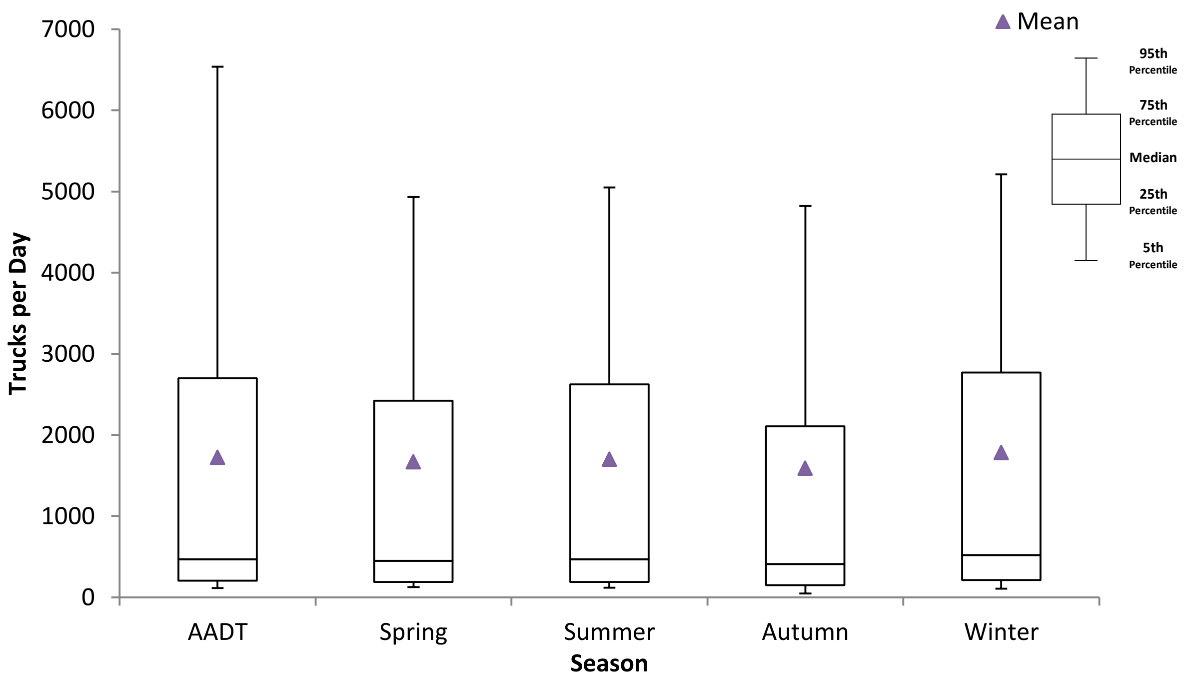
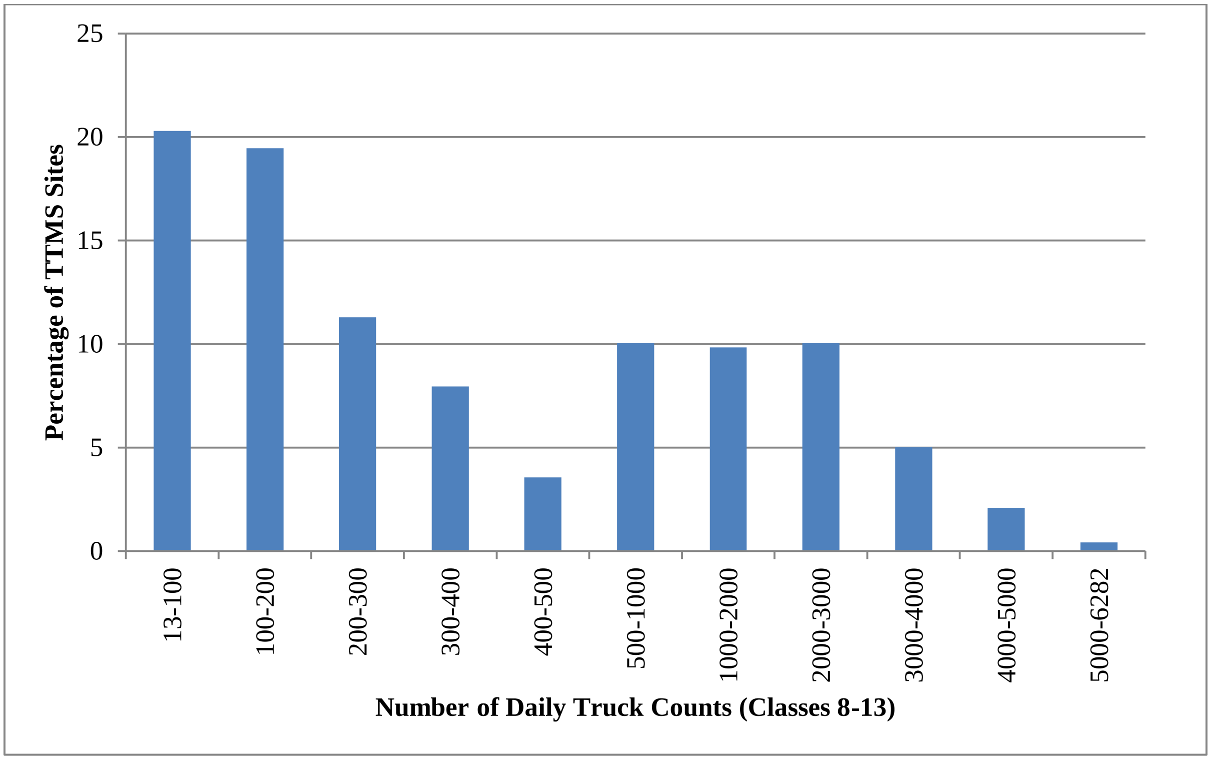
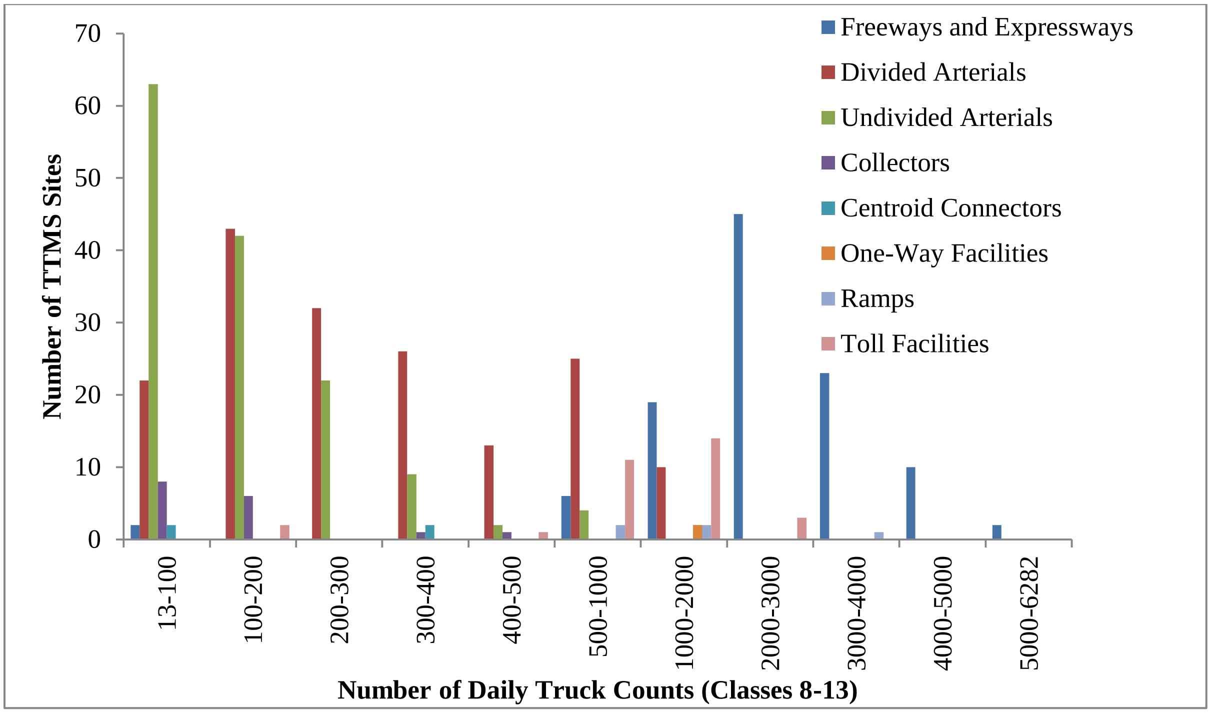


Figure D.36 Florida Truck Flows (Counts for Tractor-Trailer Trucks) for Area Type: Undeveloped Rural Areas



(a)



(b)

Figure D.37 a) Distribution of Daily Truck Counts in Traffic Sites; b) Same Distribution by Facility Type