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Truck Activity Analysis Using GPS Data

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16. Abstract

This project investigated large streams of truck Global Positioning System (GPS) data for statewide freight modeling and planning applications in Arkansas. Approximately 5% of the trucks represented movements entirely within state boundaries with average trip lengths of 30 miles and durations of 1 hour; 22% represented in and outbound movements with trip lengths of 75 to 110 miles and durations of 1.5 to 2 hours; 69% represented movements crossing state boundaries with a stop inside the state with average trip lengths of 130 miles and durations of 2.5 hours; and 4% represented pass through movements of 265 miles and 4.5 hours on average. Coverage, defined as the percent of the truck population represented by the data sample, ranged from 8% on US highways to 9% on interstates with an average coverage of 8.5% across all roadway types, and from 6% in District 3 (Southwest Arkansas) to 17% in District 9 (Northwest Arkansas) with an average coverage of 9% across all districts. By time of day (TOD), highest coverage occurred during the early morning and evening for all functional class and all days of the week. By day of week, the coverage was evenly distributed, with a minor peak in coverage on weekends. Performance measures including travel time reliability, percent of the interstate system experiencing congestion, etc. were calculated for the state-maintained roadway network. Interactive maps depicting these features were developed and published online using Environmental Systems Research Institute's Arc-Geographic Information System (ESRI ArcGIS) map tools along with an implementation guide detailing the use of the online map interfaces. Three case studies showcased unique uses of the truck GPS data including: (a) truck parking usage patterns; (b) travel time delays for trucks resulting from accidents; (c) spatial impacts of inland waterway ports. Truck GPS data uniquely fills a freight data gap by capturing spatial and temporal travel patterns that cannot be discerned from existing sources (e.g. WIM, surveys, etc.). Noting the coverage, the data was spatially and temporally representative. There is still concern about a lack of coverage of particular industries such as lumber/logging that tend to be operated by independent owner-operators, rather than large, managed fleets.

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Metric Conversions

SI* (MODERN METRIC) CONVERSION FACTORS

APPROXIMATE CONVERSIONS TO SI UNITS

Symbol	When You Know	Multiply By	To Find	Symbol
		LENGTH		
in	inches	25.4	millimeters	mm
ft	feet	0.305	meters	m
yd	yards	0.914	meters	m
mi	miles	1.61	kilometers	km
		AREA		
in^2	square inches	645.2	square millimeters	mm^2
ft^2	square feet	0.093	square meters	m^2
yd^2	square yard	0.836	square meters	m^2
ac	acres	0.405	hectares	ha
mi^2	square miles	2.59	square kilometers	km^2
		VOLUME		
fl oz	fluid ounces	29.57	milliliters	mL
gal	gallons	3.785	liters	L
ft^3	cubic feet	0.028	cubic meters	m^3
yd^3	cubic yards	0.765	cubic meters	m^3
		NOTE: volumes greater than 1000 L shall be shown in m^3		
		MASS		
oz	ounces	28.35	grams	g
lb	pounds	0.454	kilograms	kg
T	short tons (2000 lb)	0.907	megagrams (or "metric ton")	Mg (or "t")
		TEMPERATURE (exact degrees)		
^oF	Fahrenheit	5 (F-32)/9 or (F-32)/1.8	Celsius	^oC
		ILLUMINATION		
fc	foot-candles	10.76	lux	lx
fl	foot-Lamberts	3.426	candela/m^2	cd/m^2
		FORCE and PRESSURE or STRESS		
lbf	poundforce	4.45	newtons	N
lbf/in^2	poundforce per square inch	6.89	kilopascals	kPa

APPROXIMATE CONVERSIONS FROM SI UNITS

Symbol	When You Know	Multiply By	To Find	Symbol
		LENGTH		
mm	millimeters	0.039	inches	in
m	meters	3.28	feet	ft
m	meters	1.09	yards	yd
km	kilometers	0.621	miles	mi
		AREA		
mm^2	square millimeters	0.0016	square inches	in^2
m^2	square meters	10.764	square feet	ft^2
m^2	square meters	1.195	square yards	yd^2
ha	hectares	2.47	acres	ac
km^2	square kilometers	0.386	square miles	mi^2
		VOLUME		
mL	milliliters	0.034	fluid ounces	fl oz
L	liters	0.264	gallons	gal
m^3	cubic meters	35.314	cubic feet	ft^3
m^3	cubic meters	1.307	cubic yards	yd^3
		MASS		
g	grams	0.035	ounces	oz
kg	kilograms	2.202	pounds	lb
Mg (or "t")	megagrams (or "metric ton")	1.103	short tons (2000 lb)	T
		TEMPERATURE (exact degrees)		
^oC	Celsius	1.8C+32	Fahrenheit	^oF
		ILLUMINATION		
lx	lux	0.0929	foot-candles	fc
cd/m^2	candela/m^2	0.2919	foot-Lamberts	fl
		FORCE and PRESSURE or STRESS		
N	newtons	0.225	poundforce	lbf
kPa	kilopascals	0.145	poundforce per square inch	lbf/in^2

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ABBREVIATIONS, ACRONYMS, AND SYMBOLS

ArDOT – Arkansas Department of Transportation
ARNOLD – All Roads Network of Linear Referenced Data
ARSTDM – Arkansas Statewide Travel Demand Model
ATRI – American Transportation Research Institute
CFS – Commodity Flow Survey
DOW – Day of Week
DVMT – Daily Vehicle Miles Traveled
EE – External-External
EI – External-Internal
EIE – External-Internal-External
ESRI – Environmental Systems Research Institute
FAF – Freight Analysis Framework
FAST – Fixing America's Surface Transportation Act
FDOT – Florida Department of Transportation
FHWA – Federal Highway Administration
GIS – Geographic Information System
GPS – Global Positioning System
HOS – Hours of Service
HPMS – Highway Performance Monitoring System
IDE – Integrated Development Environment
IE – Internal-External
II – Internal-Internal
LOS – Level of Service
LRS – Linear Reference System
MAP-21 – Moving Ahead for Progress in the 21^{st} Century Act
MAPE – Mean Absolute Percent Error
NFSP – National Freight Strategic Plan
NHFP – National Highway Freight Program
NHS – National Highway System
NPMRDS – National Performance Measures Research Data Set
OD – Origin-Destination
PISMU – Percent of the Interstate System Mileage Uncongested
PM – Performance Measure
TAZ – Traffic Analysis Zone
TDM – Travel Demand Models
TOD – Time of Day
TSR – Truck Speed Ration
TTMS – Telemetered Traffic Monitoring Sites
TTR – Travel Time Reliability
TTV – Travel Time Variability
USGS – United States Geological Survey
V/C – Volume to Capacity Ratio

EXECUTIVE SUMMARY

Due to the increasing impacts of freight movements on transportation infrastructure, operations, and the economy, decision-makers must consider freight at every stage of the project identification and selection process. Continuing with the vision set forth in the Moving Ahead for Progress in the 21st Century (MAP-21) Act, the recently enacted Fixing America's Surface Transportation (FAST) Act established a number of provisions to ensure the safe, efficient, and reliable movement of freight. With these programs comes a push for performance-based project evaluation and benchmarking. State transportation agencies tasked with forecasting freight movements rely heavily on timely and accurate freight data. The goal of this project was to investigate the use of the American Transportation Research Institute's (ATRI) truck GPS data for statewide freight performance measurement, freight truck flow analysis, and other freight-planning and modeling applications. The project created methods and procedures to transform anonymized GPS data into truck activity patterns that could be used to develop actionable insights for freight planning.

A sample of over 338 million pings (e.g., latitude, longitude, timestamp datapoints) collected from ATRI represented 358,092 unique trucks during an eight-week sample period in Arkansas. Approximately 5% of the trucks included in the sample represented movements entirely within state boundaries with average trip lengths of 30 miles and trip durations of 1 hour; 22% represented inbound and outbound movements with trip lengths of 75 to 110 miles and durations of 1.5 to 2 hours; 69% represented movements crossing state boundaries with a stop inside the state with average trip lengths of 130 miles and durations of 2.5 hours; and 4% represented pass through movements of 265 miles and 4.5 hours on average.

Coverage, defined as the percent of the truck population represented by the data sample, ranged from 8% on US highways to 9% on interstates with an average coverage of 8.5% across all roadway types, and from 6% in District 3 (Southwest Arkansas) to 17% in District 9 (Northwest Arkansas) with an average coverage of 9% across all districts. By time of day (TOD), highest coverage occurred during the early morning and evening for all functional class and all days of the week. By day of week, the coverage was evenly distributed, with a minor peak in coverage on weekends. Coverage relating to volume was calculated as the ratio of the GPS sample volume to truck volumes measured for the same time period by Weigh-in-Motion (WIM) stations. Fluctuations in coverage stem from changes in total truck traffic rather than changes in the size of the GPS sample. Coverage estimates were in line with findings from studies conducted in other states.

Performance measures including Daily Vehicle Miles Traveled (DVMT), average truck speeds, Travel Time Reliability (TTR), Travel Time Variability (TTV), daily delay, and the Percent of the Interstate System Mileage Uncongested (PISMU), etc. were calculated separately for each link in the network and aggregated by facility types, e.g., interstates, US highways, and state highway networks. In general, performance, as measured by average travel speed, TTR, and other performance measures decreased near larger metropolitan areas. In particular, the lowest average TTR was observed in the Northwest and Central Arkansas, including Pulaski, Benton, and Washington counties. Interstates experienced higher daily delays than US highways and state highways. In addition to link-level performance metrics, travel patterns were analyzed by comparing origin-destination (OD) flows, paths, and "trucksheds", i.e., the geographic extent of a region or facility, for each Traffic Analysis Zone (TAZ) defined in the Arkansas Statewide Travel Demand Model (ARSTDM). Interactive maps depicting performance measures, OD flows, etc. were developed and published online using ESRI ArcGIS map tools along with an implementation guide detailing the use of the online map interfaces.

Several use cases exemplified the value added by truck GPS data for statewide freight planning. For intermodal terminal usage, truck GPS data allows identification of routes used by trucks serving critical inland ports such as intermodal connectors. The use-case presented in this report examined the ports of Van Buren, Little Rock, and Pine Bluff. A key finding from this use-case was the use of interstates, rather than waterways, to transport goods between ports. Further work should examine how policy and infrastructure investments can be used to shift these highway-based movements to the inland waterways. For truck parking usage and capacity estimation, complete time of day, day of week, and seasonal parking shortages can be identified with truck GPS data. Temporally continuous measures of parking usage are critical in determining where new parking capacity is needed, how often it is needed, and through what policies (e.g., enforcement, incentives) parking demands can be effectively spread across the day. A key product from this use-case was the estimation of expansion factors needed to convert truck GPS-derived counts of parked trucks to population-level parking usage estimates. Population-level estimates of parked trucks at each facility can then be used for real-time parking availability notification systems, for example. In the last use case, we examined crash-induced delays for trucks. Truck GPS data was mapped against historical crash locations in order to compare crash-induced delays to total delay, e.g., delays caused by recurring congestion. A key finding was that crash delay represented over 75% of total delay on state highways but only 9% for interstates. Thus, targeted programs to reduce the impact of crashes on highways, such as highway assistance service patrols, would benefit the trucking industry and the travelling public and the cost-benefits estimates of such a program could be aided by the used of truck GPS data.

Overall, this study concluded that the ATRI truck GPS data uniquely fills a gap in ARDOT's existing truck data sources. Truck GPS data captured spatial and temporal travel patterns that could not be discerned from existing, static sources (e.g. WIM, surveys, etc.). In regard to the coverage of the sample data, comparison to static counts and OD flows showed that the sample was spatially and temporally representative. There is still concern about a lack of coverage of the sample for particular industries such as logging that tend to be operated by independent owner-operators, rather than large, managed fleets. Although this study was not able to discern the proportions of large and small fleets within the GPS data sample, prior studies suggest the ATRI GPS data does not represent smaller fleets.

The work conducted in this project can be extended in several directions. First, while this project resulted in procedures for identifying stops and trips from anonymous GPS data, the work can be extended match stop locations to business locations to infer industry coverage of the data sample. Initial findings show this to be a promising approach. Another important extension of this work is to combine the ATRI GPS data with GPS data from independent owner-operators. With the new requirements for Electronic Logging Devices (ELDs) which capture driver status and truck position, more GPS data is likely to become available across a broader range of industries and fleet types. This could greatly alleviate the concerns regarding coverage and representativeness.

Unlike travel surveys, truck counts, and short-term observational studies, truck GPS data provides an opportunity to observe truck travel patterns over larger geographies and continuous time periods. Beyond observation, truck GPS data provides the necessary input for advanced travel demand models such as activity based or truck touring models. With advanced travel demand models, ARDOT will be able to evaluate a wider variety of policy and infrastructure scenarios than what they are currently able to do with the trip-based ARSTDM. With the ability to observe and forecast truck travel patterns, public sector decision-makers can more effectively prioritize infrastructure investments and develop targeted transportation policies to ensure an efficient freight transportation system that benefits the economy, environment, and quality of life of business and the traveling public.

CHAPTER 1: PROJECT OVERVIEW

BACKGROUND

Due to the increasing impacts of freight movements on transportation infrastructure, operations, and the economy, decision makers must consider freight at every stage of the project identification and selection process. Continuing with the vision set forth in the Moving Ahead for Progress in the 21st Century (MAP-21) Act, the recently enacted Fixing America's Surface Transportation (FAST) Act sets forth requirements to ensure safe, efficient, and reliable movement of freight (Cambridge Systematics, 2017). MAP-21 and the FAST Act highlight the development of national freight programs by creating a National Freight Strategic Plan (NFSP) and a National Highway Freight Program (NHFP). These programs recommend, and sometimes require, freight performance metrics for project-level evaluation. Although the Arkansas Department of Transportation (ARDOT), like most other state transportation agencies, collects freight data, there are still significant data gaps that limit the department's ability to monitor the performance goals of the freight network.

Many states, including Arkansas, have developed statewide freight forecasting models and more recently, state freight plans to identify freight bottlenecks and evaluate progress towards achieving performance measure goals. The Arkansas Statewide Travel Demand Model (ARSTDM) integrates freight into the traditional four-step travel demand model as a commodity-based forecast. The ARSTDM freight model uses proprietary commodity forecast data to model (i) *trip generation* to estimate how many trips are produced and attracted to each of 5,849 traffic analysis zone (TAZ), (ii) *trip distribution* to understand how trips distribute to and from each TAZ as origin-destination (OD) flows, (iii) *modal split* to determine how OD flows separate across modes, and (iv) *route choice* to determine the paths taken between each OD pair. Overall, trucking is the dominant mode for freight transport. Thus, significant attention is placed on accurately predicting truck flows on state-maintained roadway networks.

State transportation agencies tasked with forecasting freight movements rely heavily on timely and accurate freight data. National data sources for monitoring truck activity, such as the national Commodity Flow Survey (CFS) or Freight Analysis Framework (FAF) systems, lack the necessary detail pertaining to travel times, route selection, and time of day travel patterns. Similar data at the state level can be prohibitively expensive to obtain. Other traditional forms of comprehensive data collection such as traffic counts fail to provide detailed characteristics about truck trip origins, destinations, distances, travel times, and routes. Thus, it is necessary to evaluate new sources of truck activity data. Truck Global Positioning System (GPS) data, a valuable and recently available data source, can be used to support statewide planning, operations, and management programs. In several states, GPS data provided by the American Transportation Research Institute (ATRI) was used to derive freight performance measures, analyze truck trip characteristics, develop origin-destination (OD) tables of statewide freight flows, and evaluate special topics such as re-routing patterns due to traffic accidents and natural disasters. Although the ATRI data comes from a large sample of the national truck fleet, it is not a true census of all trucks. Before using the data to analyze truck travel characteristics or create origin-destination (OD) trip tables it is imperative to assess the representativeness of the data sample.

Arkansas experiences significant levels of pass-through freight movements which might indicate geographic coverage issues and/or require GPS data to be processed differently than those developed in other states, which see a high number of originating and terminating freight movements (FDOT, 2015). Hence, the methodologies developed by other states need to be contextualized to the freight activity patterns observed in Arkansas. **This research will determine whether nationally available GPS data can meet statewide planning needs in Arkansas by extending, modifying, and refining work already**

completed in other states. Considering that MAP-21 will require all commercial motor vehicles involved in interstate commerce to be equipped with an electronic logging device, it is anticipated that larger samples of GPS data will become increasingly available (FMCSA, 2014; Leandro, 2017). Thus, the findings of the proposed study can be further leveraged to make use of this emerging data source in statewide freight planning efforts.

PROJECT OBJECTIVES

The goal of this project was to investigate the use of ATRI's truck GPS data for statewide freight performance measurement, freight truck flow analysis, and other freight planning and modeling applications. The project developed methods and procedures to transform anonymized GPS data into truck activity patterns and to fuse the GPS data with other data sources, e.g., WIM truck counts, land use data, etc., to estimate data coverage. The following summarizes the project objectives.

Objective 1: Determine Coverage of GPS Data in Arkansas

The first objective was to estimate coverage of truck traffic in Arkansas. Coverage, represented by the ratio of GPS to WIM volume, was analyzed by ARDOT district, roadway functional class, time of day (TOD), and day of week (DOW). First, anonymous GPS data was converted to truck trips by (i) performing data quality checks, (ii) identifying stop locations, and (iii) mapping GPS records to the All Roads Network of Linear Referenced Data (ARNOLD) network. Each processed truck trip consists of the trip start and end times, route traveled, geographical locations of stops, total trip duration, and distance traveled. Second, once the routes for each trip were identified, GPS truck trips were compared to truck counts gathered from WIM sites to estimate coverage.

Objective 2: Identify Supplementary Data

The second objective was to depict highway freight flow patterns in Arkansas by identifying supplemental data sets to fill coverage gaps within the truck GPS dataset. Based on prior studies in Florida and other states, the ATRI truck GPS data tended to have lower coverage of smaller fleets and independent owner-operators. Since these vehicle characteristics may be tied to particular industries like agriculture and lumber, it was necessary to find alternate, independent datasets to fill gaps left in the ATRI truck GPS data. Datasets including the US Geological Survey's (USGS) Cropscape, Esri's business location layer, and public land use and business location data from the AR GIS Office were used to evaluate representativeness of the ATRI truck GPS data.

Objective 3: Analysis of Truck Travel Characteristics in Arkansas

The third objective was to analyze truck activity patterns. Truck records were divided into the following categories based on stop locations: (a) Internal movements (II), (b) Internal to External (IE), (c) External to Internal (EI), (d) External-Internal-External (EIE, i.e., passing through with a stop), and (e) External-External (EE, i.e., trucks that pass through the state and make no stop). Approximately 5% of the trucks are II, 13% are IE, 9% are EI, 69% are EIE trucks, and 4% are EE. Truck trip classes were analyzed based on (i) trip length distributions, e.g., distance between origin and destination, (ii) trip duration, e.g., time between origin and destination, (iii) number of intermediate stops by stop type, e.g., rest, pick-up/delivery, refueling, etc., (iv) percentage of trip by roadway functional class, e.g., interstates, US highway, and state highways.

Objective 4: Integration with Existing Freight Planning Efforts

The fourth objective was to determine other potential applications of truck GPS data to supplement the freight planning efforts in Arkansas. The Arkansas Long Range Intermodal Transportation Plan is a 25-year policy condition that outlines the main goals and strategic directions for the practices in the transportation system in Arkansas. This plan seeks to identify the system's need and objectives, assessing the potential strategies and policies to guide future investment in the transportation sector. Based on stakeholder needs, issues like congestion, safety, mobility, and system sustainability and reliability deserve rigorous assessment. Congestion and mobility are often used as measures of a conventional method of performance such as the analysis of level of service (LOS) and the volume-to-capacity ratio (V/C). However, these methods include both passenger cars and trucks. For the purpose of the study, the analysis of potential integration with existing freight planning efforts using GPS data was included. In the United States, several states provide a list of performance measures that help to understand freight movements in their states. In this part of the report, evaluation of some of the state practices for collecting the performance measures are considered based on the recommendations from MAP-21 and FAST Act.

Objective 5: Integration of Freight Performance Measurements

The final objective of this study was to use the pre-processed ATRI GPS data to derive freight performance measures in Arkansas to identify the most critical corridors in the state. This objective seeks to provide a list of performance measures (PM) following current in-state proposed targets suggested in MAP-21 and FAST Act. Freight performance measures defined in MAP-21 legislation, as well as several additional measures defined by the Florida Department of Transportation (FDOT) in their Source Book, were evaluated using the pre-processed truck GPS data. The following PMs were evaluated: (i) percentage of the interstate system mileage providing for reliable truck travel times, (ii) percentage of the interstate system mileage uncongested, (iii) combination[1] truck miles traveled, (iv) combination truck tonnage, (v) combination truck ton miles traveled, (vi) freight travel time reliability, (vii) freight travel time variability, (viii) combination truck hours of delay, and (ix) combination truck average travel speed. PMs (i) and (ii) are from MAP-21 and the remaining are from FDOT.

STRUCTURE OF THE REPORT

Following the Project Overview in Chapter 1, this report is organized as follows:

- Chapter 2 briefly describes truck GPS data and reviews literature on truck activity analysis using truck GPS data,
- Chapter 3 presents the pre-processing steps for converting the anonymized truck GPS data into a large database of truck trips in Arkansas,
- Chapter 4 presents the analysis of truck activity patterns using the truck trip data,
- Chapter 5 describes the coverage of the GPS data based on total traffic, ARDOT districts, roadway functional class, and temporal parameters,
- Chapter 6 presents the integration of the work into statewide freight planning efforts including estimation of performance measures, and
- Chapter 7 presents use case studies highlighting the applications of the processed truck trip data.

Chapters 5, 6 and 7 are accompanied by appendices (Appendix A, B, and C respectively) which provide additional results. Maps depicting origin-destination flows, route and path flows, and performance measures derived from the GPS data are available to ARDOT through a web-based map interface. Therefore, this Final Report is accompanied by an Implementation Report which provides instructions on how to access, use, and interpret the web-based, interactive map interface.

[1] "Combination" trucks are those that include tractor and trailer units, e.g. "semi-trucks".

CHAPTER 2: TRUCK GLOBAL POSITIONING SYSTEM DATA AND USES

This chapter describes truck GPS data sample and reviews previous studies that used anonymous GPS data to study truck travel behavior. Additionally, this chapter provides examples of GPS data applications related to highway freight performance measures.

OVERVIEW OF TRUCK GPS DATA

The American Transportation Research Institute (ATRI) is a not-for-profit research organization whose primary mission is to conduct transportation research that promotes an efficient and viable transportation system for the trucking industry. ATRI collaborated with the American Trucking Association (ATA) to collect GPS data along national freight corridors by requiring installation of communications and navigation equipment on-board commercial trucks (ATA, 2012). ATRI gathers billions of GPS data points per week from several hundred thousand of the total 2.4 million trucks registered in the US. ATRI's data has been used in prior implementations of the National Performance Measures Research Data Set (NPMRDS) (Jones et al., 2005). This dataset supplies average travel times across the National Highway System (NHS) and can be used free-of-charge by state agencies. While aggregate measures such as average travel time may be informative for general performance assessment, some states have begun to realize the benefits of using disaggregate GPS data, i.e., individual truck positions, for freight planning and modeling.

Each record included in the ATRI dataset contains truck positions as latitude-longitude pairs (referred to as "pings"), a unique but anonymous truck identification number (ID), timestamp, heading, and instantaneous speed. The unique truck ID is a random digit identifier, not related to the original truck identification number. Valuable freight data are often anonymized before releasing to the public to protect privacy. Consequently, key characteristics such as vehicle type, commodity carried, and purpose of travel are not available. This data is typically collected from major trucking companies representing larger fleets; the data does not typically contain data from independent owner-operators.

EXISTING APPROACHES TO ANALYZE TRUCK GPA DATA

To realize the full potential of the anonymized GPS data for freight planning and modeling, ping data needed to be converted to truck 'trips'. A truck trip is characterized by origin and destination locations, intermediate stop locations and durations, routes, travel times, and speeds. There exists a large body of research describing algorithmic methods for identifying routes and stops from anonymous GPS data.

- Giovannini (2011) developed an algorithm to analyze traffic flows for passenger vehicles using low-sampling GPS data. His algorithm reconstructs routes for 35,273 unique vehicles with 17.3 million GPS pings.
- Quddus and Washington (2015) proposed a map-matching algorithm using low-frequency GPS data. The map-matching algorithm determined the network link that corresponds to each GPS ping (e.g. latitude, longitude point) based on proximity, among other factors. These algorithms identify the shortest routes between GPS pings for passenger cars, buses, and light duty vehicles.
- Prior work by Pinjari et al. (2015) included an algorithm to identify stops and distinguish valid pick-up and delivery stops from traffic congestion-related stops, traffic control stops, and rest stops using heuristic methods and Geographical Information systems (GIS) analysis tools.
- Bernardin et al. (2015) developed a procedure based on GPS pings that mapped data to Traffic Analysis Zones (TAZs) prior to identifying stops.

- Camargo et al. (2017) developed an algorithm that used truck GPS data to identify stop locations and reconstruct routes. The algorithms were applied to more than 56 million GPS pings covering the metropolitan area of Phoenix, Arizona using open-source programming and GIS tools. The results of the Stop Identification and map-matching algorithms were used to develop an activity-based travel demand model and estimate freight performance measures for the metro region.

In addition to converting pings to trips, one of the key issues in using GPS data to study truck activity characteristics is evaluating the coverage of the data because it only represents a sample of the entire population of the truck fleet. Thus, before using the data to analyze truck travel characteristics, it is imperative to assess the representativeness of the data sample. In Florida, Zanjani et al. (2015) compared a one-week sample of ATRI GPS data to Telemetered Traffic Monitoring Sites (TTMS) and assessed coverage by facility type and spatial distribution in the state. In other studies conducted in Florida and Iowa, the sample of ATRI truck GPS data was concluded to represent around 10% of heavy truck counts (Zanjari et al., 2015; Bernardin et al., 2011).

APPLICATIONS OF TRUCK GPS DATA

Indiana was the first state to incorporate anonymized GPS data in an update of its statewide travel demand model in 2012 (Bernardin et al., 2011). In this study, Indiana used 300,000 trucks to define 2 million truck trips and used the truck trip characteristics for model validation. The study reported a 32% decrease in mean absolute percent error (MAPE) when comparing observed truck counts to model output using anonymized truck GPS samples as input. Additionally, Bernardin et al. (2011) identified possible bias in the ATRI truck GPS data. An OD trip table was updated using anonymized truck GPS samples that had been “factored-up” to represent statewide truck flows. Subsequently, Tennessee and Florida integrated anonymized truck GPS data into their statewide planning models (Golias et al., 2012; Pinjari et al., 2014). These studies exemplified why having a clear understanding of the representativeness of the ATRI’s truck GPS data is necessary before incorporating such data into statewide TDMs.

In addition to TDM model improvements, ATRI truck GPS data has been used to derive freight performance measures. For example, freight performance measures from GPS data include average and 95th percentile travel times and speeds, travel time indices and reliability measures, bottleneck identification, and benchmarking of roadway performance before and after infrastructure change (Jones et al., 2005; McCormack et al., 2011). Such performance measures can be used to support freight planning according to the recommendations outlined in MAP-21 and the FAST Act.

Some states have also developed comprehensive lists of freight performance measures that have the potential to be supported by truck GPS data (FDOT, 2016; Liao, 2014). For example, FDOT developed the Multimodal Mobility Performance Measures Source Book (Source Book) as a compilation of performance metrics from a number of sources (FDOT, 2016). In the current work, a subset of performance measures from the FDOT Source Book relating to freight were used including:

- combination truck miles traveled,
- truck miles traveled,
- combination truck tonnage,
- combination truck ton-miles traveled,
- truck value of freight,
- freight travel time reliability,
- freight travel time variability,
- combination truck hours of delay,
- combination truck average travel speed,
- miles severely congested,
- vehicles per lane mile, and
- combination truck backhaul tonnage.

CHAPTER 3: ALGORITHMS TO CONVERT ANONYMIZED GPA DATA INTO TRUCK TRIPS

This chapter describes the anonymous truck GPS data used in this study and provides a detailed description of the process used to convert ping data to truck trips. It will also include a description of the data quality checks, Stop Identification algorithm, and map-matching (e.g. route identification) algorithms.

DESCRIPTION OF STUDY DATA

The main data used in this study include (1) truck GPS data from ATRI, (2) the ARNOLD roadway network, and (3) traffic count data from ARDOT Weigh-in-Motion (WIM) sensors. Each source is briefly described in this section.

Truck GPS Data

This study used data from four, two-week periods within the state boundary plus a ten-mile buffer (Table 1). The ten-mile buffer region was used to truck crossing the state boundary for short portions of their trips as well as to capture Metropolitan Planning Organizations (MPOs) that extend into Missouri and Texas. The data contain a unique, but anonymous, truck identification number (ID), timestamp, latitude and longitude, instantaneous (or point) speed, and heading (e.g. azimuth). For instance, the August/September data has 83,112 unique truck records with 88,241,136 pings and covers the state and 10 mile buffer(Figure 1). The sample periods across the four quarters were chosen to capture seasonality in freight patterns. The fall harvest season spans August and September. Thus, the sampled data for the third quarter of the year aimed to capture truck movements related to agriculture activity. It should be noted that the number of trucks and number of pings fluctuates across quarters may also be due to increasing participation of companies sharing data with ATRI.

To determine the number of unique trucks represented in each sample period, records were grouped by truck ID. Overall, the number of unique trucks was higher on weekdays than on weekends across sample periods (Figure 2). Each unique truck may travel in Arkansas for one or more days. Trucks with pings on only one day are likely passing through the state whereas those with pings across multiple days are likely local delivery trucks. Most trucks are seen for less than three days during each two-week period (Figure 3).

Table 1. Summary of GPS Data Sample

Parameter	Quarter 1 (Q1)	Quarter 2 (Q2)	Quarter 3 (Q3)[2]	Quarter 4 (Q4)	Totals and Averages
Dates	February 1-15	May 1 – 15	August 27-31; Sept. 1 – 12	November 1 – 15	8 weeks
File size	5.3 GB	5.8 GB	6.9 GB	8.3 GB	26.3 GB
Total Number of Pings	67,698,440	75,005,740	88,241,136	107,358,819	338,304,135
Average Pings per Day	4,513,212	5,000,386	5,190,655	7,157,254	5,465,376.75
Unique Truck IDs	82,770	81,891	83,112	110,319	358,092
Average Time Between Pings[1]	152 seconds (2.5 minutes)	160 seconds (2.7 minutes)	195 seconds (3.3 minutes)	173 seconds (2.9 minutes)	172 seconds (2.9 minutes)
Median Time Between Pings	60 seconds				60 seconds

1. Summary statistics taken when the truck speed is greater than 10 mph. A 10 mph threshold was chosen to discard pings that correspond to rest breaks or overnight parking.
2. The third quarter is referred to as the 'August' data in the remainder of this report for brevity.

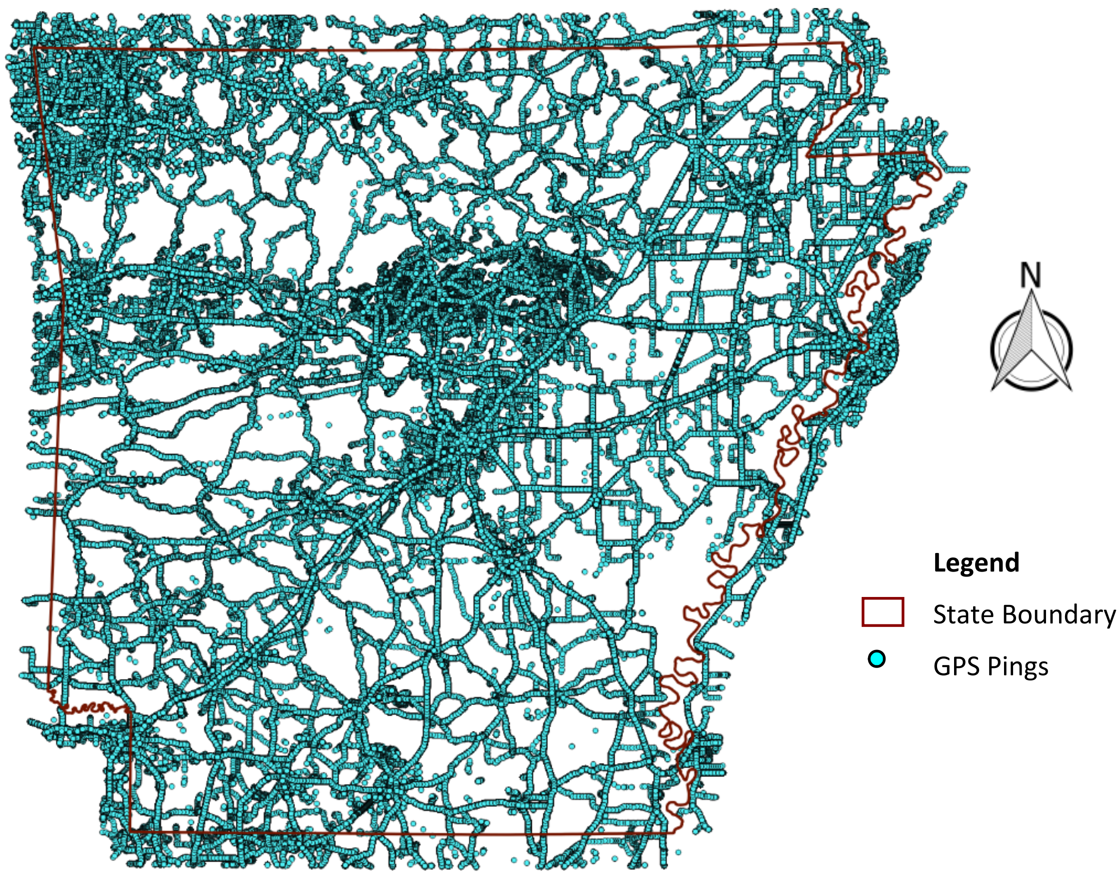


Figure 1. Anonymous Truck GPS Data for a Two-Week Period in Arkansas

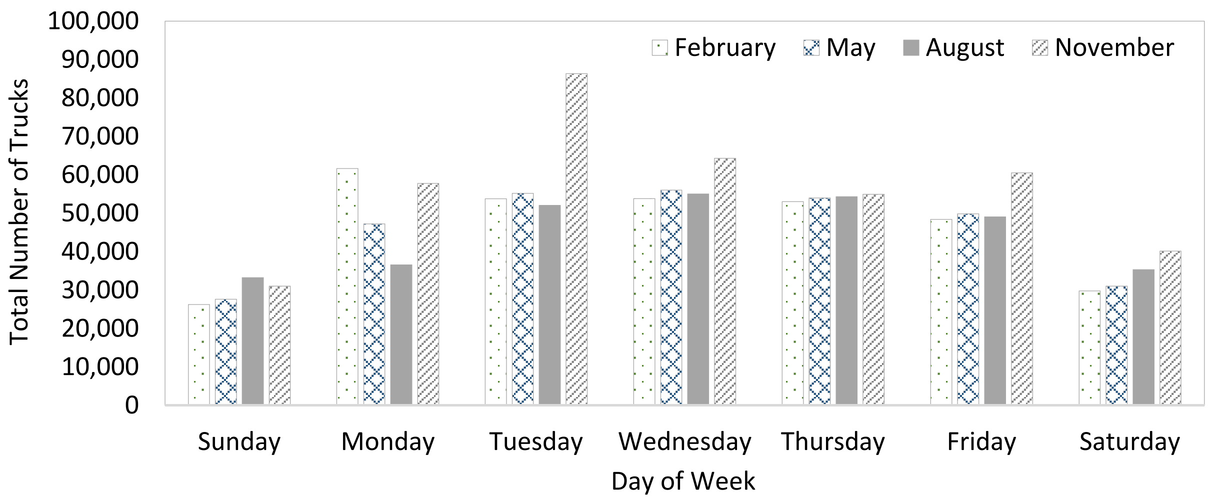


Figure 2. Total Number of Trucks by Sample Period and Day of Week

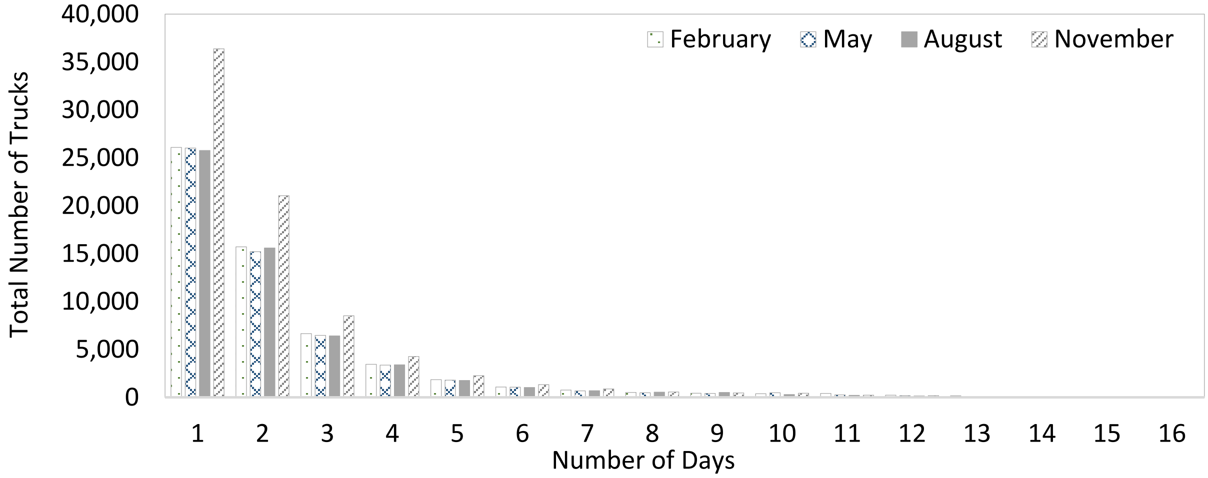


Figure 3. Number of Unique Trucks by Number of Days in Occurrence Across Sample Periods

All Roads Network of Linear Referenced Data (ARNOLD) Network

The All Road Network of Linear Referenced Data (ARNOLD) is a geospatial database of all public roads and complies with practices and rules set forth by the Federal Highway Administration (FHWA). The FHWA required all states to convert their state specific Linear Reference System (LRS) data to a common format referred to as ARNOLD. The ARNOLD map is used for federal data reporting requirements, including the Highway Performance Monitoring System (HPMS) volume and condition reports, reporting of crashes, performance measurement, etc.

The ARNOLD maps consist of the following features: centerline geometry, road identification number, functional class, road design, road length, and others. The ARNOLD map was chosen for use in this project because it is physically representative of the centerline topography of all public roads (Figure 4).

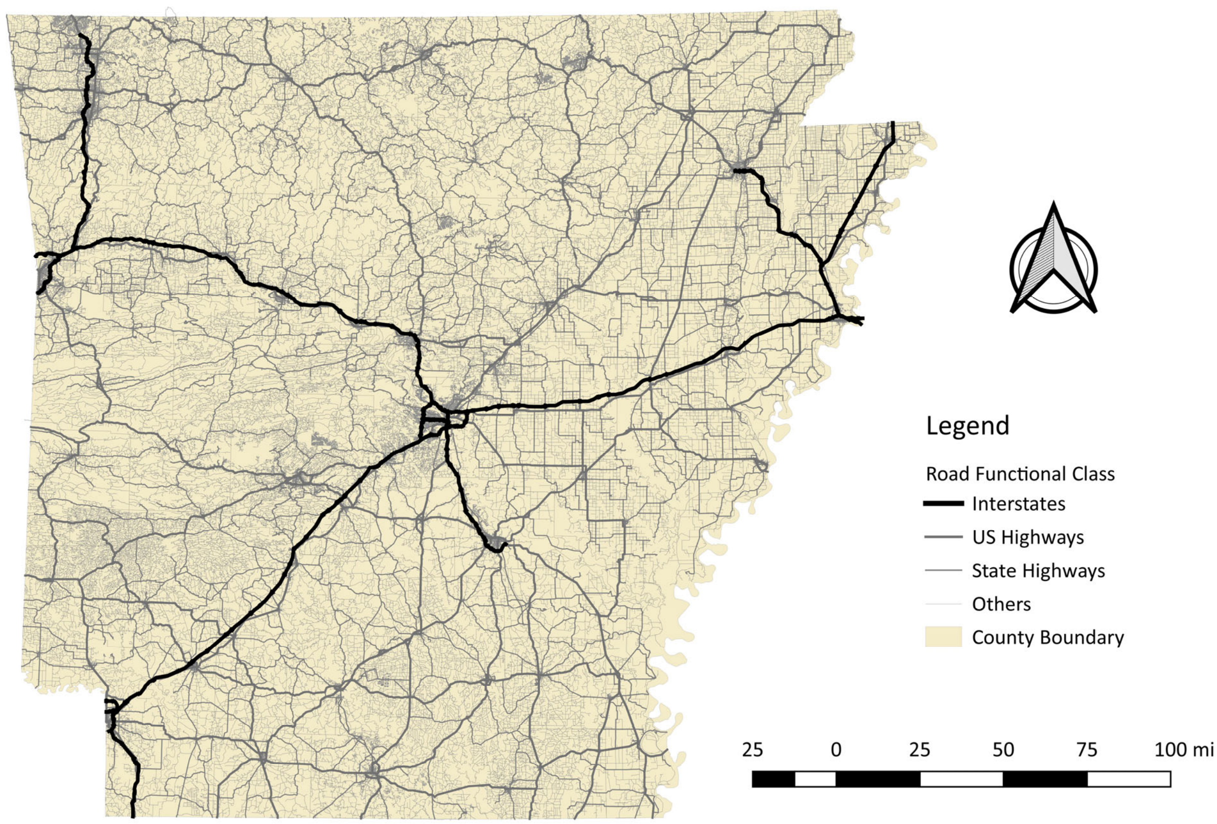


Figure 4. ARNOLD Road Network in Arkansas

ARDOT WIM Data

There are 69 WIM stations in Arkansas that collect traffic volumes, vehicle configuration, and weight 24 hours a day, 7 days a week (Figure 5). WIM sensors measure axle configuration, axle weight, vehicle length, and speed to predict vehicle type according to the commonly referenced Federal Highway Administration (FHWA) Scheme F (FHWA, 2013). WIM data also includes highway functional class, i.e., interstate, US highways, state highways, and others. In this study, FHWA classes five through 13 were used to calculate GPS coverage of trucks. Classes five through 13 correspond to common freight carrying trucks while vehicles in classes 1 through four are passenger vehicles or light duty trucks not carrying freight.

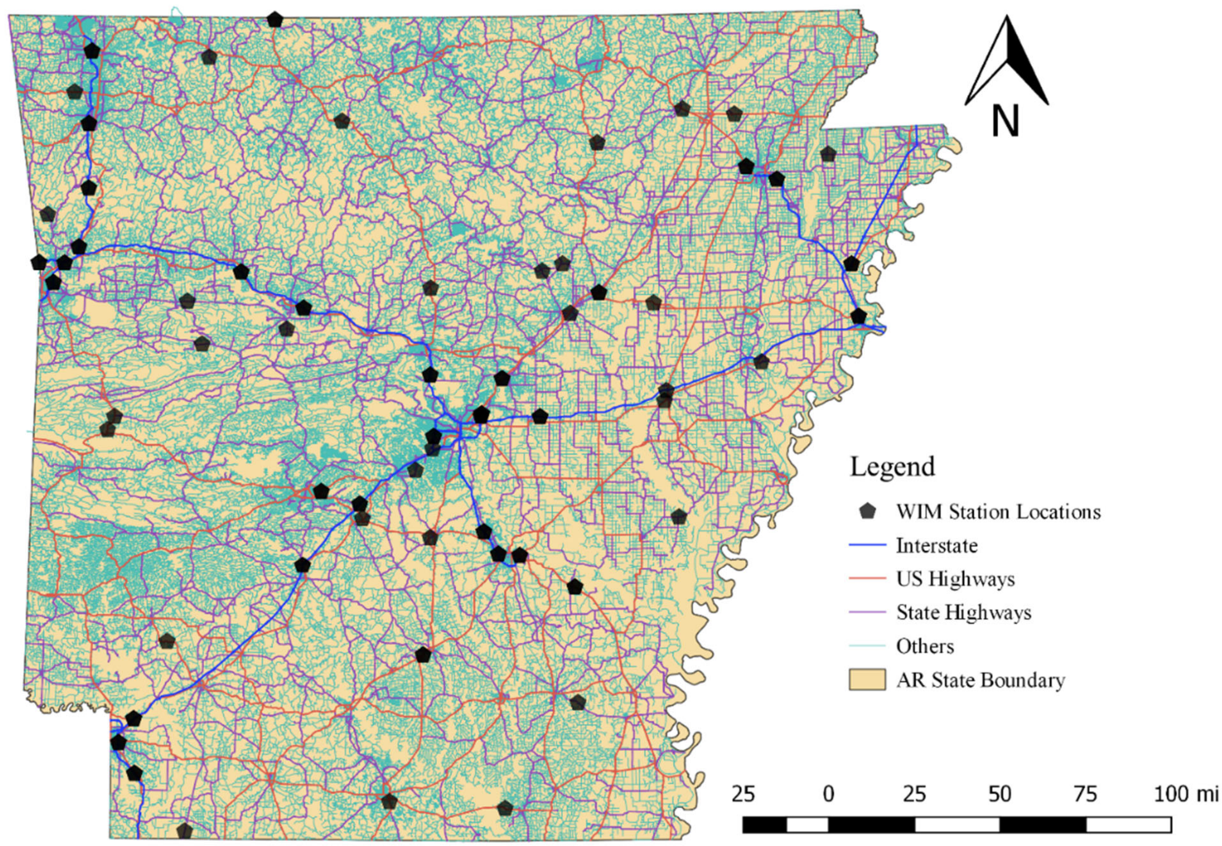


Figure 5. Spatial Distribution of Arkansas's Roadway Network and WIM Stations

DATA PROCESSING REQUIREMENTS

Data pre-processing followed three main steps (Figure 6). First, a quality check was performed to remove erroneous records resulting from GPS tracking errors. Such errors are often found in urban or mountainous areas where the GPS signal may be obstructed. Second, GPS pings were reduced to a set of stops using a Stop Identification algorithm. Stop Identification is necessary to prevent over counting of stops. For example, a truck parked at a loading facility will continue to record GPS pings through the duration of the stop such that 10 pings may be recorded for a two hour stop (e.g. 1 ping every 15 minutes on average). Simply considering pings with zero speed as stops would result in a count of 10 stops when in reality, only one stop occurred. The Stop Identification algorithm groups consecutive pings into the same stop and calculates the duration of the stop. Lastly, the complete truck path, e.g. a series of connected links, was identified using a map-matching algorithm. For example, trucks traveling at 55 mph traverse many links between pings, especially when links can be as short as a tenth of a mile. Thus, simply matching pings to nearby links does not produce a connected path. Instead, a map-matching algorithm was created to reconstruct the complete and connected series of links from the ping data.

The large stream of GPS data required use of a PostGIS database and Python scripting. In this study, PostgreSQL 9.6.3 was used as the database to store anonymized GPS pings. PyCharm 2017.1.4, an Integrated Development Environment (IDE) for Python language, was used to implement data quality, Stop Identification, and map-matching algorithms in Python 2.7. Python script was written to communicate directly with the PostGreSQL database. In addition, an open-source GIS platform called

QGIS, i.e. QGIS 2.18.9, was used for spatial analysis. Google satellite imagery was used within the QGIS platform for algorithm validation tasks.

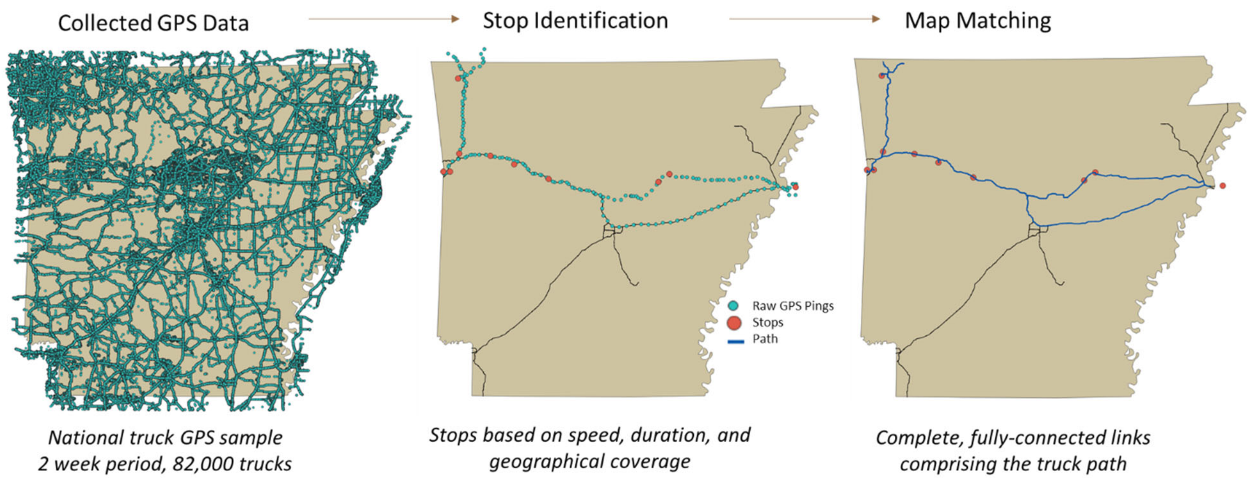


Figure 6. Overview of GPS Pre-Processing Steps

Data Quality Check Algorithm

A data quality check (QC) algorithm (Figure 7) was developed and applied to improve data consistency and relevancy (Camargo et al., 2017). The QC algorithm identified unusual truck records and flagged those records for further analysis. The algorithm checks the total number of pings corresponding to each truck record and removes records with fewer than 20 pings. Trucks with less than 20 pings are unlikely to have used the highway network (usually they are operating within a freight transfer facility) and were deemed irrelevant to the applications of this work, e.g. freight performance measures and travel demand modeling. If a truck record had more than 20 pings, space-mean-speed and travel time between each consecutive pair of pings was calculated. Next, records with space-mean-speed exceeding 81 miles per hour (130 km/hour) for more than two minutes (120 seconds) were removed. Then the geographic coverage area for a truck was calculated. Geographic coverage was defined as the diagonal of the rectangular bounding box that surrounds all pings of a truck. Truck records were removed from the data where the geographic coverage was less 1.2 miles (2 km). Again, trucks not leaving a 1.2-mile bounded area were not using the highway network, and thus were irrelevant to the applications of this work. Parameter values described above were based on the work by Pinjari et al. (2015) and Camargo et al. (2017) and adapted for Arkansas through a rigorous manual review process.

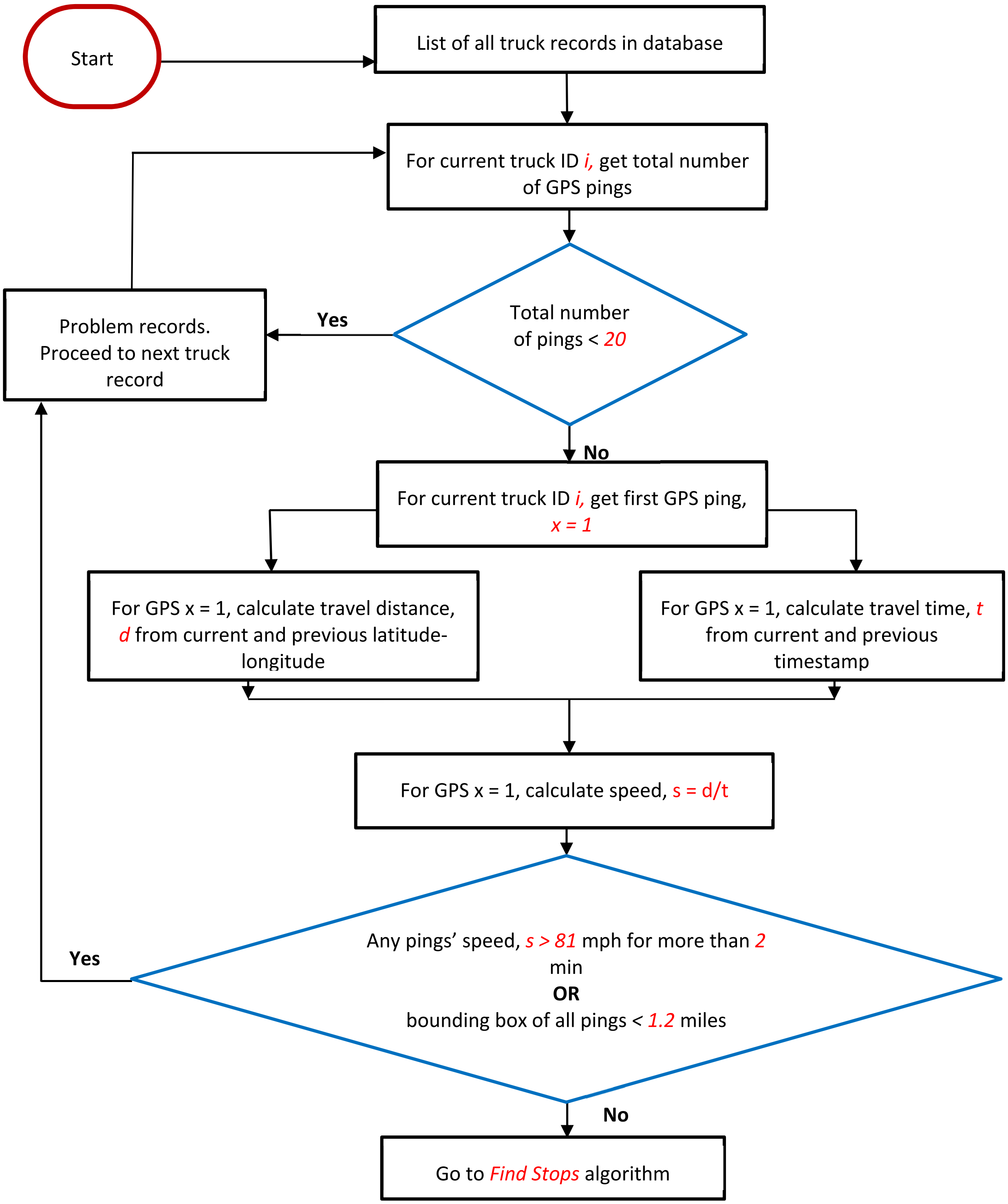
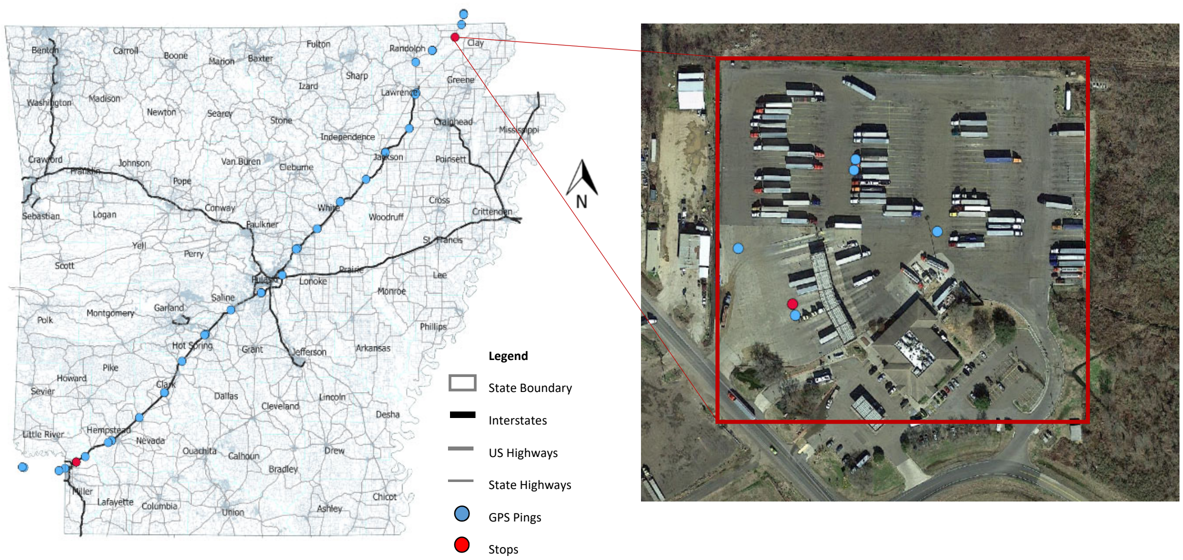


Figure 7. Algorithm for Data Quality Check

Stop Identification Algorithm

The Stop Identification algorithm determined the locations of potential freight activity stops (e.g. pick-up/delivery, rest stops, and fuel stops) among a set of GPS pings for a given truck. Figure 8(a) depicts a typical truck movement contained in the GPS data set. Clusters of pings represent possible stops (Figure 8(b)). When examining freight activity patterns, it is necessary to represent a cluster of pings as a single stop location so that later the number of stops per truck or per region can be estimated accurately. If all pings below a low speed threshold were considered a stop, freight activity would be overestimated. This, in essence, is what the Stop Identification algorithm accomplished by determining which stops belong to the stop cluster, depicting the cluster location as either the geometric center of the cluster or another representative physical location, calculating the stop duration, and inferring the stop purpose.



(a)

GPS Pings With Identified Stops for a Truck

(b)

Stop Cluster Within a Bounding Box for a Truck

Figure 8. Stop Identification Results for One Truck

The Stop Identification algorithm used in this project was originally developed by Camargo et al. (2017). Camargo's algorithm was calibrated and validated using truck GPS data from a metropolitan area of approximately nine thousand square miles. Comparatively, the study area of this project encompasses the state of Arkansas, an area of approximately fifty-three thousand square miles. In addition to the increase in geographic scale, there are complexities related to freight activity that require specific modifications to the original algorithm developed by Camargo. Therefore, the values of the algorithm parameters were tailored to the Arkansas GPS data to identify stops more accurately. Table 2 juxtaposes the original and modified parameter values for the Stop Identification algorithm.

The Stop Identification process was applied to all sample periods (358,902 trucks) using the original parameter values. Then, a number of truck records were sampled for manual verification of the identified "stops". Detailed manual comparisons of identified stops to land use layers were performed to verify the Stop Identification algorithm and determine key characteristics of the trucks included in the GPS sample. Stops identified through the algorithm were verified by comparing to Google Earth satellite imagery. Then publicly available business and facility layers[2] were added into QGIS to provide more intensive information of these stop and ping locations. Each of the spatial layers gave a comprehensive picture of truck business patterns and refinement of the Stop Identification algorithm.

Manual verification showed that the locations of “stops” are not accurate for all stops using the original parameters defined in the Stop Identification algorithm. For instance, the original algorithm defined a stop as the geometric centroid of the set of stops included in the stop cluster. In some cases, the geometric centroid of the cluster of stops did not match with the physical locations of businesses. Therefore, the Stop Identification criteria related to spatial aggregation of a cluster of stops was modified: stop coverage changed from 0.5 miles (0.8 km) to 0.2 miles (0.3 km). Additionally, the original algorithm defined a vehicle as “stopped” when space-mean-speed (e.g. speed calculated between consecutive stops) was below 5 mph (8 km/h). Based on the manual stop verification, a speed of 3 mph (4.8 km/h) was found to give better results.

Table 2. Values of Stop Parameters

Stop Parameters	Original Value	Modified Value
Speed	5 mph (8 km/h)	3 mph (4.8 km/h)
Time	5 minutes (300 seconds)	5 minutes (300 seconds)
Coverage Area	0.5 miles (0.8 km)	0.2 miles (0.3 km)

Source: Camargo et al., 2017

The revised Stop Identification algorithm (Figure 9) started with a data quality check described in Section 3.2.1. After identifying valid truck records, the algorithm identified the location of “stops” from the set of truck GPS pings. First, space-mean-speed between consecutive pings was calculated. If the space-mean-speed was less than 3 mph (4.8 km/h), the space-mean-speed between the next pair of consecutive pings is calculated. The algorithm continued checking consecutive pings, to produce a series of pings that meet the modified speed criteria. Next, total “stop time” and “stop coverage” for all consecutive pings in the series were calculated. If a group of pings covers at most 0.2 miles (0.3 km) for at least five minutes (300 seconds), then the group was considered a stop cluster. The geographical center of the stop cluster was marked as the location of the “stop”. Thus, the set of GPS pings for a truck record are reduced to a set of stops characterized by a location, start and end time. Stops may be pick-up/delivery stops, rest, or fuel stops, or unintended stops due to congestion.

[2] GIS layers of business, land-use, and building data were gathered from the Arkansas GIS office: https://gis.arkansas.gov/

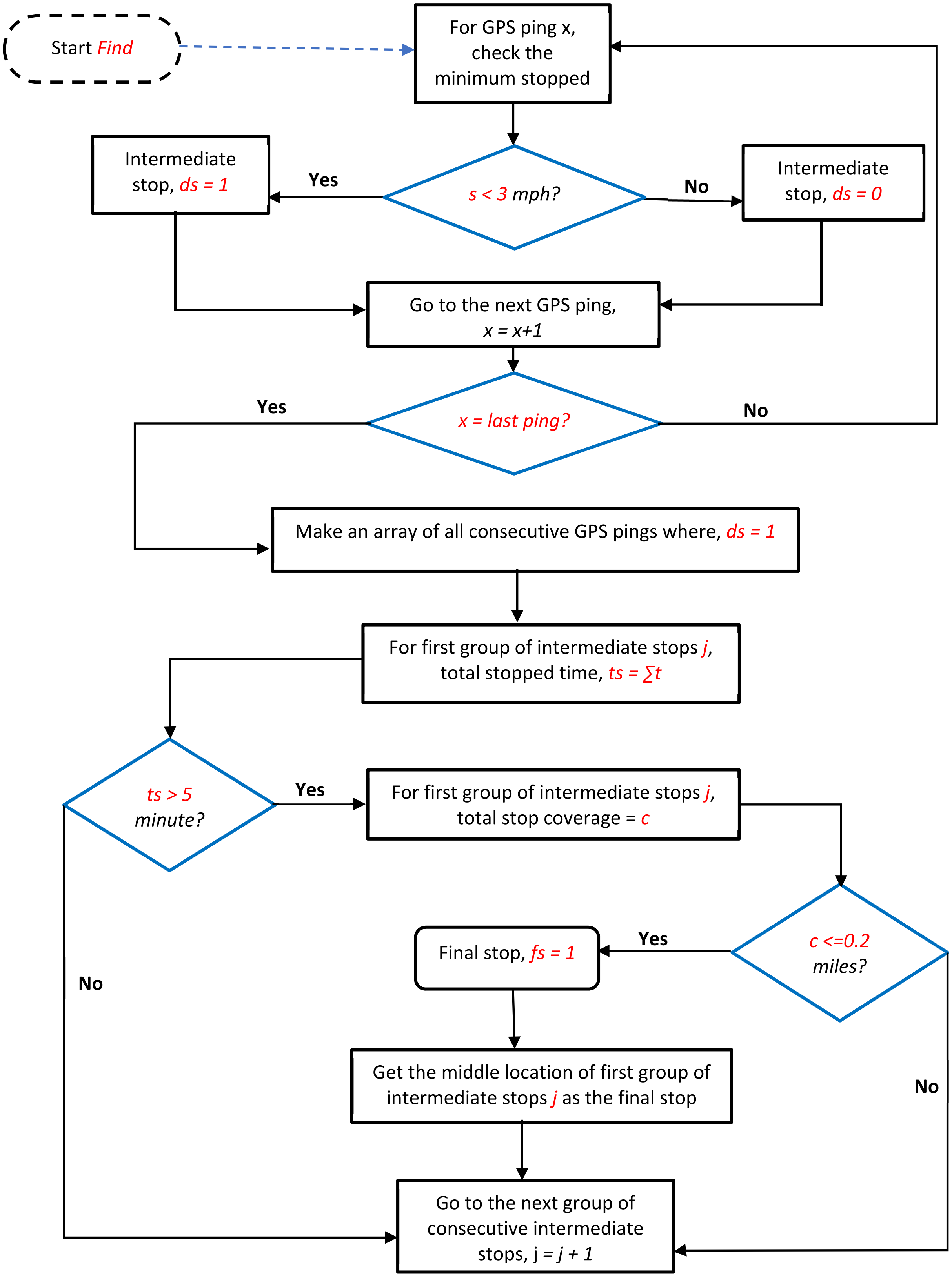


Figure 9. Algorithm for Stop Identification

Map-Matching Algorithm

The map-matching algorithm found the set of links that comprise the complete path between consecutive pings (Figure 11). Due to the temporal coarseness of the GPS pings and the density of the network links, this was a critical step in determining truck volumes along each link of the transportation network. First, a spatial buffer was created around each network link that helped to account for small, inherent inaccuracies in the GPS ping positions. Next, each GPS ping was paired with a network link based on proximity. Due to the temporal sparsity of the GPS ping data where pings may be separated by as much as 15 minutes, the set of links matched to pings in not necessarily connected, e.g. there may be unmatched links along the true truck path. To repair gaps in the path the shortest path between consecutive pings was determined. The shortest path algorithm requires a measure of link cost, which can be link travel time, length, or another comparable measure.

Similar to the Stop Identification algorithm, modifiable parameters (i.e. buffer distance and link cost) for the map-matching algorithm were modified from Camargo et al. (2017) (Table 3). A goal of this study was to use the common, statewide linear reference system, the All Roads Network of Linear Referenced Data (ARNOLD) (FHWA, 2014).

Table 3. Values of Map-Matching Parameters

Path Parameters	Original Value[1]	Modified Value
Link Buffer	1,654 feet	36 feet
Cost Parameter	Link length	Travel time

Source: Camargo et al, 2017

By using the ARNOLD map for model calibration, transferability to other states/regions is ensured. Since the ARNOLD network was more dense (e.g. more roadways per square area) than the network used by Camargo et al. (2017) and includes interstates, highways, and local roads, the link buffer distance was altered. Additionally, the modified algorithm defined link cost as the estimated free flow travel time instead of link length. Since the ARNOLD network does not include road speed limit, this study estimated the speed limit based on the road functional class, i.e., interstates, US highways, state highways, and others (Table 4). Furthermore, a method to segment trips into in and out of state portions was needed since the ARDNOLD network was only available for Arkansas. "Break points" were defined each time a truck traversed the state boundary such that a trip was divided into two portions, e.g., outside the state to the boundary and inside the state to the boundary. Figure 10(b) shows that by separating a truck trajectory into multiple segments, the map-matching algorithm was able to identify the within state routes more accurately.

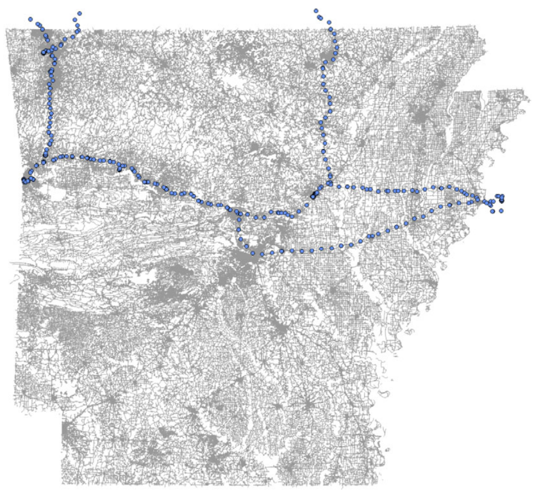
Table 4. Estimated Truck Speed on Roads in Arkansas

Road Functional Class	Estimated Speed (mph)
Interstates	65
US Highways	55
State Highways	55
Others	45

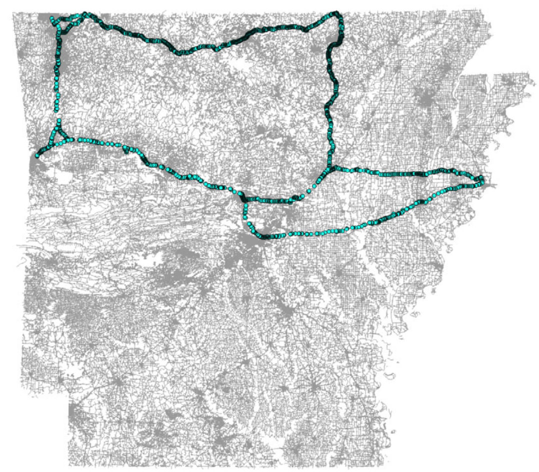
To validate the map-matching algorithm, a statistical verification procedure was developed and applied to a random sample of truck records. First, a buffer was created around the links found to be part of the complete path of a truck resulting from the map-matching algorithm. Next, the number of GPS pings for that truck contained within the link buffer was found. Then, the percentage of pings matched to a network link along the complete path was calculated. This value was referred to as the “map-matching accuracy”. This value represents the ability of the algorithm to capture the complete path of the truck. A map-matching accuracy close to 100% is ideal. The map-matching algorithm with the modifications described in the previous sections has an average map-matching accuracy of 87% for Arkansas (Table 5).

Table 5. Map-Matching Accuracy for Sample Period in Arkansas

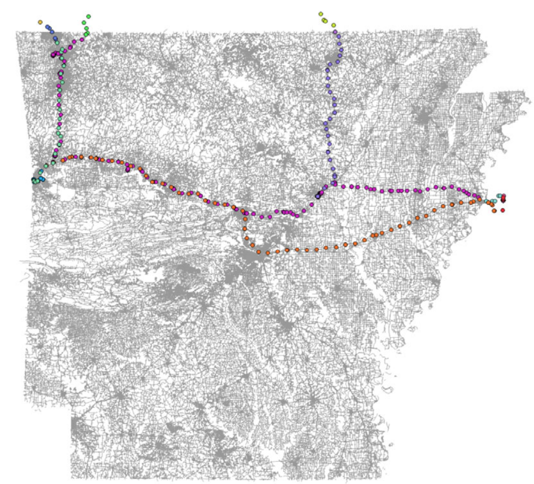
Sample Period	Accuracy (%)
February	88
May	87
August/September	87
November	86



(a) GPS Pings



(b) Identified Route Before Segmentation



(c) Break-Segments

(d) Identified Routes With Break-Segments

Figure 10. Map-Matching Process Incorporating Break Point Segmentation

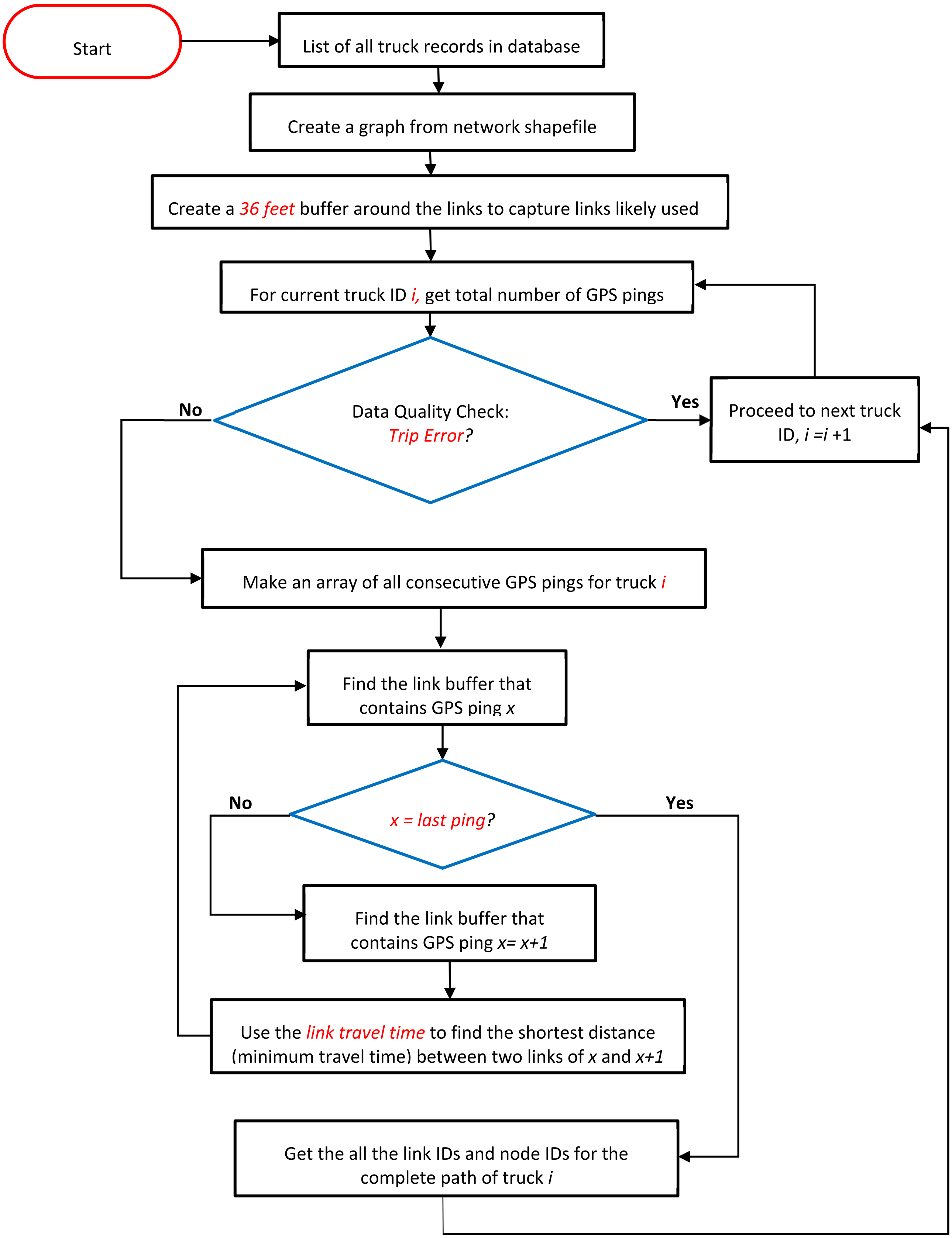


Figure 11. Algorithm for Map-Matching

CHAPTER 4: CHARACTERISTICS OF TRUCK TRIPS

This chapter reviews the characteristics of truck trips derived from the anonymous truck GPS data. The truck travel characteristics analyzed included truck type, trip length, stop and trip duration by time of day, average trip speed by time of day, and origin-destination (OD) truck flows. Each of these characteristics was derived at a statewide level as well as for different regions in the state.

TRUCKS BY TRIP TYPE

Each truck contained in the GPS sample was characterized by its stops. Stops include origin (the first ping location), destination (the last ping location), and a set of intermediate stops. A trip was defined as a movement between consecutive stops. This could be a movement from an origin to an intermediate stop, a movement between two consecutive intermediate stops, or in the case of no intermediate stops, the movement from the origin to the destination. Trucks were categorized as follows:

- **Internal:** Trucks classified as Internal-Internal (**II**) make stops entirely within the state boundary such that the origin, destination, and intermediate stops are all within the state boundary,
- **Cross State Border**: Trucks that cross the state border with an origin inside the state and a destination outside the state were classified as Internal-External (**IE**) trucks and those with an origin outside the state and a destination inside the state were classified as External-Internal (**EI**) trucks,
- **Pass-through with stop:** Trucks classified as External-Internal-External (**EIE**) stops are those that had an external origin, external destination, and had at least one stop inside the state, and
- **Pass-through**: Trucks classified as External-External (**EE**) were pass-through movements with an external origin and external destination and no intermediate stops within the state[3].

Across all sample periods, EIE trucks (passing through with internal stops) were the most common, representing 69% of the total trips (Table 6). Internal (II) and pass-through (EE) trucks represented the least common patterns within the data sample, at 5% and 4% of the total trips, respectively. The proportion of trip types were consistent across all sample periods.

Table 6. Trip Characteristics by Truck Type

Truck Classification		February (Q1)	May (Q2)	August (Q3)	November (Q4)	*Total Trucks*
Internal	II	3,456	3,623	3,493	4,141	*14,713 (5%)*
Internal/External	IE	9,732	9,883	10,127	13,329	*43,071 (13%)*
	EI	6,975	6,800	6,604	10,160	*30,539 (9%)*
Pass-Through	EIE	52,367	51,634	53,138	69,517	*226,656 (69%)*
	EE	2,800	2,851	2,509	3,597	*11,757 (4%)*
Total Trucks		*75,330*	*74,791*	*75,871*	*100,744*	*326,735*

Concentration of stops by region did not vary across sample period however, stops associated with various truck classifications were concentrated in different regions of the state (Figure 12). Internal (II) movements were concentrated in the Little Rock area and in Conway County (Central Arkansas) (Figure 12a). The Little Rock area is urbanized and the II trucks in this region represented activities such as local

[3] As the truck records include a 10-mile buffer around the state boundary, 9% of the trucks included in August/September periods never entered the state. Those trucks were identified as the "Out of State" trucks and excluded from further analysis.

deliveries. On the other hand, North Conway County is a rural area; thus, the II trucks were not due to local deliveries. During 2016, North Conway County had significant activity related to fracking, a type of drilling technology used for extracting oil, natural gas, and other elements from deep underground. Fracking produces significant truck activity to transport water and oil/gas to and from well sites.

Most of the stops for external movements including IE, EI, and EIE trucks were found along major interstates and state highways. For IE and EI trucks, the heaviest stop concentration was seen in Benton/Washington, Sebastian/Crawford, Pulaski, and Crittenden counties (Figure 12b and c). These trucks and associated stops were likely related to pick-up/delivery stops. Most of the stops associated with pass-through movements, specifically EIE trucks, were concentrated in Crittenden County (West Memphis) (Figure 12d). In this area, the heaviest concentration of stops for EIE trucks was found outside the state boundary in the Memphis region. The West Memphis area is a logistics crossroad serving as a gateway to the Memphis region. Memphis is home to the country's top cargo airport, five Class 1 railroads, and a major east-west interstate corridor (Interstates 40). EI-, IE-, and EIE-associated stops in the West Memphis region were likely pick-up/delivery, fueling, and/or rest stops.

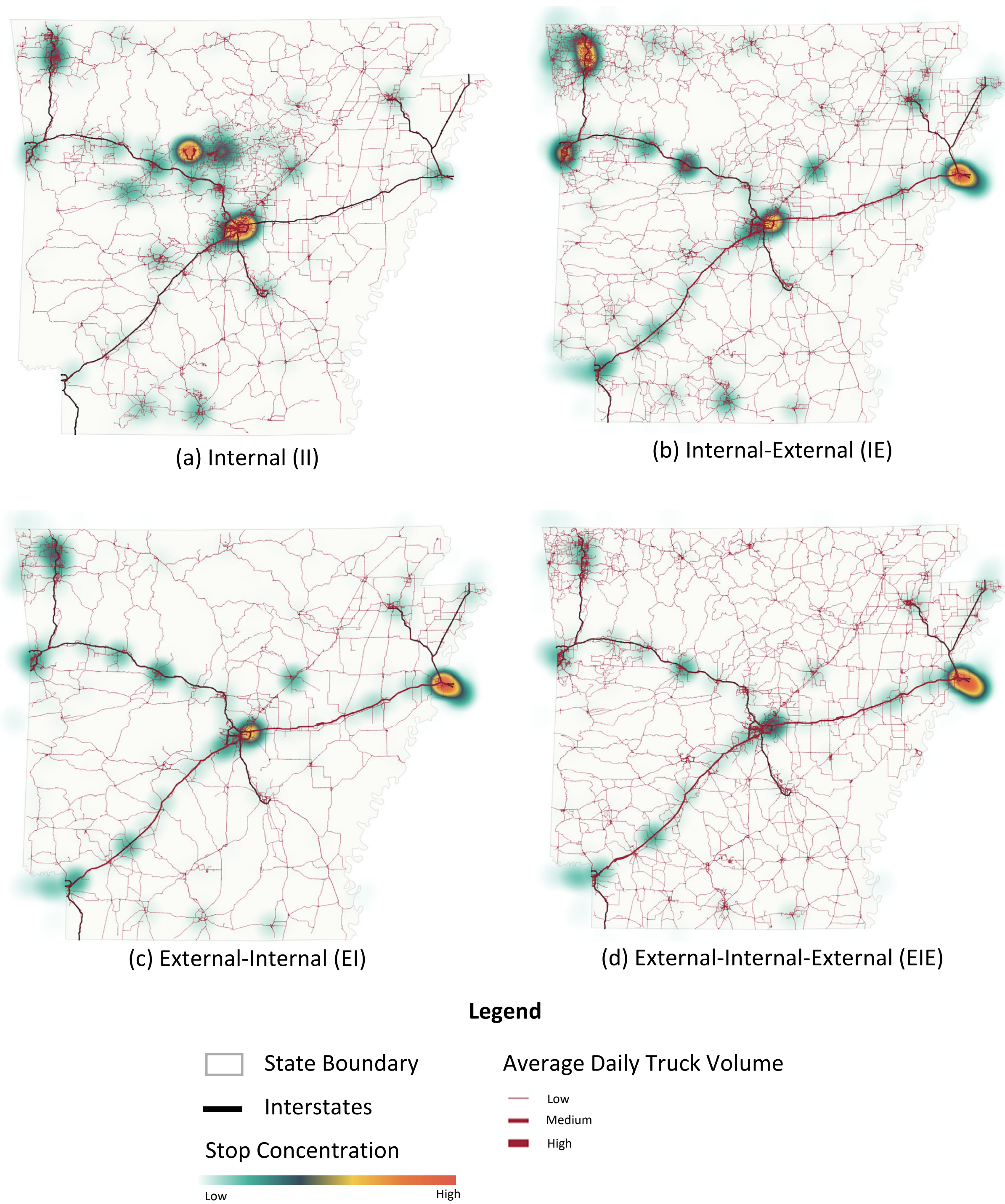


Figure 12. Maps of Stop Concentration and Average Daily Truck Volume by Truck Type for August Sample

TRIP LENGTH

Trip length was defined as the length in miles between a pair of consecutive stops[4]. Average trip lengths were 30, 75, 110, 130, and 265 miles for II, IE, EI, EIE, and EE trucks, respectively (Figure 13). Internal (II) trucks were those making local deliveries, and thus make many shorter trips between stops. On the other hand, pass-through trucks with stops (EIE) typically made longer trips with only one stop for refueling or rest. Pass-through trucks with no stops (EE) had the longest trips as they traveled across the state's east-west corridors (Interstate 40 and Interstate 30)[5]. Across all four sample periods, the average number of stops per truck were 7, 3, 2, 2, and 0 for II, IE, EI, EIE, and EE trucks, respectively. By definition, the number of stops for an EE truck is zero.

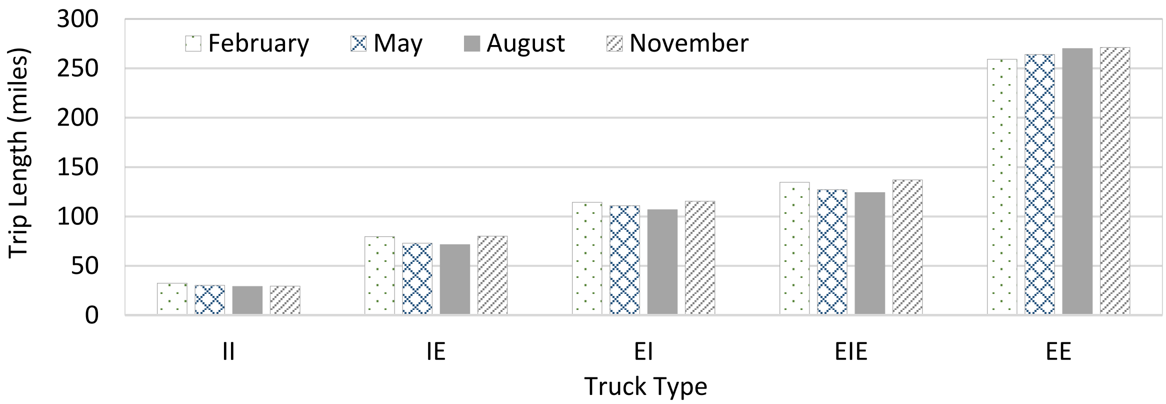


Figure 13. Average Trip Length Distribution by truck type and sample period

STOP AND TRIP DURATION BY TIME OF DAY

Stop duration was defined according to the Stop Identification algorithm (Section 3.2.2) as the time elapsed while a truck has a speed less than 3 mph. Trip duration was defined as the travel time between consecutive stops. Total duration is the sum of the stop and trip duration. Average trip, stop, and total duration represented an average of each truck with a trip or stop beginning in the specified hour of the day. For example, the stop duration of all trucks with a stop beginning at 8 a.m. were averaged to compute the average stop duration for 8 a.m.. A similar calculation was done for average trip duration.

Stop and trip duration vary by time of day, with stop duration peaking in the early evening (3 p.m. to 8 p.m.) (Figure 14). The time of day trends were consistent by sample period. The longer stop durations in the evening hours likely captured required 8-10 hour rest periods as dictated by the Hours of Service (HOS) regulations. Comparing trip durations to stop durations, stop durations often exceed trip durations across all times of the day. Again, this is likely due to need for required 8-10 hour rest periods.

[4] To clarify, trip length was defined as the distance in miles between consecutive stops and not as the total distance from the origin to destination. In this way, a truck can make several trips as it travels from its origin to its destination if it makes intermediate stops along the way.

[5] The State of Arkansas has an east-west "width" of 270 miles and a north-south "length" of 240 miles.

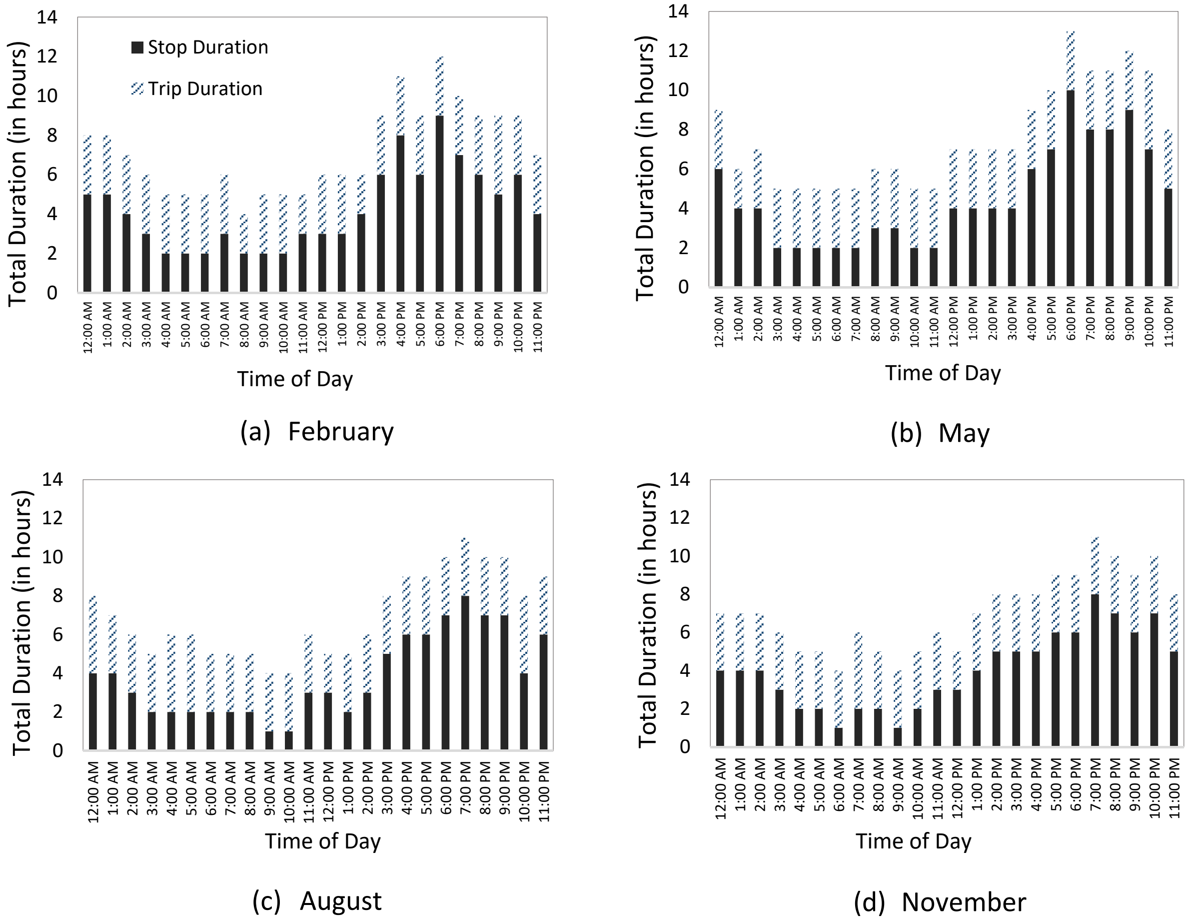


Figure 14. Average Trip and Stop Duration by Time of Day and Sample Period

AVERAGE TRIP SPEED BY TIME OF DAY

Trip speed was defined as the trip length (in miles) divided by the trip duration (in hours) for each trip. Average trip speed by roadway functional class and time of day was calculated by summing the trip speeds for all trucks on a specific roadway class for the hour that the trip began. Average trip speeds decreased most dramatically on interstates during peak periods, e.g. the AM peak period from 6 a.m. to 9 a.m. and the PM peak period from 4 p.m. to 6 p.m.. A small decrease in average speed during the AM peak was also seen for US and state highways. Overall, average speeds on interstates are consistent with assumed speed limits (Table 4) on each roadway class (Figure 15).

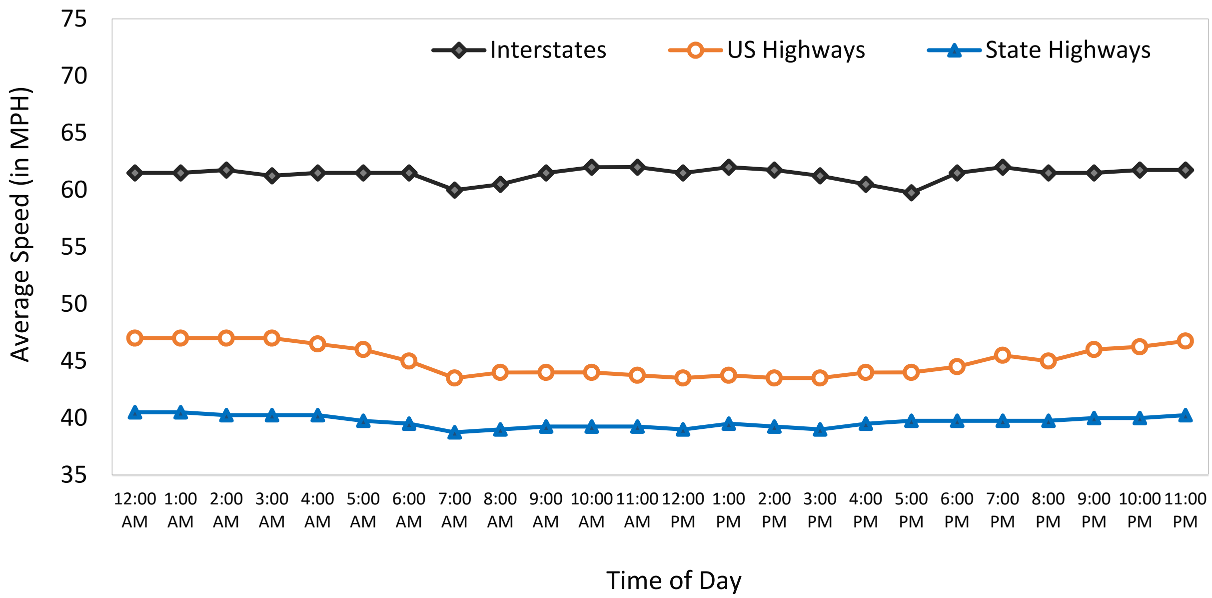


Figure 15. Average Trip Speed by Time of Day and Facility Type

ORIGIN-DESTINATION (OD) TRUCK FLOWS

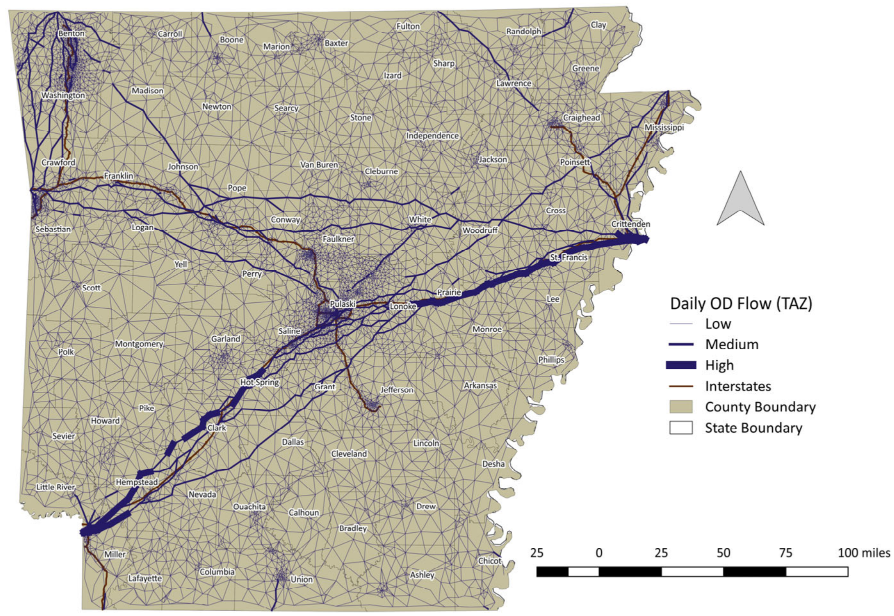
One of the tasks in this project involved the exploration of the use of ATRI's truck GPS data to generate truck travel time and routes between several locations (i.e., origin-destination pairs). This information can be used in future studies to analyze the route choice behavior of trucks, to inform truckers 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 Arkansas Statewide Travel Demand Model (ARSTDM).

OD flows, most commonly depicted in tabular form, can be difficult to visualize due to the multitude of OD pair combinations with non-zero flows. Instead of showing individual OD flows as lines connecting the origin and destination on a map, Delaunay Triangulation aggregates OD flows through common paths representing zone to-zone flows. To allow for better visualization, a Delaunay Triangulation method was applied to the GPS-derived OD flows and common paths were defined among Traffic Analysis Zones (TAZs) and counties. Delaunay Triangulation allows for a simplified visual comparison of desired paths with observed paths.. This is different from a map showing truck volumes on each network link which would show observed path flows. OD flows from the GPS-derived truck trips were defined between any consecutive set of stops, and not necessarily the origin and destination of the trip, as this is unknown. Each stop was treated as the origin or destination of a trip.

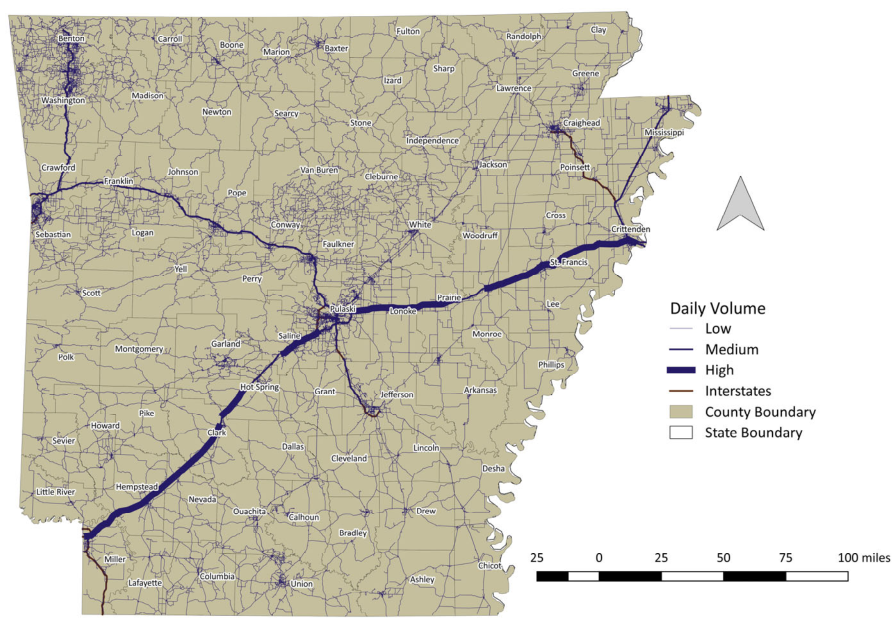
The Delaunay Triangulation OD flow map, created from the truck GPS trips (Figure 16a), showed demand for east/west trips parallel to Interstate 40 and southwest/east trips parallel to Interstate 30 that do not have a need to stop in Central Arkansas (e.g., Little Rock). There was a noticeable divergence of OD demand flow parallel to Interstate 49 in Northwest Arkansas indicating the desire to travel west across the AR border north of the Interstate 40 crossing. Lastly, there was a concentration of OD flow from Central Arkansas (Little Rock), east toward Northeast Arkansas near Jonesboro and Blytheville, indicating the desire to travel directly between these areas rather than along Interstate 30.

The heaviest observed OD flows were observed along Interstate 40 east of Little Rock connecting West Memphis, Arkansas to West Memphis/Memphis, Tennessee and along Interstate 30 from Texarkana to

Little Rock (Figure 16b). This trend was consistent across the four sample periods. Differences between the desired (Figure 16a) and observed (Figure 16b) flows can help indicate where additional highway capacity may be warranted.



(a) Delaunay Triangulation of Origin-Destination (OD) Truck Flows



(b) Daily Truck Volume on Road Links

Figure 16. Daily Truck Flows in Arkansas

CHAPTER 5: COVERAGE ANALYSIS

This chapter presents an analysis of the coverage of truck GPS data in Arkansas by roadway functional class, ARDOT district, and time period. Coverage is generally defined as the percentage of the total truck population that the GPS data sample represents. Alternative sources of truck and traffic data were used for the coverage analysis including traffic counts, and truck weight sensor data. More specific definitions of coverage are provided in each of the following sections. Overall, the sample truck GPS data included in this report constitutes coverage of around 9%. This is consistent with the results of previous studies. For example, in Florida, an ATRI data sample for a one-week period in 2010 had approximately 10% coverage (Pinjari el al., 2010). It is necessary to determine the coverage so that the performance measures can be effectively expanded for the total truck population.

Coverage of total truck traffic was defined as the percentage of the total truck volume measured by a Weigh-in-Motion (WIM) traffic sensor that was represented by the GPS data sample for the same time period (Eq. 1). To calculate coverage, WIM data corresponding to each specific time period of the GPS sample was needed. Due to maintenance and weather, the number of operating WIM sites varies from month to month (Table 7), therefore, approximately 80% of all WIM stations were used to compare with the GPS truck coverage in Arkansas (See Appendix A.1 for more detail). Moreover, only WIM-measured truck volume, as opposed to actual total truck volume, was considered in the coverage calculation. WIM sensors detect axle configuration and classify trucks according to a 13-class scheme (commonly referred to as FHWA Scheme F). Classes 1 through 4 correspond to passenger vehicles and classes 5 through 13 correspond to trucks, the most common being classes 5 (two-axle, single-unit trucks) and 9 (five-axle tractor-trailers). Class 5 trucks most often perform short-haul, local delivery operations. Trucks in classes 8 through 13, e.g. single- and multi-trailer tractor trailers, tend to serve long-haul operations. In relation to the GPS data, the high proportion of pass-through (EIE and EE) trucks suggested that the truck GPS data was more representative of long-haul operations. However, because truck axle configuration classes within the GPS data were unknown, coverage was assessed by comparing the GPS volume to the corresponding WIM volume of class 5 through 13 trucks.

To determine the GPS volume at a given WIM site, for any given hour and day, the results of the map-matching algorithm were used. As a result of the map-matching algorithm, each truck trip was characterized by a list of traveled links. The links that contained a WIM station were identified and the GPS volume on these links was found.

$$C_i^{t,d} = \frac{GPS_i^{t,d}}{WIM_i^{t,d}} \times 100\% \qquad \text{Eq. 1}$$

Where,

$C_i^{t,d}$	is the coverage (in percent) for site i, during hour t, on day d
$GPS_i^{t,d}$	is the GPS-derived volume at site i, during hour t, on day d
$WIM_i^{t,d}$	is the WIM-measured volume for FHWA Class 5-13 trucks at site i, during hour t, on day d

Overall coverage by period ranges from 9% to 10% (Table 7). In this chapter, the description and analysis of the results include general findings. Detailed coverage analysis by month, WIM site, etc. is provided in Appendix A.

Table 7. Weigh-in-Motion (WIM) Stations with Data Available for Coverage Analysis by Sample Period

Summary Statistic	February (Q1)	May (Q2)	August (Q3)	November (Q4)
Number of WIM Stations with Available Data	36	33	33	36
ATRI GPS Data Coverage	10%	9%	9%	10%

COVERAGE BY FUNCTIONAL CLASS

Average coverage, calculated according to Eq. 1, stratified by roadway functional class was compared. Note that for the roadway functional class coverage analysis, only three functional classes were included: interstates, US highways, and state highways. This is because WIM sites are not located along lower functional classes, e.g. arterials, local roads, etc. On average, 12 WIM sites were available for coverage calculations (Table 8). Interstates carried the highest truck volume compared to US highways and state highways for both WIM and GPS samples (Table 8).

Overall, the GPS data sample showed consistent coverage of truck movements for different functional classes. Coverage by functional class ranged from 6 in Q3 on interstates to 15% in Q4 on state highways with a weighted average of 9.6% (Table 9). Coverage did not vary significantly by sample period, however higher coverage was found along the interstates. This corresponded to the higher proportion of external trucks (EI, IE, and EIE) found in the GPS sample considering external trucks capture long-haul movements that favor interstate routes.

Table 8. WIM and GPS Volume by Functional Class

Functional Class	Number of WIM Stations (percent of total)	Total Mileage	Total Volume	
			WIM (percent of total)	GPS (percent of total)
Interstates	12 (32%)	2,033	3,389,783 (82%)	323,340 (85%)
US Highways	15 (39%)	4,699	512,581 (13%)	40,784 (11%)
State Highways	11 (29%)	13,571	207,290 (5%)	16,653 (4%)
Total	***38***	***20,302***	***4,109,654***	***380,777***

Table 9. Summary of Percent-Coverage by Functional Class and Sample Period

Functional Class	Coverage (%)				*Average Coverage (%)*
	February (Q1)	May (Q2)	August (Q3)	November (Q4)	
Interstates	8	7	6	9	7.6
US Highways	9	8	8	9	8.6
State Highways	14	15	13	15	14.2
Total	10	9	9	10	9.6

COVERAGE BY ARDOT DISTRICT

To understand the spatial coverage of the truck GPS data, coverage was assessed for each ARDOT district. ARDOT divides the state into 10 districts (Figure 17) each of which contain a varied number of WIM stations used for coverage calculations (Table 10). Coverage at each WIM site calculated according to Eq. 1 was averaged across all WIM sites in a district. Note that total WIM and GPS volumes were dependent on the number of WIM sites in the district and were not necessarily representative of the total truck volume in that region. Interstate, US highway and state highway mileage also varied by district, further accounting for the variation in total truck volumes by district.

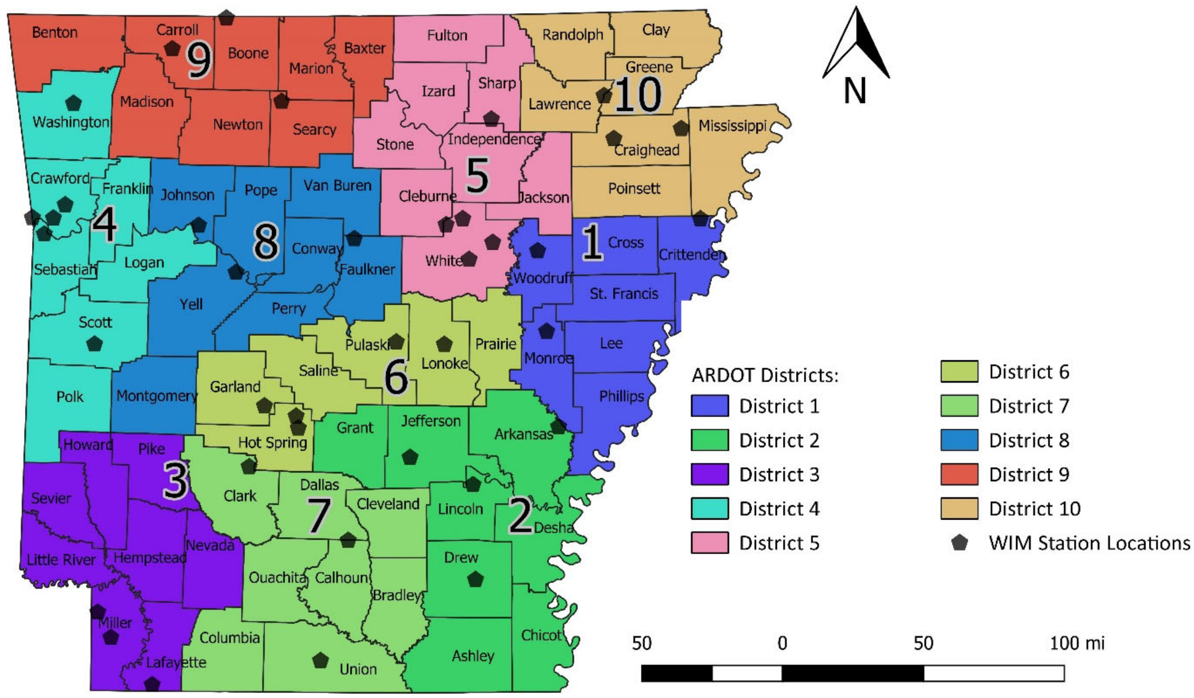


Figure 17. ARDOT District Map and WIM Station Locations

Table 10. Mileage, WIM, and GPS Volume by ARDOT District

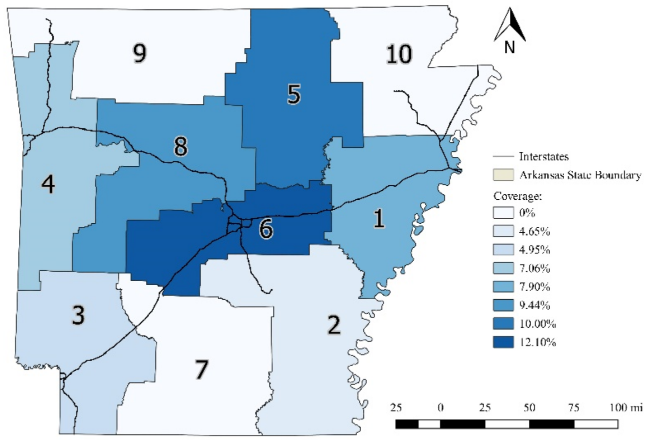
ARDOT District (City)	Number of WIM Stations (percent of total)	Roadway Mileage (miles)			Total Volume (number of trucks)	
		Interstate	US Hwy.	State Hwy.	WIM	GPS
1 (Wynne)	3 (8%)	278	418	1,263	489,953 (12%)	44,663 (12%)
2 (Pine Bluff)	4 (11%)	81	710	1,299	186,719 (5%)	12,133 (3%)
3 (Hope)	3 (8%)	250	517	1,068	171,403 (4%)	10,070 (3%)
4 (Barling)	6 (16%)	314	409	1,340	941,076 (23%)	68,180 (18%)
5 (Batesville)	5 (13%)	0	406	1,650	98,108 (2%)	9,972 (3%)
6 (Little Rock)	5 (13%)	508	439	1,101	1,091,952 (27%)	124,908 (33%)
7 (Camden)	3 (8%)	70	675	1,115	586,846 (14%)	61,157 (16%)
8 (Russellville)	3 (8%)	250	255	1,674	387,731 (9%)	38,398 (10%)
9 (Harrison)	3 (8%)	46	423	1,525	23,103 (1%)	3,622 (1%)
10 (Paragould)	3 (8%)	235	447	1,535	132,763 (3%)	7,674 (2%)
Total	***38***	2,033	4,699	13,571	***4,109,654***	***380,777***

Coverage by district ranged from 7.1% to 15% (Table 11). Districts 3, 4, 6, 7, and 10 had lower coverage, e.g., less than 10%. Coverage of around 10% was found for Districts 1, 2, and 8, which correspond mainly to East Arkansas. District 9, in Northwest Arkansas, had the highest coverage nearing 15%.

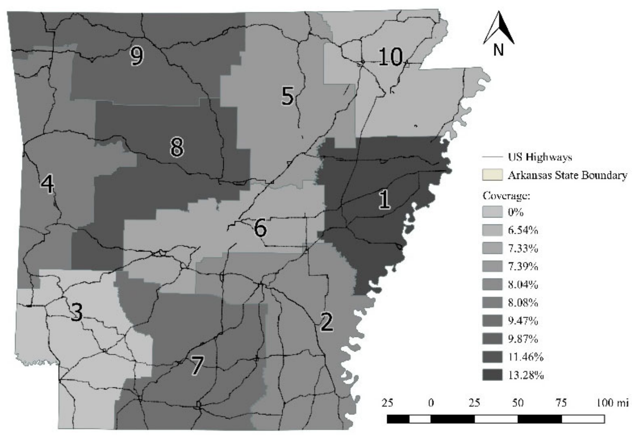
Variation in coverage by ARDOT district, and more generally by region of the state, was likely tied to truck classification in the dataset (e.g. II, EI, etc.) and mileage of roadway by functional class. Coverage by functional class and ARDOT district is depicted in Figure 18 to better show the variation in coverage when both the region and the roadway type are considered. For Figure 18, coverage for a district was computed by taking the average coverage of at each WIM site corresponding to each functional class(interstates (a), US highways (b), and state highways (c). Considering only interstates, District 6 in Central Arkansas had the highest coverage at 12.1%. Considering US highways, District 1 in East Arkansas had the highest coverage at 13.3%. Considering state highways, District 3 in Southwest Arkansas had the highest coverage at 22%. Overall, the variation in spatial coverage indicated good spatial representation with no significant gaps in coverage.

Table 11. Summary of Coverage by ARDOT District and Roadway Type

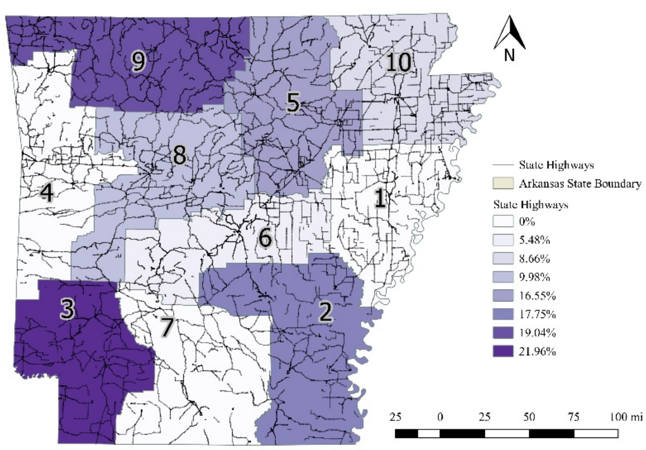
ARDOT District (City)	**Coverage by Roadway Type** (%)			**Average Coverage** (%)
	Interstate	**US Hwy.**	**State Hwy.**	
1 (Wynne)	7.9	13.3	14.2	10.5
2 (Pine Bluff)	4.7	8.0	17.8	9.9
3 (Hope)	4.9	8.6	22.0	8.3
4 (Barling)	7.1	8.1	14.2	7.4
5 (Batesville)	10.0	7.4	16.5	13.2
6 (Little Rock)	12.1	7.3	5.5	8.4
7 (Camden)	7.6	9.5	14.2	9.5
8 (Russellville)	9.4	11.5	10.0	10.1
9 (Harrison)	7.6	9.9	19.0	15.0
10 (Paragould)	7.6	6.5	8.7	7.1
Weighted Average	7.6	8.6	14.2	9.6



(a) Interstates



(b) US Highways



(c) State Highways

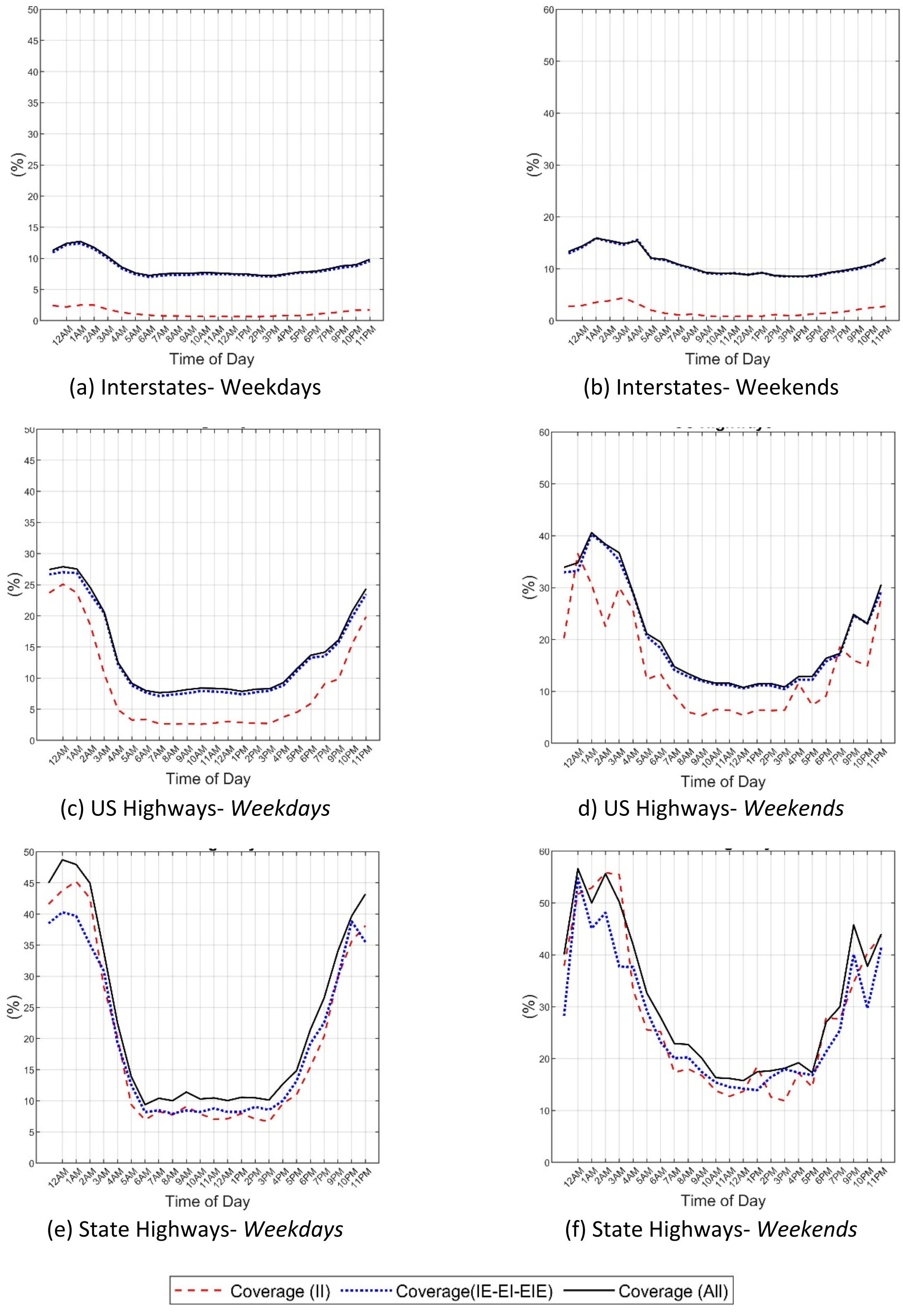
Figure 18. Coverage by Functional Class and ArDOT District

COVERAGE BY TIME OF DAY AND DAY OF WEEK

Further coverage comparisons include time of day and day of week analyses. To take into consideration differing operational characteristics of local (e.g. II) and long-haul (e.g. EI, IE, and EIE) trucks, coverage was calculated and compared independently for different truck classifications.

A similar time of day pattern was observed in coverage for US highways and state highways for all truck classifications: coverage of II and EI/IE/EIE trucks decreased to below 10% during daytime hours, from around 5 a.m. to 5 p.m.; during nighttime hours, 10 p.m. to 3 a.m., coverage was highest at around 20% (Figure 19 c and e). A different pattern was observed for interstates where more constant coverage (around 8%) was experienced throughout the day (Figure 19a). This discrepancy was likely due to having a fixed number of GPS trucks at all times of the day but experiencing a higher number of total trucks during daytime hours. Coverage on weekdays (Figure 19 a, c, and e) and weekends (Figure 19 b, d, and f) differed slightly in overall magnitude but exhibited the same time of day patterns.

An analysis for the day of week by functional class showed that there was an increase in coverage during weekends. This was likely due to having a fixed number of trucks in the GPS sample but experiencing a lower truck volume on the weekends. The highest coverage and most variation in coverage by day of week was found for state highways during weekends while the lowest coverage was observed for interstates (Figure 20).



(a) Interstates- Weekdays

(b) Interstates- Weekends

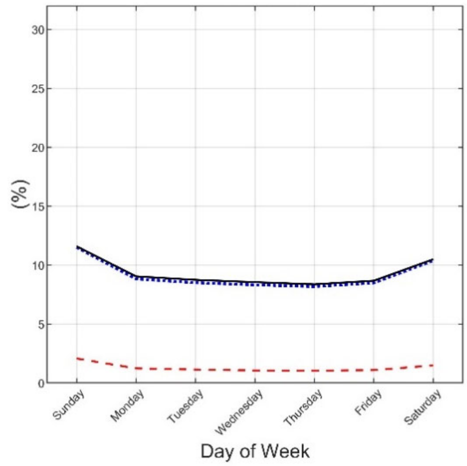
(c) US Highways- *Weekdays*

d) US Highways- *Weekends*

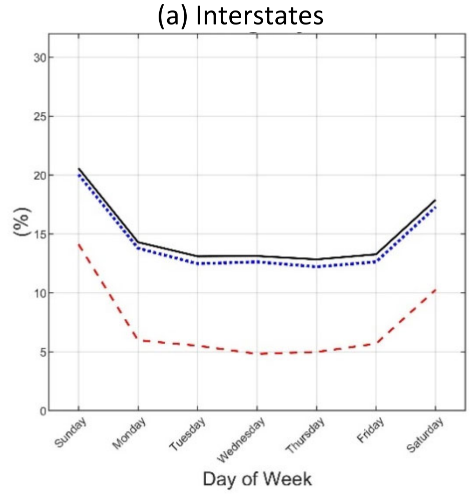
(e) State Highways- *Weekdays*

(f) State Highways- *Weekends*

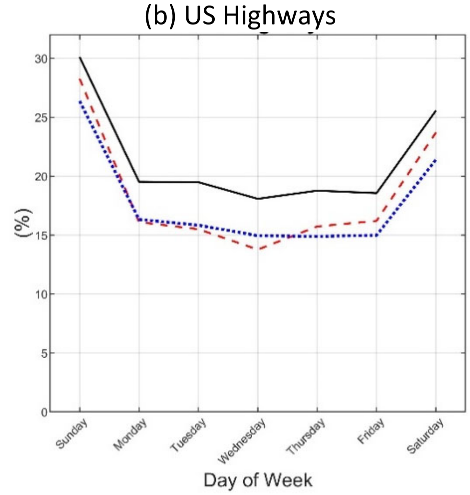
Figure 19. Coverage by Time of Day by Functional Class and Truck Class



(a) Interstates



(b) US Highways



(c) State Highways

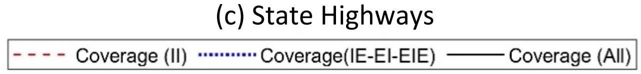


Figure 20. Coverage by Day of the Week, Functional Class, and Truck Class

CHAPTER 6: INTEGRATION WITH EXISTING FREIGHT-PLANNING EFFORTS

The results of the Stop Identification and map-matching algorithms, coupled with the estimated data coverage by functional class and region, were used to derive a set of freight performance measures for interstates and highways in Arkansas. Six key freight performance metrics are described in this section: (1) Daily Vehicle Miles Traveled, (2) Average Truck Speeds, (3) Average Travel Time Reliability, (4) Average Travel Time Variability, (5) Average Daily Delays, and (6) Percent of the Interstate System Mileage Uncongested. The FDOT Source Book was used as the primary reference for performance measure equations. Appendix B provides the full formulations and descriptions of freight performance measures described in this section. Interactive maps of performance measures are included in this work and described in the Implementation Report. In this chapter, only maps for February (Q1) are shown. Maps for all other sample periods, (e.g., May, August, and November) can be viewed using the web-based application.

DAILY VEHICLE MILES TRAVELED (DVMT)

Daily Vehicle Miles Traveled (DVMT) was defined as the total distance traveled by all trucks on all road segments per day (Eq. 2). To get population level DVMT from the GPS sample data, estimated DVMT was multiplied by an expansion factor to calculate the average DVMT for the total truck population. Here, the expansion factor is the inverse of the percent coverage, leading to the DVMT estimate for the total truck population below.

$$DVMT_{pop} = \frac{\sum_{i,d} L_i \times V_{i,d} \times EF_i}{D} \qquad \text{Eq. 2}$$

Where,

$DVMT_{pop}$	is population-level DVMT estimate (vehicle miles)
L_i	is the length of road segment *i* (miles)
V_i	is the combination truck volume for road segment *i* and day *d*, e.g. the GPS estimated truck volume (trucks)
EF_i	is the expansion factor for road segment *i*, calculated as the inverse of the percent coverage corresponding to the functional class and district location of roadway segment *i* (percent)
D	is the total number of days included in the average (days)

The highest DVMT was observed during the fall season, corresponding to August (Table 12). Since Arkansas has about 13.8 million acres of farmland (USDA, 2017), DVMT likely increased during this time due to harvest activities. DVMT was also examined by interstate corridor (Table 13). Interstate 40 had the highest DVMT with 7,027 thousand vehicle-miles, followed by I-30 with 3,838 thousand vehicle-miles, and Interstate 630 had the lowest with 14.5 thousand vehicle-miles. There is a distinct drop in DVMT between Interstate 40 and Interstate 30 as well as the other eight interstate corridors.

Table 12. Average Daily Vehicle Miles Traveled (DVMT) by Sample Period

Sample Period (Quarter)	DVMT for Month (million vehicle-miles)
February (Q1)	11.7
May (Q2)	12.2
August (Q3)	13.9
November (Q4)	13.2
Total (Annual)	***4,745***

Table 13. Average Daily Vehicle Miles Traveled (DVMT) by Interstate Corridor

Corridor	DVMT (thousand vehicle miles)
I-40	7026.8
I-30	3838.1
I-55	846.0
I-49	829.7
I-440	244.0
I-530	229.1
I-555	167.7
I-540	99.3
I-430	43.4
I-630	14.5
Total (Daily)	**13338.5**

TRUCK SPEEDS

Average speeds on interstates and highways were estimated for peak periods. First, space-mean-speed (SMS) was calculated for each pair of consecutive GPS pings. Next, calculated space-mean-speed was assigned to its corresponding ARNOLD road link via the map-matching algorithm. Lastly, SMS's corresponding to interstates and highways during the peak periods (6 a.m. – 9 a.m. and 4 p.m. – 7 p.m.) of the day were used to compute average speeds for each segment (Eq. 3).

$$Speed_i = \frac{\sum(CTMT_i \text{ x } Combination\ Truck\ Average\ Travel\ Speed_i)}{\sum(CTMT_i)} \quad \text{Eq. 3}$$

Where,

$Speed_i$ is average speed on road segment *i*

$CTMT_i$ is Combination Truck Miles Traveled on road segment *i*

$Combination\ Truck\ Average\ Travel\ Speed_i$ is the average speed of combination trucks (FHWA Classes 5-13) calculated as described above on road segment *i*

Average peak hour speed for most of interstate segments was greater than 55 mph (Figure 21). Lower average peak hour speeds (less than 25 mph) were observed on interstates and highways near large metropolitan areas in Pulaski, Benton, and Washington counties.

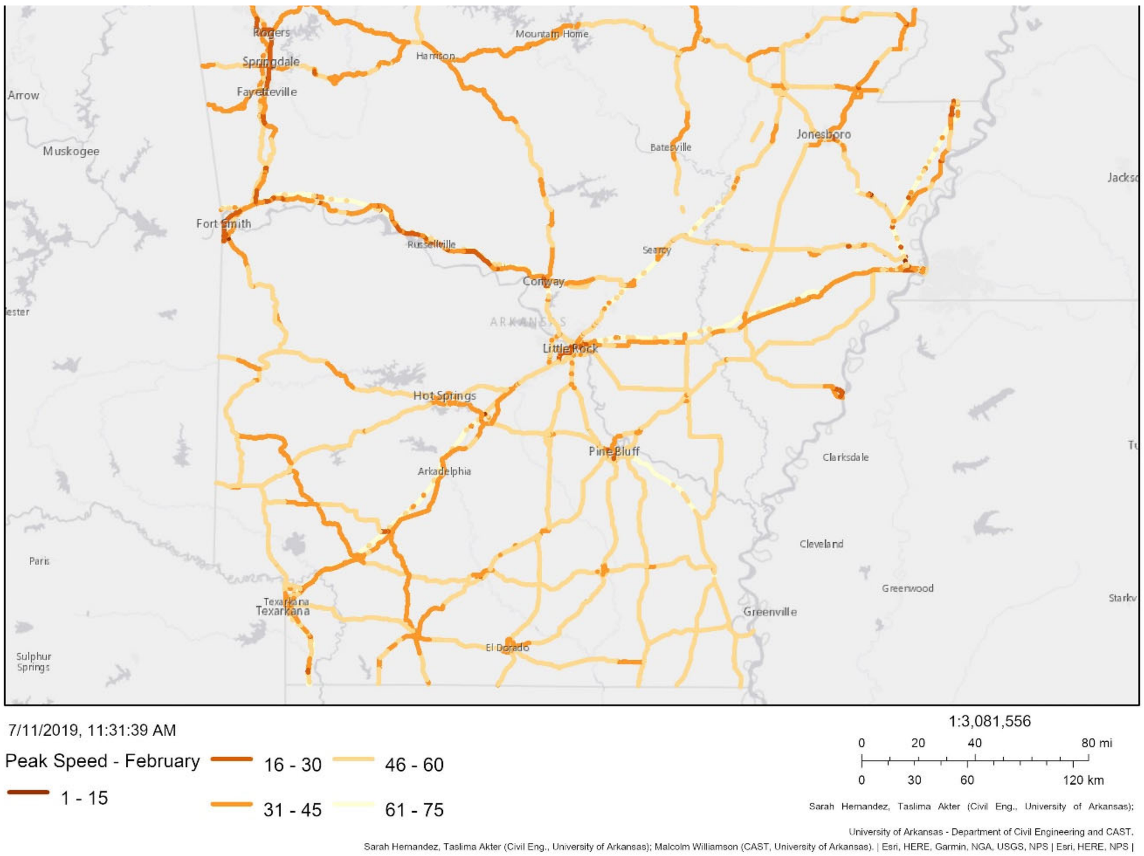


Figure 21. Average Peak Hour Speed on Interstates and Highways

TRAVEL TIME RELIABILITY (TTR)

Average Travel Time Reliability (TTR) is defined according to Equations 4 and 5 for interstates and highways for the peak period (6 a.m. – 9 a.m. and 4 p.m. – 7 p.m.). TTR captures the variation in travel time relative to posted speed limits. In order to calculate TTR, the following assumptions were made:

- Since the ARNOLD road network database does not contain speed limit attributes, speed limits of 65 mph and 55 mph were assumed for interstates and highways, respectively.
- These speed limits reflect trucks speeds, and are thus lower for interstates than the posted speeds.
- Formulations for TTR provided in the FDOT Source Book suggest different assumed deviations from posted speeds for rural and urbanized areas so it was assumed that TTR for interstates and US highways, which are more often located near large metropolitan areas, would be calculated according to Eq. 4 and TTR for state highways, which are more often in rural areas, would be calculated according to Eq. 5.

Average TTR for most of the interstates and highways were above 60% (Figure 22). The lower value of TTR indicates higher travel time delays during the peak period. Lower average TTR (≤20%) were observed in the Northwest and Central regions of the state. Consistent with average truck speed, average TTR decreases near larger metropolitan areas.

For interstate and US highways,

$$TTR_i = \frac{\sum(CTMT_i|Combination\ Truck\ Travel\ Speed_i \geq 45mph)}{\sum(CTMT_i)} \times 100\% \qquad \text{Eq. 4}$$

Where,

TTR_i is Travel Time Reliability on road segment *i*

$CTMT_i$ is Combination Truck Miles Traveled on road segment *i*

$Combination\ Truck\ Travel\ Speed_i$ is the travel speed (in mph) of combination trucks (FHWA Classes 5 through 13) on road segment *i*

For State Highways,

$$TTR_i = \frac{\sum(CTMT_i|Combination\ Truck\ Travel\ Speed_i \geq (Speed\ Limit_i - 5mph))}{\sum(CTMT_i)} \times 100\% \qquad \text{Eq. 5}$$

Where,

$Speed\ Limit_i$ is posted speed limit on road segment *i*

All other terms previously defined

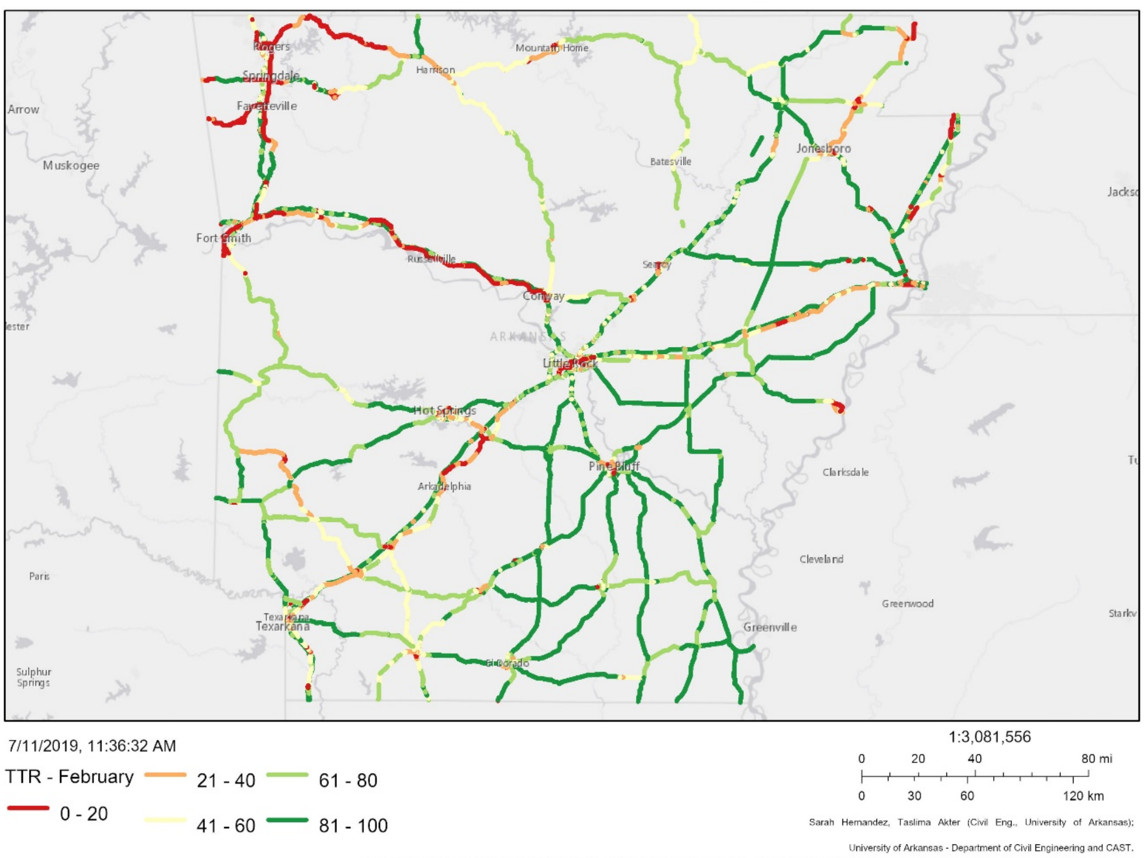


Figure 22. Average Travel Time Reliability (TTR) on Interstates and Highways

TRAVEL TIME VARIABILITY (TTV)

The Travel Time Variability (TTV) is defined as the ratio of the 95th percentile travel time to free-flow travel time for a road segment according to Eq. 6. TTV is similar to TTR in that it captures variation in travel times relative to free-flow conditions. Free-flow travel time was calculated using the assumed posted speed limit of a road segment (Table 4). TTV differs from TTR in that it does not represent a weighted average (weighted by truck volume) and references the 95th percentile speed instead of the average speeds above a given threshold, e.g. 45 mph in Eq. 4 or the speed limit in Eq. 5. Average TTV was estimated for interstates and highways during the peak period (6 a.m. – 9 a.m. and 4 p.m. – 7 p.m.). Free-flow travel time was calculated using the assumed speed limit, i.e. 65 mph and 55 mph for trucks on interstates and highways, respectively.

A TTV greater than one can be interpreted as 95 percent of trucks that used the link during the peak period had a shorter travel time than the free-flow travel time. A TTV less than one can be interpreted as congestion occurrence. The main interstates, e.g., Interstate 40, Interstate 30, and Interstate 55, offer TTV greater than one, i.e. minimal or no congestion effects (Figure 23). State and US highways of North Arkansas appeared to have TTV less than one, however it is less likely to be due to congestion in these areas and more likely due to roadway topography affecting truck speeds. To enhance the accuracy of TTV in future work, a true measure of free-flow travel time is needed, including these topography factors.

$$TTV_{i_{95}} = \frac{Travel\ Time_{i_{free\ flow}}}{Travel\ Time_{i_{95th\ percentile}}} \qquad \text{Eq. 6}$$

Where,

$TTV_{i\ 95}$	is 95th percentile Travel Time Variability on road segment *i*
$Travel\ Time_{i\ free\ flow}$	is travel time with free-flow conditions on road segment *i*
$Travel\ Time_{i\ 95th\ percentile}$	is travel time of 95 percent of trucks on road segment *i*

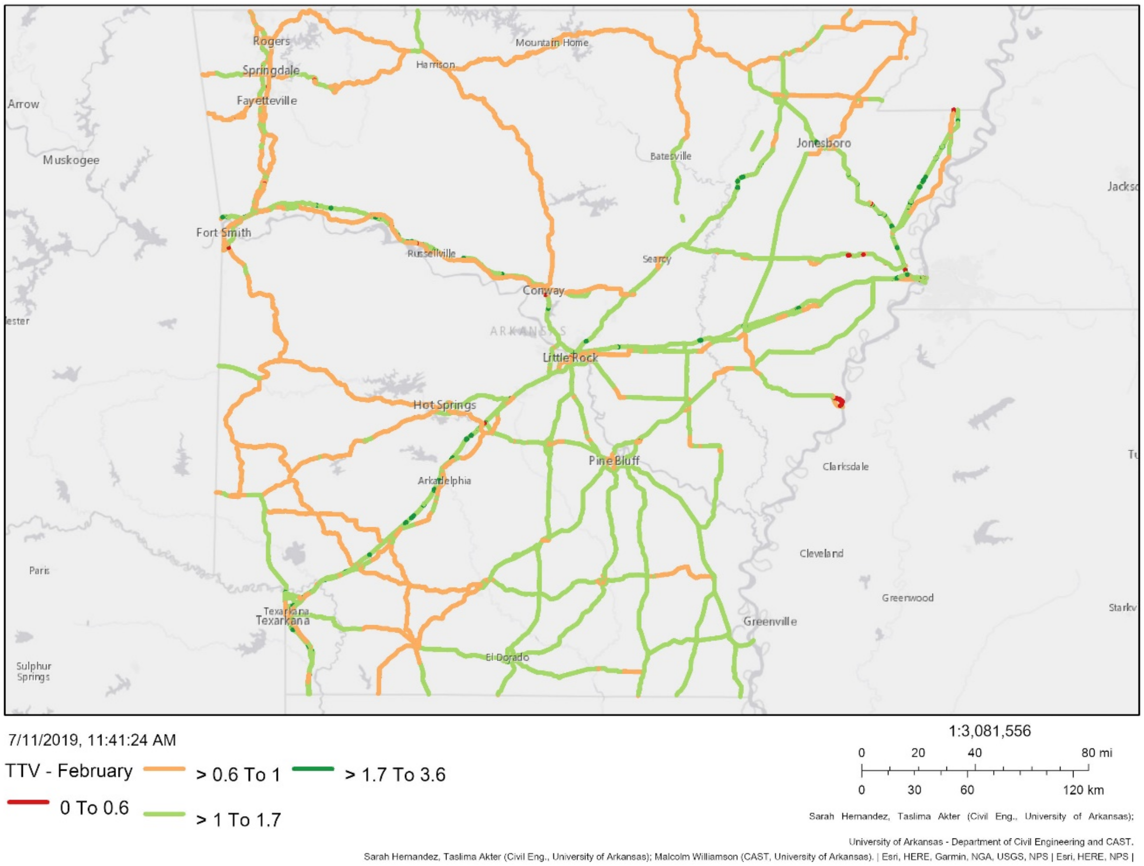


Figure 23. Average Travel Time Variability (TTV) on Interstates and Highways

DAILY DELAY

Daily delay was calculated as the difference in average daily GPS-derived travel time and free-flow travel time for each link (Eq. 7). The measure represents the total delay along a link in total hours of delay such that the delay for each vehicle is summed to estimate daily delay. Similar to TTR and TTV, assumed speed limits were used to estimate free flow travel time.

Much of the US and state highway network did not experience daily delay (Figure 24). Overall, interstates had higher daily delay than other functional classes. Daily delay exceeding around seven hours occurred on the border between Crawford and Washington counties, Crawford and Franklin counties, Lonoke and Prairie counties, and along I-30 between Hot Springs and Saline.

$$Delay_i = \frac{\sum_{d=1}^{D}\sum_{j=1}^{N}\left(Travel\ Time_{i_{j_{d\,observed}}} - Travel\ Time_{i_{free\ flow}}\right)}{D} \qquad \text{Eq. 7}$$

Where,

$Delay_i$	is average daily delay on road segment i in hours
$Travel\ Time_{i\ free\ flow}$	is travel time with free flow conditions on road segment i
$Travel\ Time_{i\ j\ d\ observed}$	is observed travel time of truck j on road segment i for day d
N	is total number of trucks on road segment i
D	is total number of observed days on road segment i

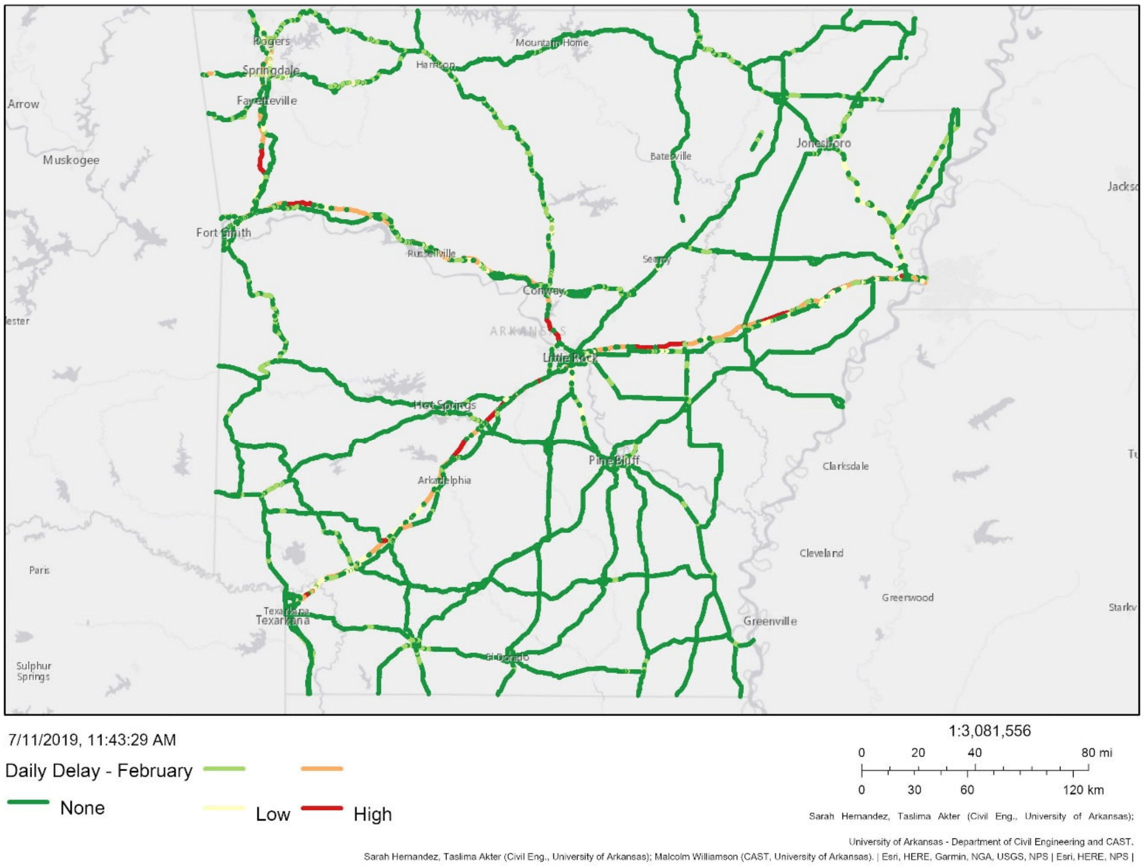


Figure 24. Daily Delays on Interstates and Highways

PERCENT OF THE INTERSTATE SYSTEM MILEAGE UNCONGESTED (PISMU)

The Percent of the Interstate System Mileage Uncongested (PISMU) was calculated as the percent of uncongested road segments relative to all road segments by length (Eq. 8). For PISMU, uncongested road segments were defined to have average speeds greater than 50 mph.

90 percent of all interstate miles were uncongested in Arkansas. PISMU is an aggregate number meant to represent the entire state. As a means to examine individual interstate segments, the percent of trucks with speeds greater than 50 mph, i.e. those traveling during uncongested conditions, was calculated (Figure 25). As shown with prior performance measures, urban areas experience a lower percent of uncongested conditions (e.g., higher occurrence of congestion).

$$PISMU = \frac{\sum_g^U SL_g}{\sum_i^T SL_i} \times 100\% \qquad \text{Eq. 8}$$

Where,

PISMU	is the Percent of Interstate System Mileage Uncongested (percent)
g	is the index for uncongested interstate segments, defined as a segment that has an average truck speed greater than 50 mph, g = 1 to *U*
U	is the total number of uncongested interstate segments
i	is the index for all interstate segments, i = 1 to T
T	is the total number of interstate segments
SL	is the segment length, to the nearest hundredth of a mile, of an interstate System (miles)

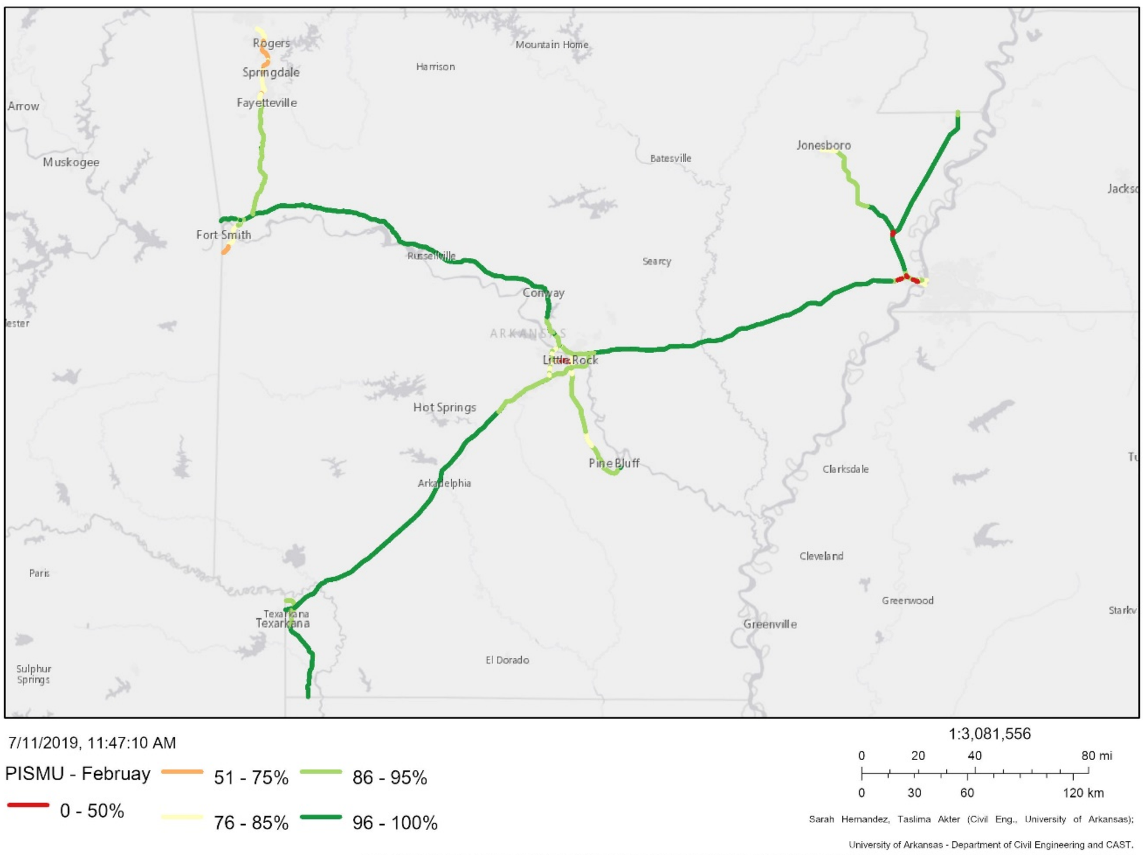


Figure 25. Percent of Uncongested Truck Volume on Interstates

ORIGIN-DESTINATION (OD) FLOWS

In this study, OD matrices from two different sources, (e.g., Arkansas Statewide Travel Demand Models (ARSTDM) and ATRI truck GPS data) were compared. The purpose of the comparison was two-fold: First, the comparison served as a way to validate the ARSTDM OD flows that are derived from Transearch, a proprietary commodity and economic database. Second, the comparison helped to indicate what industries may be missing within the truck GPS data. Delaunay Triangulation was performed using the centroids of the counties to obtain county-to-county flows. Note that the time frame of ARSTDM and GPS data differed (e.g. GPS data was from 2016 and the ARSTDM base year data was from 2010). This could factor into some of the discrepancies.

From the ARSTDM, the tonnage OD flows were converted to truck OD flows for 15 independent commodity groups by applying a truck payload factor, which was specific to each commodity. ARSTDM OD matrices were comprised of 15 commodity groups, (e.g., farm products, mining, coal, nonmetallic minerals, food, consumer manufacturing, non-durable manufacturing, lumber, durable manufacturing, paper, chemicals, petroleum, clay-concrete-glass, primary metal, and miscellaneous mixed). Each commodity group had a unique pattern of OD flows considering truck volume and route choice (Figure 26, note that larger images of each commodity OD flow map is included in Appendix D). OD flows of nonmetallic minerals, clay, concrete, glass, and miscellaneous mixed commodities were scattered all over Arkansas while consumer manufacturing, paper, and lumber flows were concentrated in the Southern region of the state. Food products had similar OD patterns as farm products but with a higher number of truck trips. Figure 27 shows the annual OD flows of all commodity groups in Arkansas. Since Arkansas has a high number of pass-through truck movements, the highest number of OD flows were observed between the Southeast and Southwest counties (Figure 27).

For the GPS data, the method described in Section 4.4 was applied at the county level, rather than Transportation Analysis Zone (Figure 28). Unlike ARSTDM OD matrices, GPS OD matrices did not contain commodity or industry information, and thus cannot be subdivided by commodity. Note that GPS OD matrices defined origins and destinations including all stop types, e.g., rest, refuel, pick-up/delivery. The ARSTDM, on the other hand, considers locations of pick-up/delivery, e.g., freight activity, as origins and destinations. This distinction between the two datasets may lead to some of the discrepancies in their comparison. From the GPS data, much of the OD flows are parallel to the major interstates, e.g., Interstate 40, Interstate 30, and Interstate 49 (Figure 28), likely due to the need for rest and fuel, and not due to freight activity. The heaviest GPS OD flows were observed between West Memphis and Crittenden County (Figure 28).

The absolute difference between the GPS and ARSTDM OD flows was evaluated (Figure 29). GPS OD flows did not represent the high OD flows seen in the ARSTDM between the Southeast and Southwest part of the state. Comparing the trip length frequency distribution, the majority of GPS OD flows were between 50 and 100 miles while the majority of the ARSTDM flows were between 100 and 200 miles (Figure 30). Since GPS OD flows included stops that not either pickup or delivery location, e.g. long rest break, it had a lower percent of longer trip length (origin-destination distance) than ARSTDM trucks (Figure 30).

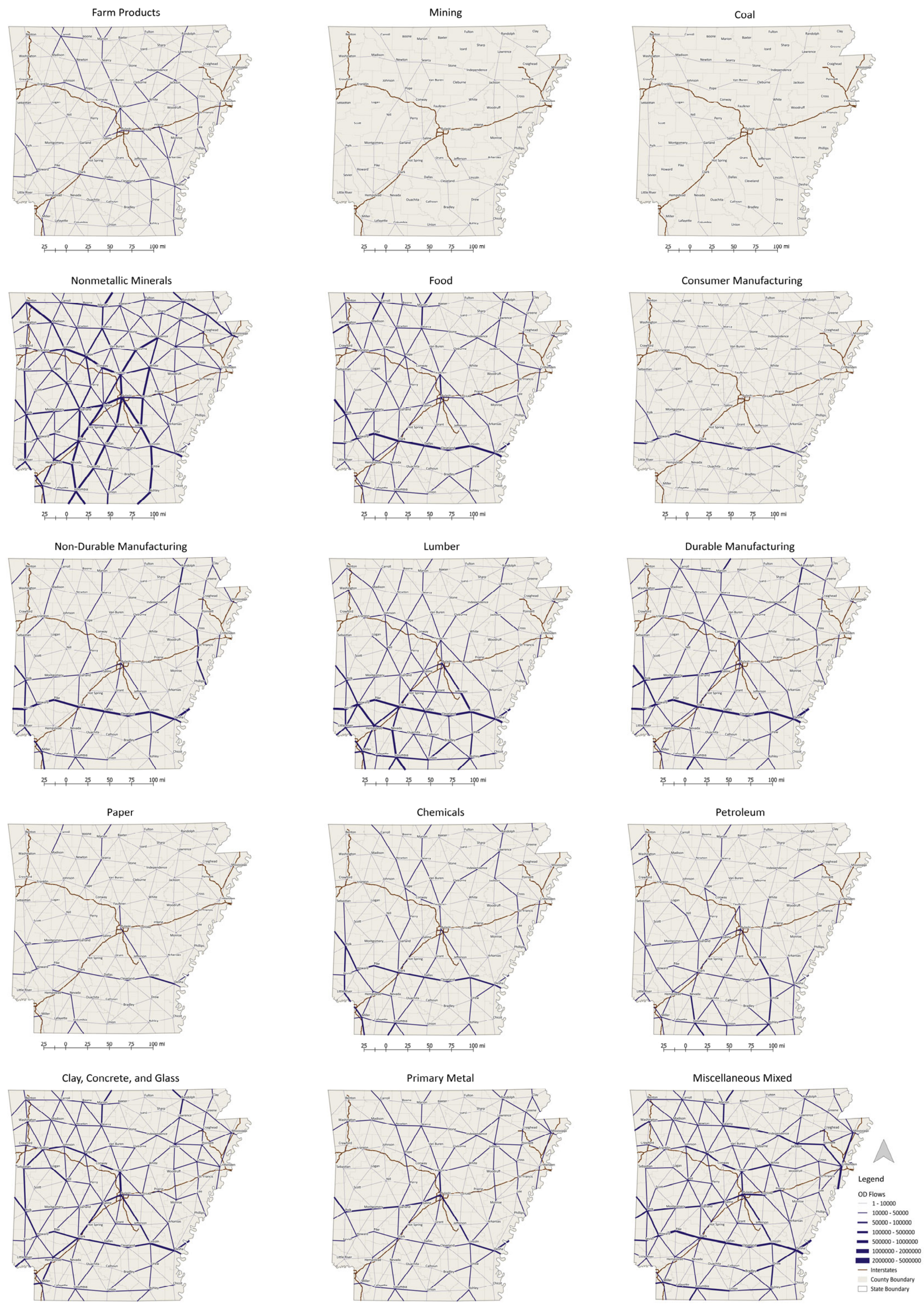


Figure 26. Annual Origin-Destination (OD) Flows of Different Commodity Groups in Arkansas

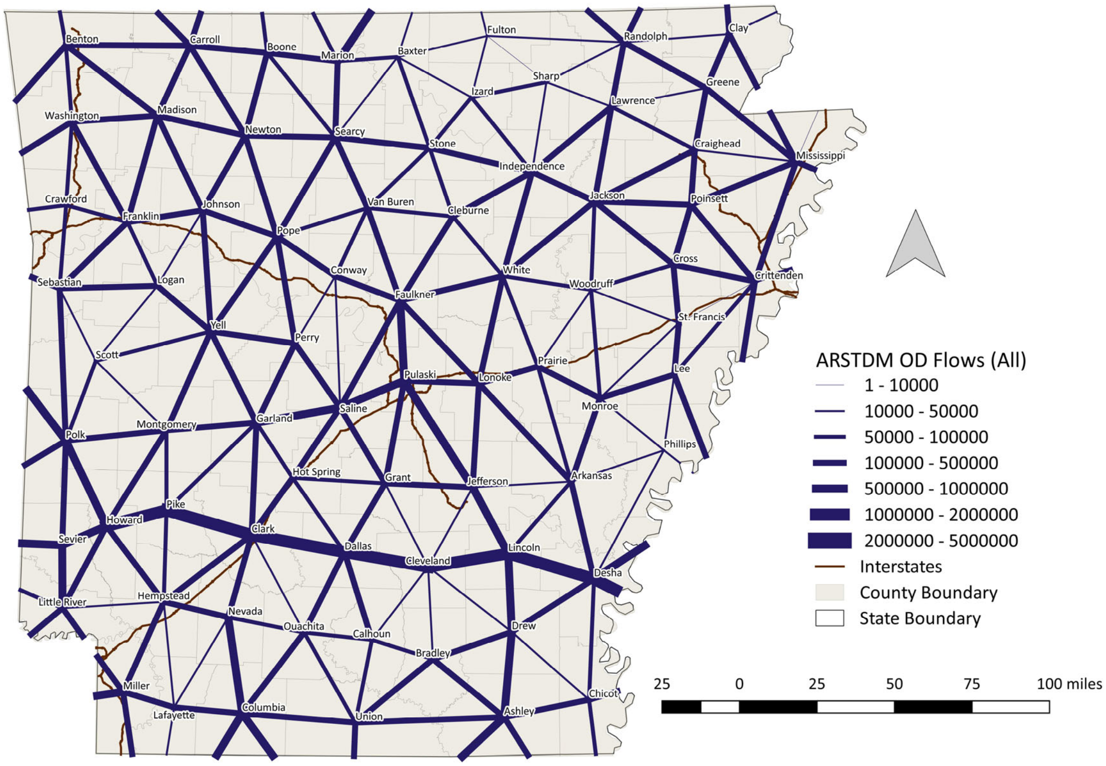


Figure 27. Annual Origin-Destination (OD) Flows of All Commodity Groups in the ARSTDM in Arkansas

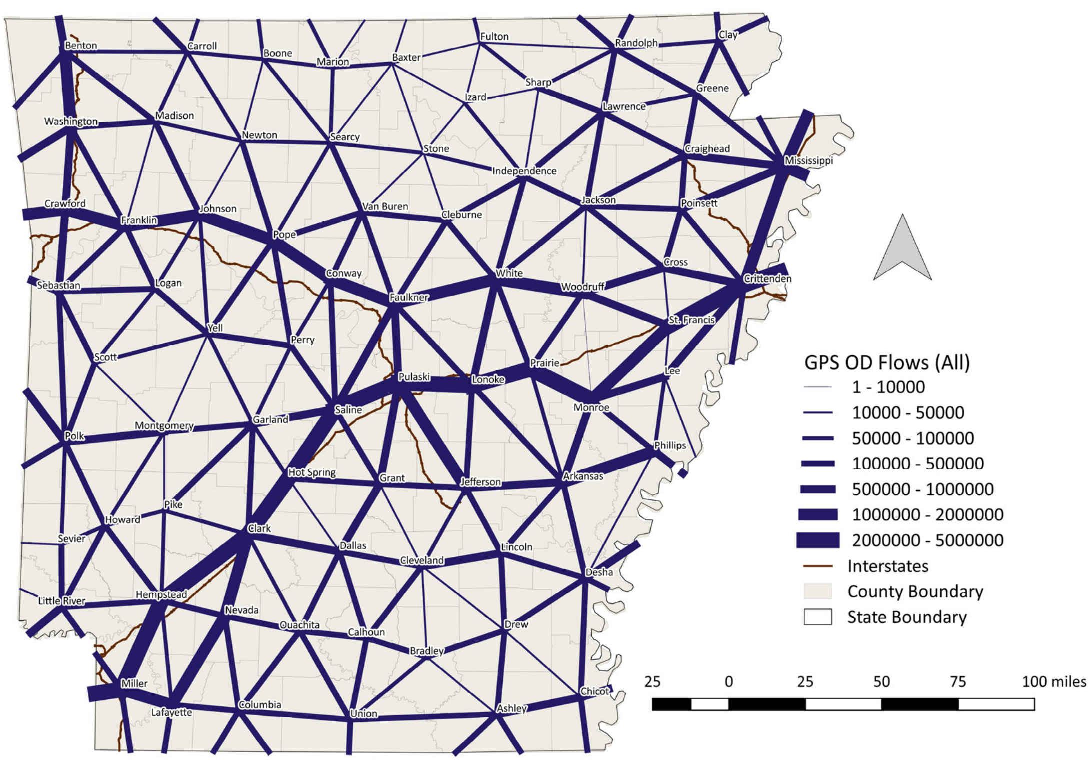


Figure 28. Annual Origin-Destination (OD) Flows of All GPS Trucks in Arkansas

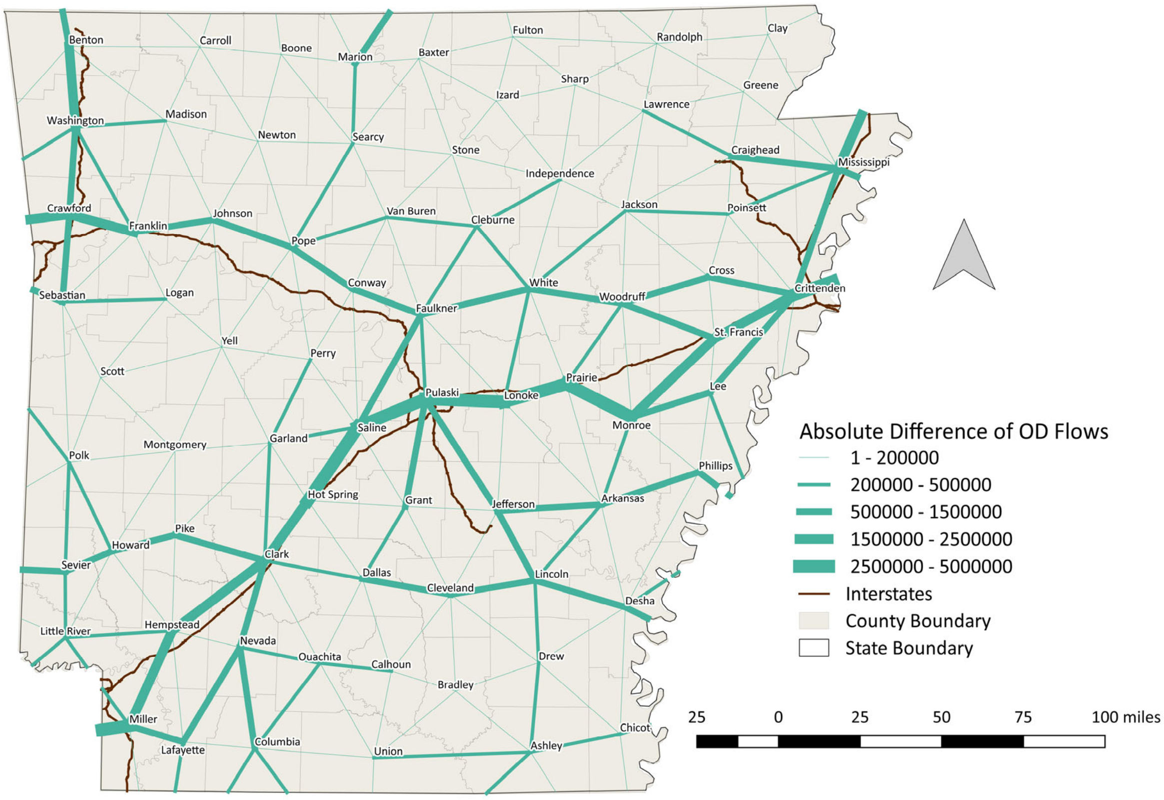


Figure 29. Absolute Difference Between ARSTDM and GPS Origin-Destination Flows

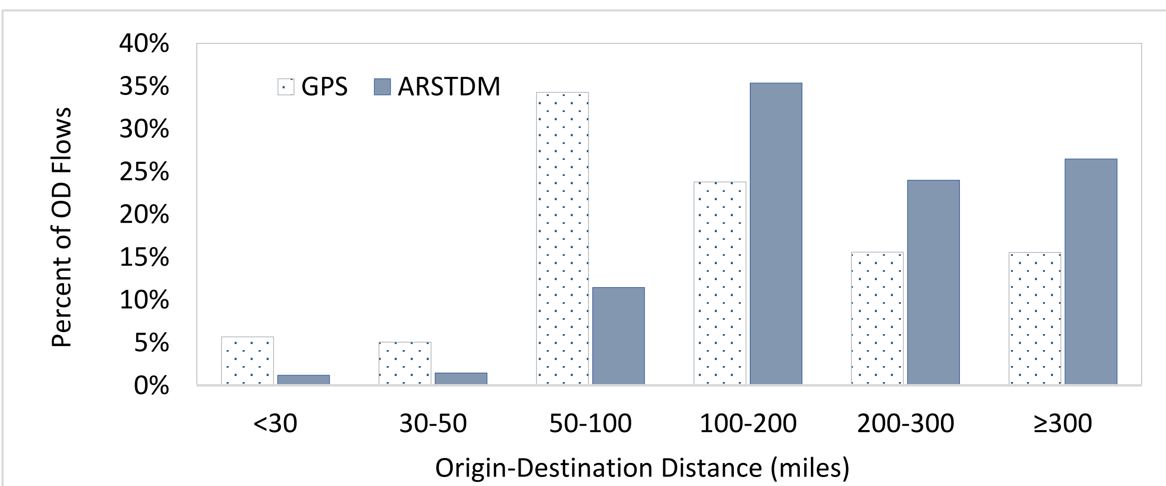


Figure 30. Trip Length Frequency Distribution

CHAPTER 7: USE CASE APPLICATIONS

This section contains three use cases of the processed truck GPS data. The three cases include: (1) examination of the characteristics of intermodal connectors, (2) usage and capacity assessment of truck parking, and (3) analysis of crash data. These case studies highlight the applications and use of the truck GPS data.

USE CHARACTERISTICS OF INTERMODAL CONNECTORS AND PORTS

Truck GPS data can be used to monitor performance of intermodal infrastructure such as inland waterway ports. This use case identified the in-state routes followed by trucks found at the three port intermodal connectors (ICs) in Arkansas, and the location of the stops made along those routes. ICs are short segments of the National Highway System (NHS) that connect intermodal terminals such as ports to the NHS. The study looked at the inland waterway ports, or port areas, in Van Buren, Little Rock, and Pine Bluff. The goal of this case study was to qualitatively and quantitatively describe truck volumes by time of day, season, and region at each of three inland waterway ports. Related work, further detailing the usage of ICs in Arkansas can be found on the Maritime Transportation Research and Education Center (MarTREC) website[6].

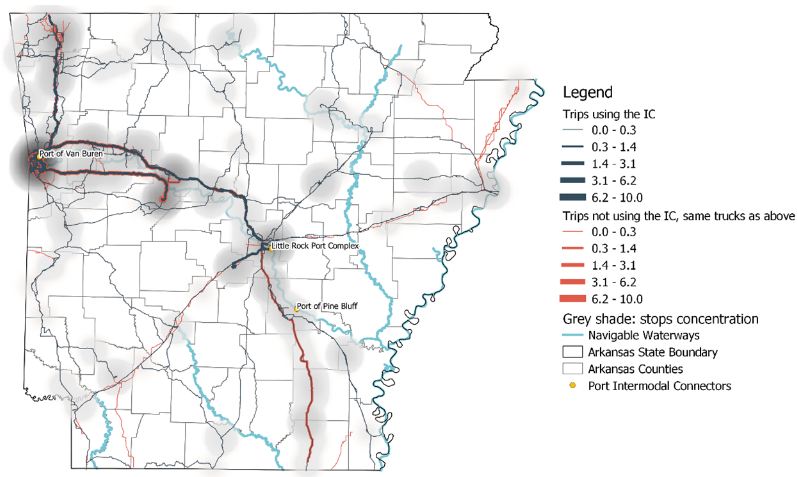
Methodology

The number of trucks accessing each inland waterway port was estimated using the results of the Stop Identification and map-matching algorithms. Trucks using the IC and other port access roads were counted from the GPS data via the map-matching results. The resulting sample was expanded based on coverage factors corresponding to the sample time period (e.g. quarter) and region (e.g. ARDOT district) to produce a daily average truck count for each port during each quarter (Table 14). The spatial usage pattern for each port was defined as a *catchment area*, which is the geographic extent covered by the set of truck trips which accessed the port via the port access roads and had an origin or destination at the port. In general, the catchment area represented the landside impacts of the port (Figure 31a-c).

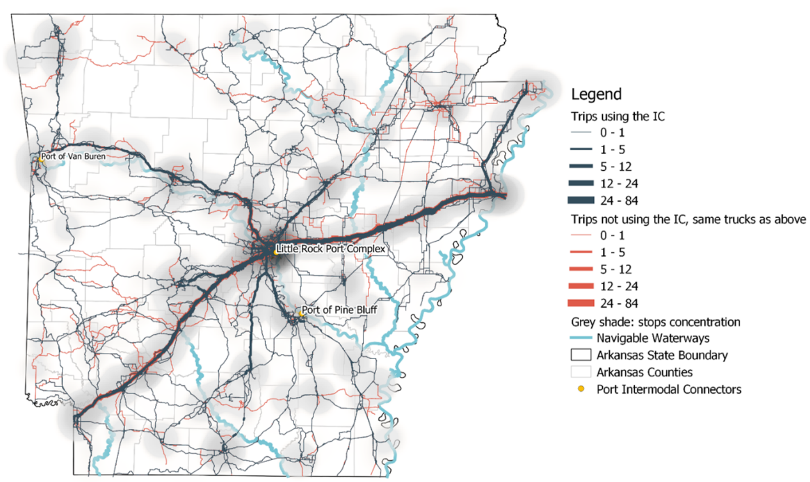
Table 14. Daily Average Volumes by Sample Period of Trucks Accessing Inland Waterway Ports

Usage Statistics	February Q1	May Q2	August Q3	November Q4	*Total*
Van Buren					
Volume	28	23	8	27	*86*
VMT (vehicle-miles)	427	656	132	1,382	*631*
Total Number of Stops	195	301	100	590	*1,205*
Little Rock					
Volume	83	220	185	186	*674*
VMT (vehicle-miles)	5,413	4,247	3,679	6,750	*5,071*
Total Number of Stops	1,323	3,307	3,140	2,415	*10,104*
Pine Bluff					
Volume	35	58	51	56	*201*
VMT (vehicle-miles)	1,702	2,405	1,179	1,925	*1,727*
Total Number of Stops	597	979	566	732	*2,807*

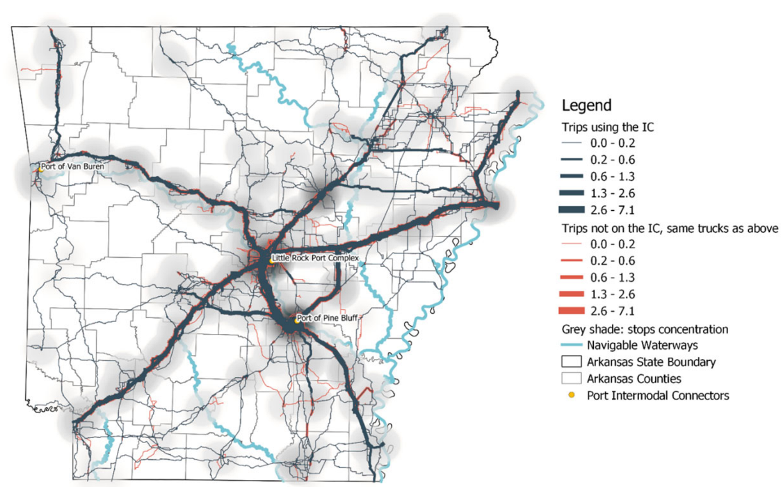
[6] MarTREC Website and link to the report "Evaluating the Performance of Intermodal Connectors": https://martrec.uark.edu/research/infrastructure.php



(a) Port of Van Buren



(b) Port of Little Rock



(c) Port of Pine Bluff

Figure 31. Catchment Areas for Each Inland Waterway Port Derived from Truck GPS Data

Key Findings

This use case indicated the usage of roads that serve the inland waterway ports of Van Buren, Little Rock, and Pine Bluff by season and mapped the spatial patterns of trucks accessing each port. Assuming GPS data to be a representative random sample of the total population of trucks moving freight within Arkansas, spatial and temporal patterns of usage identified from the GPS data provide insight into seasonal commodity movements.

Van Buren was the third-most active port of the three as measured by estimated daily truck volume, Vehicle Miles Traveled (VMT), and number of stops. Trucks accessing the Port of Van Buren had a high concentration of subsequent stops in Benton/Washington counties, Pulaski county, and Russellville/Dardanelle/Centerville areas (Figure 31a). The heaviest concentration of stops was in the Northwest Arkansas region. August saw the lowest activity at the port, with activity more evenly distributed across the remaining quarters. The Port of Little Rock was the most active of the three ports with triple the daily volume of Pine Bluff and an order of magnitude greater than Van Buren. Trucks accessing the Little Rock Port Complex had subsequent stops concentrated in the eastern and southern regions of Arkansas. The heaviest concentration of stops was found in Memphis and in cities located along Interstate 30, south of Little Rock. Truck activity peaked in May and declined in February. Trucks accessing the Port of Pine Bluff made subsequent stops in the southeast region of Arkansas. The heaviest concentration of stops was found along Interstate 530 between Pine Bluff and Little Rock. Truck activity declined in February but was evenly spread across the remaining three quarters.

Interestingly, from the catchment area analysis, some trucks traverse routes that are parallel to navigable waterways, indicating a potential for the cargo to continue by water for a longer stretch than it currently does. Moreover, the GPS data reveals the usage patterns of these parallel routes serving the same city pairs. This indicates that truck GPS data could be used to identify and quantify “preferred” routes by carriers. This may be of interest to design detours in cases where roadway infrastructure needs to be temporarily shut down. This seasonality analysis supports several planning and infrastructure decisions. For example, seasons experiencing the lowest volumes of freight movements can be targeted to perform maintenance and construction work on existing highways or port infrastructure and dredging activities in a way that minimizes disruptions to freight flows. Locations of stops indicate what commodities move through the port area—information that is often cited as another major data gap needed to understand port activities. For example, Centerville is an active agricultural region, and thus the volume of trucks making stops before/after visiting the Port of Van Buren can be used as a proxy for the tonnage of agricultural products moving through the Port. If truck GPS data were also available for a broader region (e.g., adjacent states), this analysis could expand the limits of the state to incorporate out-of-state portions of long-haul trips and allow for analysis of the entire region affected by port activities on the landside.

USAGE AND CAPACITY ASSESSMENT OF TRUCK PARKING

ARDOT conducts the Overnight Truck Parking Study (referred to as the *Overnight Study*) annually during the first week of September between 10 p.m. and 6 a.m.. Truck GPS data can be used to replace or supplement the Overnight Study to reduce data collection costs and to expand spatial and temporal coverage of the Overnight Study sites. This use case compared truck parking counts collected through direct observation as part of the Overnight Study to those derived from GPS data to determine appropriate GPS expansion factors, e.g. ratio of the GPS sample to the truck population, for different facility types. Unlike the ARDOT Overnight Study, truck GPS data provided continuous estimation of truck parking usage in terms of number of trucks parked and duration of parking for each of 400+ public as well as private parking facilities in Arkansas. A detailed discussion of the methods and results of this study can be found in Corro, Akter, and Hernandez (2019)[7].

Methodology

For the Overnight Study, teams of observers record the number of trucks parked at each facility by visual inspection including legal and illegal (along on and off ramps and shoulders) truck parking. Observation sites for the study are located at each exit of Interstates 30, 40, 55, 440 and 540, as well as Highway 67 (Figure 32). Sites include ARDOT facilities where truck parking is permitted (e.g. public rest stops), private truck stops, and private commercial businesses with and without designated truck parking (e.g. Walmart, Home Depot, and restaurants). Overall, 70% of the 400 study sites were private truck stops, 20% were private commercial properties, and 10% were public facilities. This study evaluated 102 of these facilities that pertain to legal and designated parking areas (Table 15).

Table 15. Summary of Parking Facilities by Type

Facility Type	Number of Facilities (% of Total)	Overnight Study Count (Standard Deviation)	GPS Count (Standard Deviation)	Capacity (Standard Deviation)
Public Rest Stop	10 (10%)	27 (8)	4 (3)	32 (15)
Commercial Property	21 (21%)	16 (18)	4 (5)	84 (60)
Private Truck Stop	71 (70%)	50 (68)	13 (19)	81 (87)
Average	102 (100%)	41 (59)	10 (17)	77 (79)

This study used the Overnight Study data from 2016 spanning Monday, August 29th through Friday, September 2nd in addition to the corresponding truck GPS data sample. Along with the observation counts, the study data included a latitude and longitude point for each facility, route, description of the parking location, and classification of the facility (e.g., public, private, restaurant). For some facilities, observers recorded an approximate capacity which were verified and supplemented using Google Satellite imagery.

The goal of the study was to derive expansion factors to apply to the GPS-derived parking counts to estimate population-level parking usage. First, geographic bounding boxes were created for each parking facility. The bounding box defines the parking area so that square footage and number of parking spaces could be estimated. Second, for each bounding box, e.g. parking facility, the number of trucks parked during each hour of the day were counted from the GPS data. Parked trucks were defined by the Stop Identification algorithm criteria, (e.g. less than 3 mph for more than 5 minutes). Third, because the exact day and time of the ARDOT Overnight Study observation was not available, a method to match the ARDOT observation to the GPS data was developed as follows:

- The count of parked trucks derived from the GPS data was sampled at 15-minute time slices during each 10 p.m. to 6 a.m. time window between August 29th and September 2nd, 2016.
- Each collection day had thirty-two 15-minute time segments (e.g. eight hours per collection window divided by four 15-minute time segments per hour).

[7] Corro, K., Akter, T., and Hernandez, S., Comparison of Overnight Truck Parking Counts to GPS Derived Counts for Truck Parking Facility Utilization Analysis, in Transportation Research Record, Journal of the Transportation Research Board, Online First, April 2019. Available at https://journals.sagepub.com/doi/full/10.1177/0361198119843851

- For each 15-minute time segment, the number of GPS trucks with arriving before or departing after that specific time segment were counted as parked. For instance, for the time segment of 08/30/16 11:00 p.m., trucks that arrived before 08/30/16 11:00 p.m. and departed after 08/30/16 11:00 p.m. were counted as parked during this segment of time (see example in Figure 32 where vertical lines represent the concept of a time segment).

Key Findings

From the GPS data, the arrival, duration, and departure patterns of the parked trucks for the case study facilities during the time period (10 p.m. to 6 a.m.) and day of the Overnight Study are shown in Figure 33 and Figure 34. Generally, drivers arriving prior to 10 p.m. parked for longer, overnight (8+ hour) rest periods, at the private facility while the public facility shows longer parking durations throughout the night and early morning periods.

With population-level estimates of parked trucks derived from GPS data, facility utilization characteristics such as overcrowding by time of day and day of week, arrival rates, and duration patterns can be determined. Such information greatly improves upon what is available through existing observational and driver surveys. While surveys can provide some insight into usage patterns and identify locations of significant congestion, they can be costly to conduct, and thus difficult to regularly update. Truck GPS data, on the other hand, provides a more repeatable and systematic data source and has the potential to be collected in real-time. This presents opportunities for real-time parking availability applications, if accurate expansion of the GPS samples can be carried out. Knowledge of detailed parking usage characteristics can improve the ways in which state and federal agencies plan and prioritize parking facility improvement projects. Moreover, detailed, accurate, and timely illustrations of the truck parking problem can help practitioners relay the importance of funding parking facility improvement projects to the public and stakeholders.

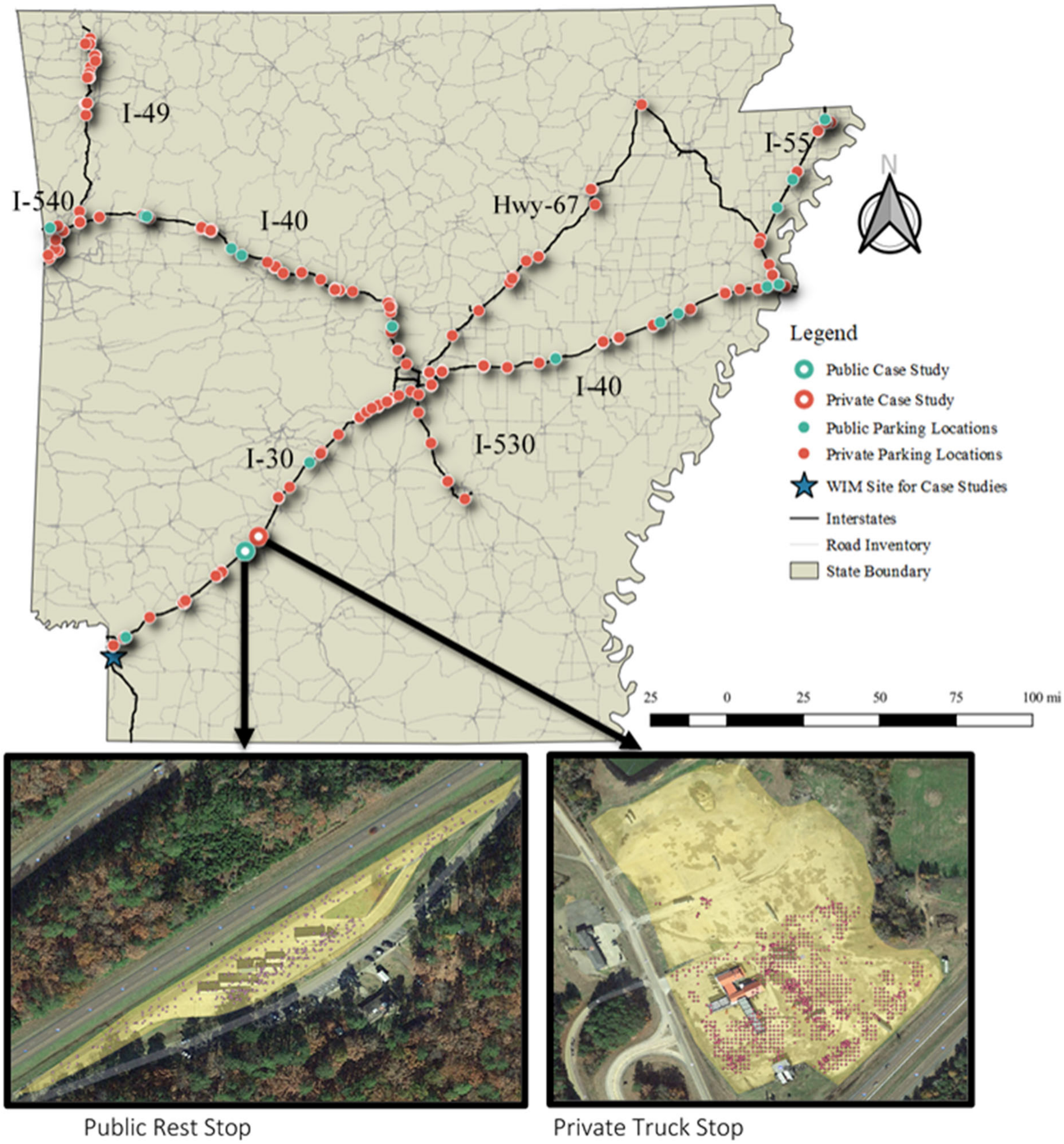


Figure 32. Public and Private Truck Parking Facility Locations in Arkansas

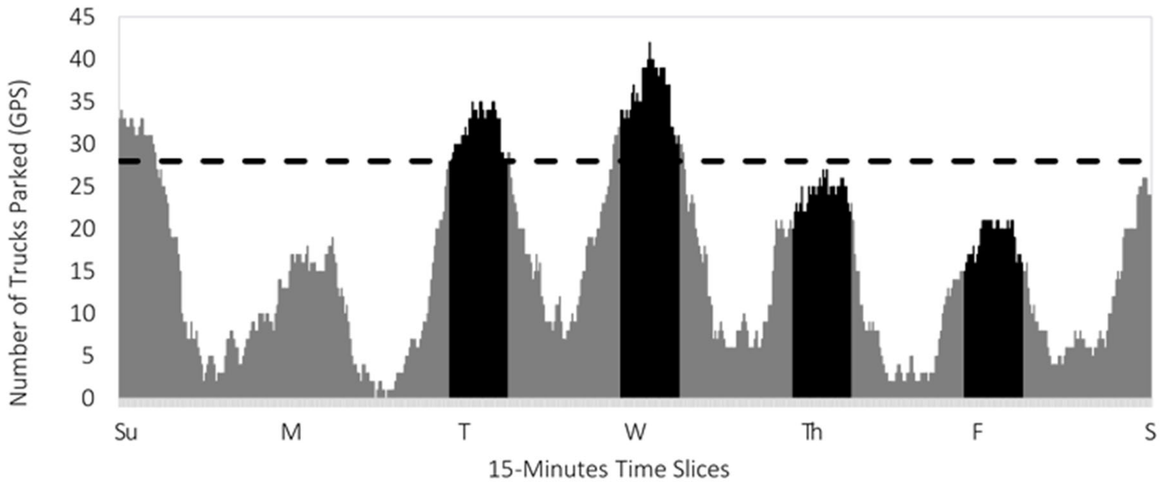


Figure 33. Fifteen Minute Time Slices for Truck Parking Use Estimation from Truck GPS Data

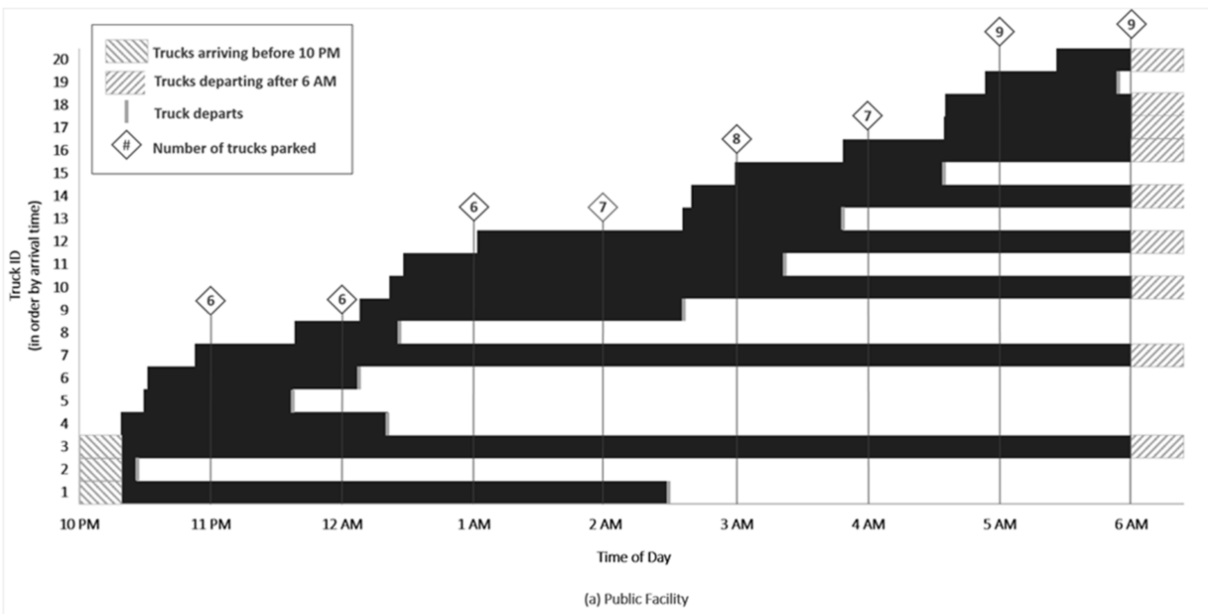


Figure 34. Method to Count Parked Trucks Using Truck GPS Data

CRASH-INDUCED DELAY FOR TRUCKS

Truck GPS data in combination with location and timestamped crash records can be used to estimate crash induced delay. In Section 6.5 of this report, truck GPS data was used to estimate Daily Delay. Daily Delay includes delay due to recurring congestion and nonrecurring congestion induced by accidents, weather, and construction, among others. For this case study, crash records indexed by time and location collected by the Arkansas State Police (ASP) were merged with the truck GPS data. The goals were to determine the effects of crashes on truck travel speeds and to identify corridors that experience a higher proportion of crash induced delays.

Methodology

ASP crash records contained location (e.g. latitude-longitude), time of incident, and crash severity, among other variables. Crashes occurring during the GPS sample periods were mapped to the nearest ARNOLD network link. All crashes were considered in the analysis regardless of severity or truck involvement. From the GPS data, average truck speeds were estimated for each link associated with a crash for the hour before and the hour after the crash. A Truck Speed Ratio (TSR) was then estimated to represent the effect of the crash on hourly average truck speeds (Eq. 9).

$$TSR = \frac{Speed_{During\ Crash}}{Speed_{After\ Crash}} \qquad \text{Eq. 9}$$

Where,

TSR	is the Truck Speed Ratio (unitless)
Speed $_{During\ crash}$	is the estimated hourly average truck speed in the hour during the crash (mph)
Speed $_{After\ crash}$	is the estimated hourly average truck speed in the hour after the crash (mph)

Additionally, truck travel time delay due to crashes was calculated using Eq. 7 in Section 6.5. In this formulation, 'Daily Combination Truck Travel Time' was replaced with the travel time during the hour of the crash. Delay was measured against free flow travel time as specified in Section 6.5.

Key Findings

The average daily crashes estimated from the ASP crash data varied by sample period and roadway functional class (Figure 35). US highways experienced the highest proportion of crashes in all sample periods except February, and overall had the highest average daily crashes. Note that average daily crashes is not the same as a crash rate, as it was not indexed by traffic volume or vehicle miles traveled. To add some context, approximately 2,000 miles of interstate, 5,000 miles of US highways, and 14,000 miles of state highways were represented in the ARNOLD network. State highways had the lowest average daily crashes despite having the highest mileage.

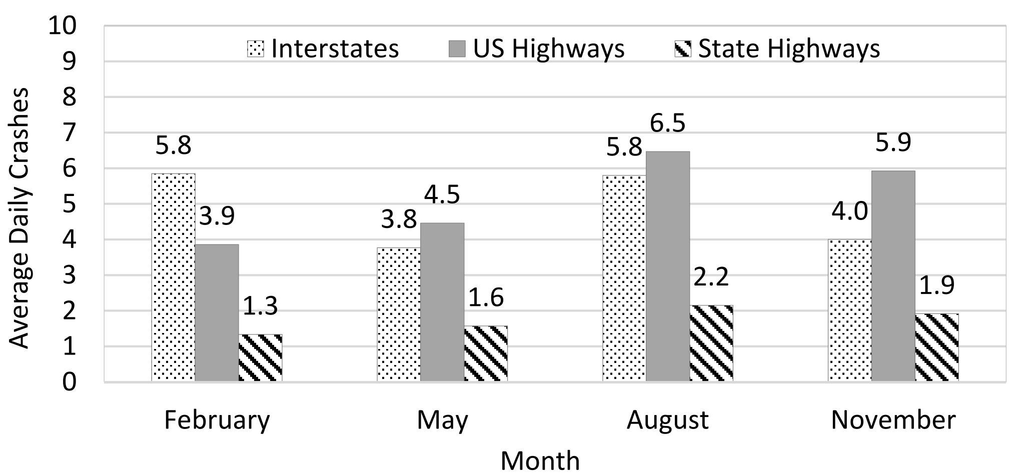


Figure 35. Average Daily Crashes by Functional Class and Sample Period

As expected, crashes resulted in decreased truck traffic speeds as represented by the TSR. A higher TSR represented minimal delay effects due to crashes while a lower TSR represented more severe effects. The greatest impacts of crashes on TSR occurred in the Fort Smith/Van Buren (Northwest Arkansas), Conway County (Central Arkansas), and Little Rock (Central Arkansas) (Figure 36).

In comparing total and crash-induced delays, crash-induced delays accounted for around 9% of total delay for interstates, 29% of total delay for US highways, and 76% for state highways (Figure 37). Thus, crash-related delay was the main component of total delay for trucks on state highways, in contrast to interstates and US highways. It can be assumed that delay on interstates and US highways may be attributed to recurring congesting, construction, or other non-crash related causes.

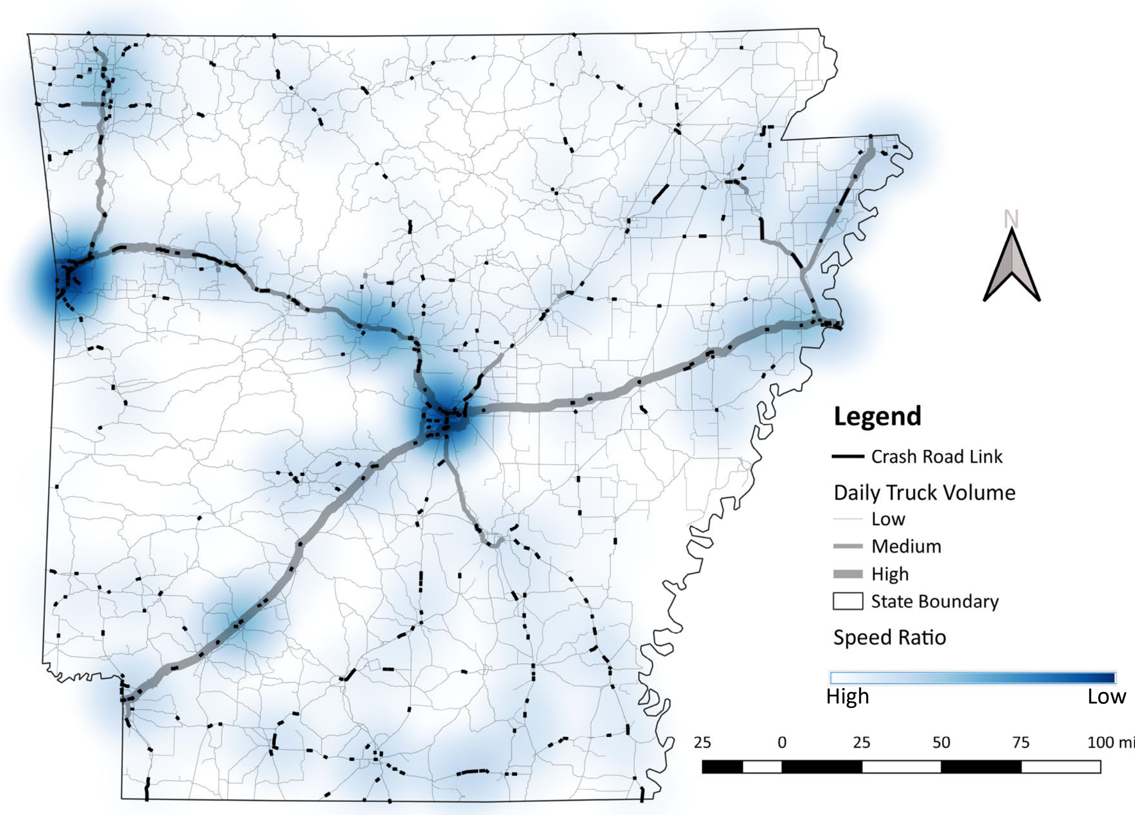


Figure 36. Crash Locations, Daily Average Truck Volume, and Truck Speed Ratio (TSR)

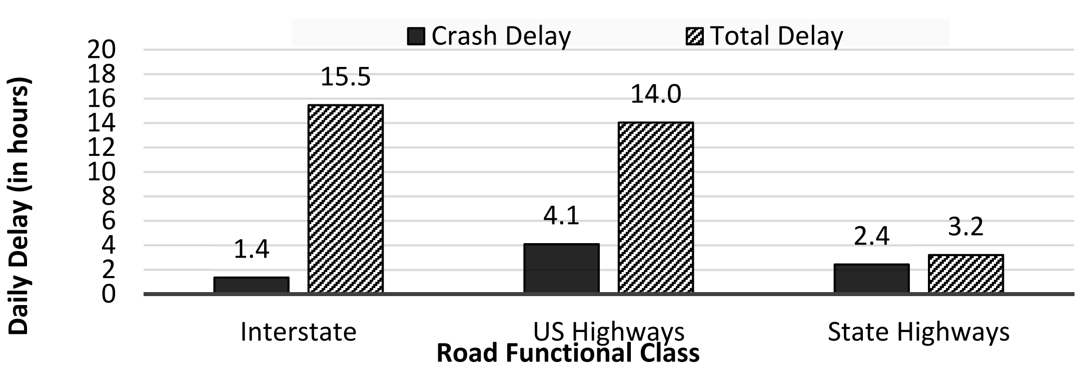


Figure 37. Total Delay and Crash-Related Delay by Functional Class

CHAPTER 8: CONCLUSIONS

The goal of this project was to investigate the use of ATRI's truck GPS data for statewide freight performance measurement, freight truck flow analysis, and other freight planning and modeling applications. The project developed methods and procedures to transform anonymized GPS data into truck activity patterns and to fuse the GPS data with other data sources (e.g., WIM truck counts, land use data, etc.) to estimate data coverage.

This study examined four two-week samples of GPS data from 2016 representing over 338 million pings (latitude-longitude and timestamp tuples) and 358,092 truck records. Trucks were classified into those that operate entirely within state boundaries (e.g. Internal or II), those that travel in and out of the state (e.g. External-Internal, EI or Internal-External, IE), and those that pass through the state with stops (e.g. External-Internal-External EIE) and without stops (e.g. External-External EE). EIE trucks made up the majority (69%) of the data sample and had average trips lengths of around 125 miles. II and EE trucks were the least common representing 5% and 4% of the data sample and the lowest (25 miles) and highest (250+ miles) per trip, respectively. EI and IE trucks represented approximately 9% and 13% of the data with trip lengths around 110 and 75 miles, respectively.

By comparison with truck traffic volumes measured by Weigh-In-Motion (WIM) sites throughout the state, coverage of approximately 8.5% was determined. Coverage generally represents the size of the sample relative to the total truck population. Across ARDOT Districts, used in this study to capture spatial coverage of the data, coverage ranged from 6% to 17%. These coverage percentages generally correspond to those found in prior studies conducted in Florida. The research team did not find any significant gaps in data coverage by region, time of day, or day of week.

By quantifying data coverage, population-level performance measures were able to be calculated. These included Daily Vehicle Miles Traveled (DVMT), Truck Speed, Travel Time Reliability (TTR), Travel Time Variability (TTV), Daily Delay, and Percent of Interstate System Miles Uncongested (PISMU). Each metric helps highlight subtleties in network performance. Overall, the collection of performance metrics repeatedly suggested freight bottlenecks in urbanized areas including Benton/Washington, Crawford/Sebastian, Pulaski, and Crittenden counties. DVMT was highest in the August at around 14 million vehicle-miles per month with average DVMT per month around 13 million vehicle-miles. Extrapolating monthly average DVMT to an annual estimate, there were approximately 4,725 million vehicle-miles in 2016. This value aligns with FHWA published VMT estimates for trucks per state, e.g., according to FHWA, in 2016, annual VMT for trucks was approximately 5,564 million vehicle miles[8]. For comparison, California had around 26,294 million truck annual VMT, Florida had 15,563 million truck annual VMT, and Texas had 31,186 million truck annual VMT in 2016 according to FHWA. In terms of congestion and delay, 90% of the interstate miles were found to be uncongested (e.g. PISMU).

While performance metrics were a key use case for the truck GPS data, three additional use cases were explored in this report: usage characteristics of intermodal connectors, estimation of truck parking availability and capacity, and quantification of crash-induced delay. These use cases exemplify the value-added by truck GPS data. For intermodal terminal usage with truck GPS data, routes used by trucks serving the ports of Van Buren, Little Rock, and Pine Bluff were identified. This can help better understand the spatial impacts of port operations. A key finding was the use of interstates to transport goods between ports. Further work can examine how to shift such goods to the inland waterways

[8] FHWA Policy and Governmental Affairs, Office of Highway Policy Information, Highway Statistics 2016, Available online from https://www.fhwa.dot.gov/policyinformation/statistics/2016/ps1.cfm

through policy and infrastructure investments. For truck parking usage and capacity estimation, with truck GPS data, complete time of day, day of week, and seasonal parking shortages can be identified. A key finding were the expansion factors needed to convert the truck GPS-derived count of parked trucks to population-level parking usage estimates. Population-level estimates of parked trucks at each facility can then be used for real-time parking availability notification systems. For crash-induced delay, mapping truck GPS data against crash locations allowed for the comparison of crash induced to total delay. A key finding was that crash-induced delay represented over 75% of total delay on state highways but only 9% for interstates.

The work conducted in this project can be extended in several directions. First, while this project resulted in procedures for identifying truck stops and truck trips from anonymous GPS data, the 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 characterize truck travel patterns like trip chaining behaviors by industry type. Another important extension of this work is to combine the ATRI GPS data with GPS data from independent owner-operators. Although this study was not able to discern the proportion of large fleets within the ATRI GPS data, prior studies suggest the ATRI GPS data does not represent smaller fleets. To use this data for state planning, it would be valuable to understand how travel patterns and behaviors of large and small fleets differ to ensure real-world bottlenecks, travel times, etc. are represented.

Unlike travel surveys, truck counts, and short-term observational studies, truck GPS data provides a significant opportunity to better understand truck route choice and develop truck route choice models. Combining the data with additional surveys on trucking companies and drivers' route choice decisions can lead to significant advances in truck route choice modeling. This can also help improve the truck traffic assignment algorithms currently used in statewide travel demand models. Such applications were only lightly touched upon in this study in several of the use cases. Future work can expand on these use cases to conduct full-scale applications.

Not all segments of the transportation network serve as critical freight corridors, and thus should receive different priority in the planning process. Through a better understanding of truck travel patterns, public sector engineers, planners, and decision-makers can more effectively prioritize infrastructure investments and develop targeted transportation policies.

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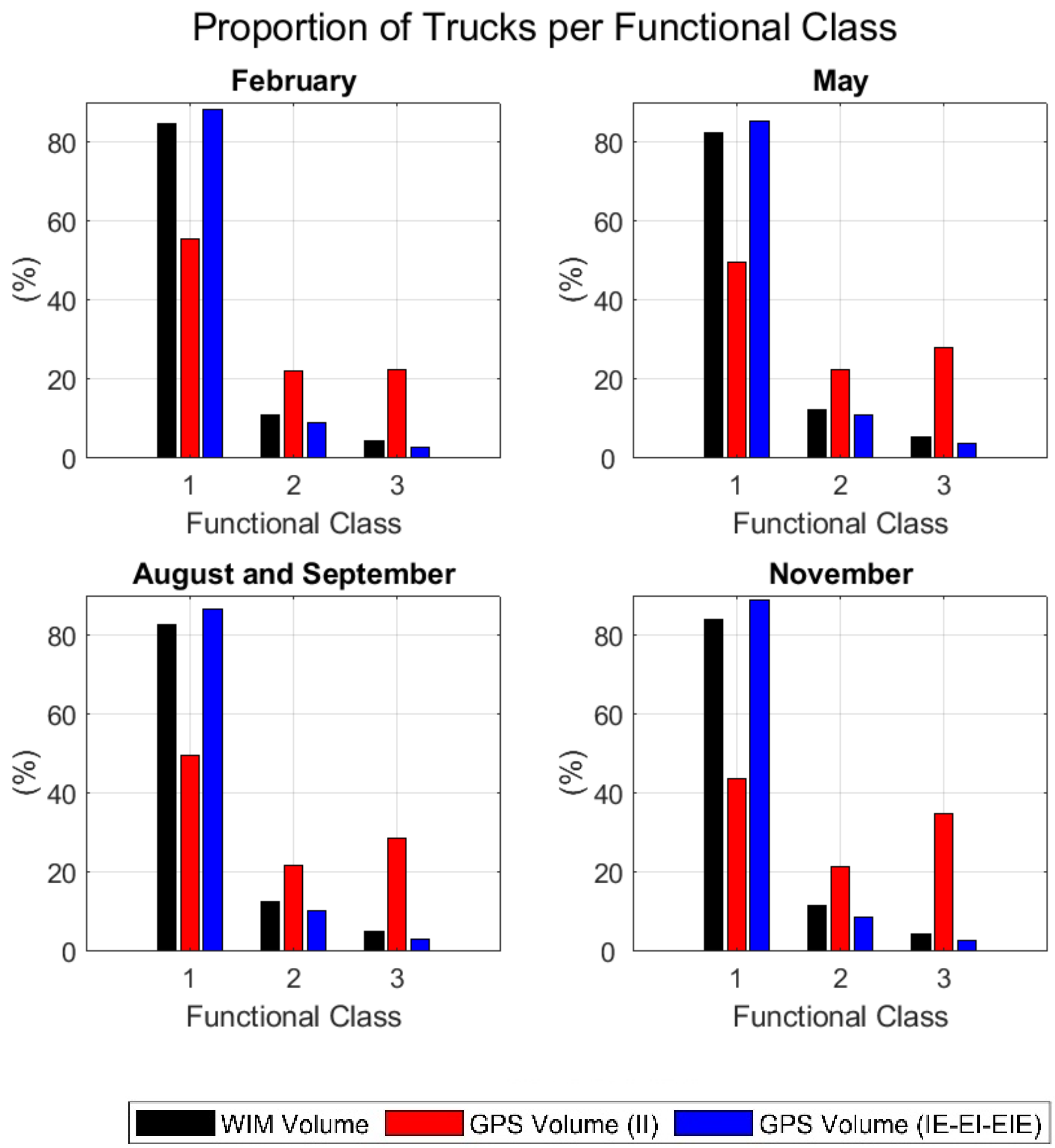
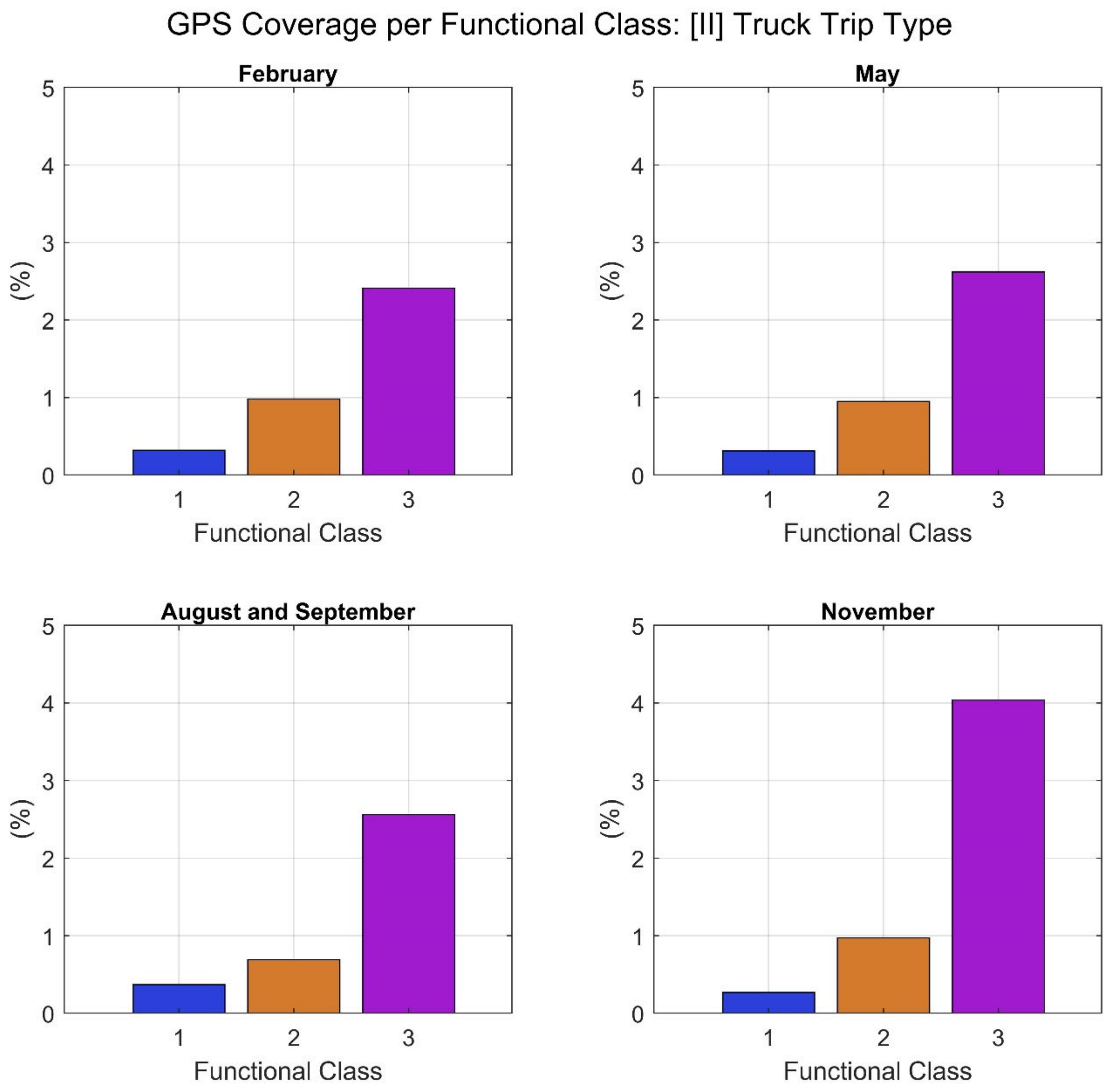
APPENDIX A

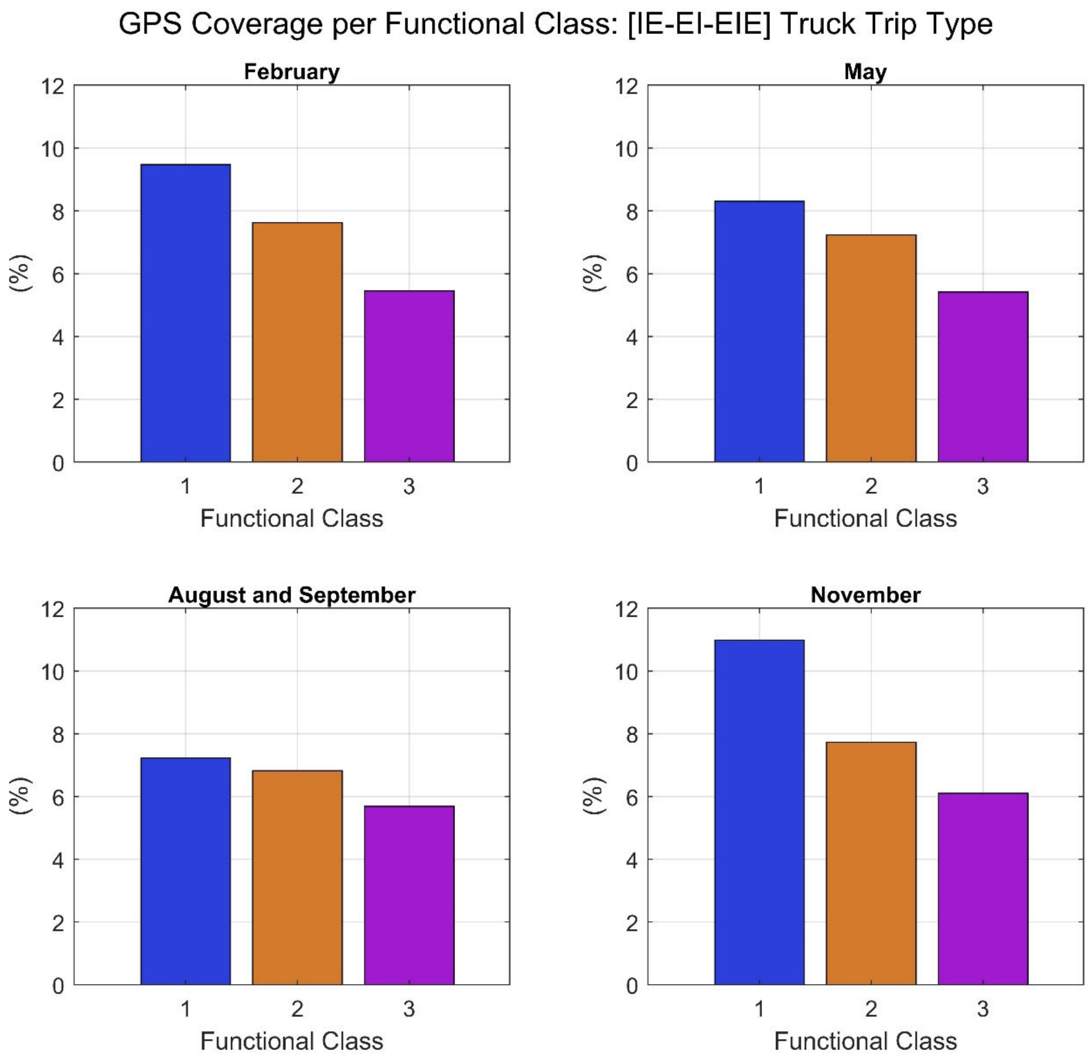
GPS Coverage by Roadway Functional Class, ARDOT District, and Temporal Characteristics (e.g., Weekday and Weekend)

A.1 PROPORTION OF TRUCKS BY FUNCTIONAL CLASS AND SAMPLE PERIOD



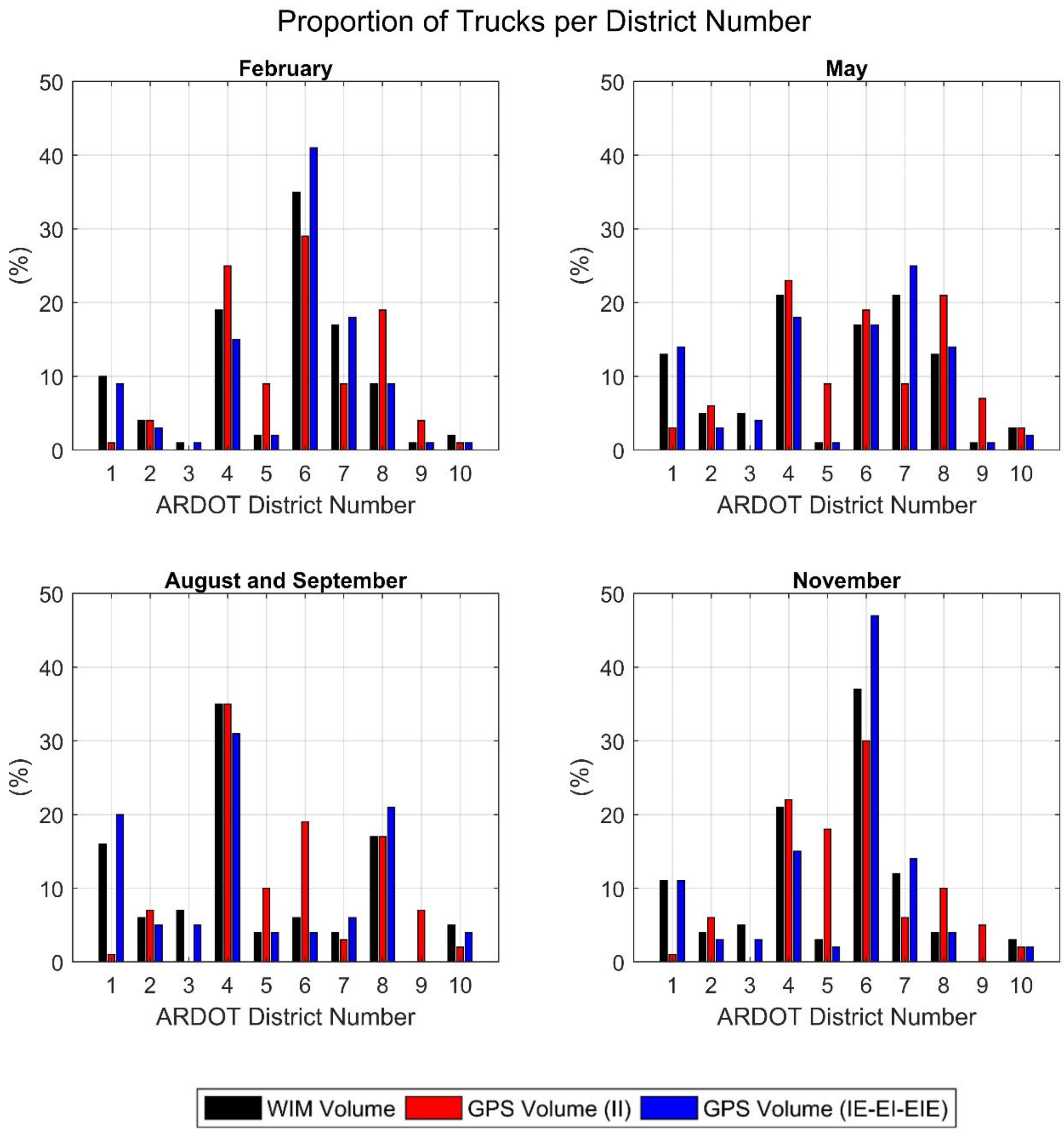
A.2 COVERAGE BY FUNCTIONAL CLASS AND SAMPLE PERIOD



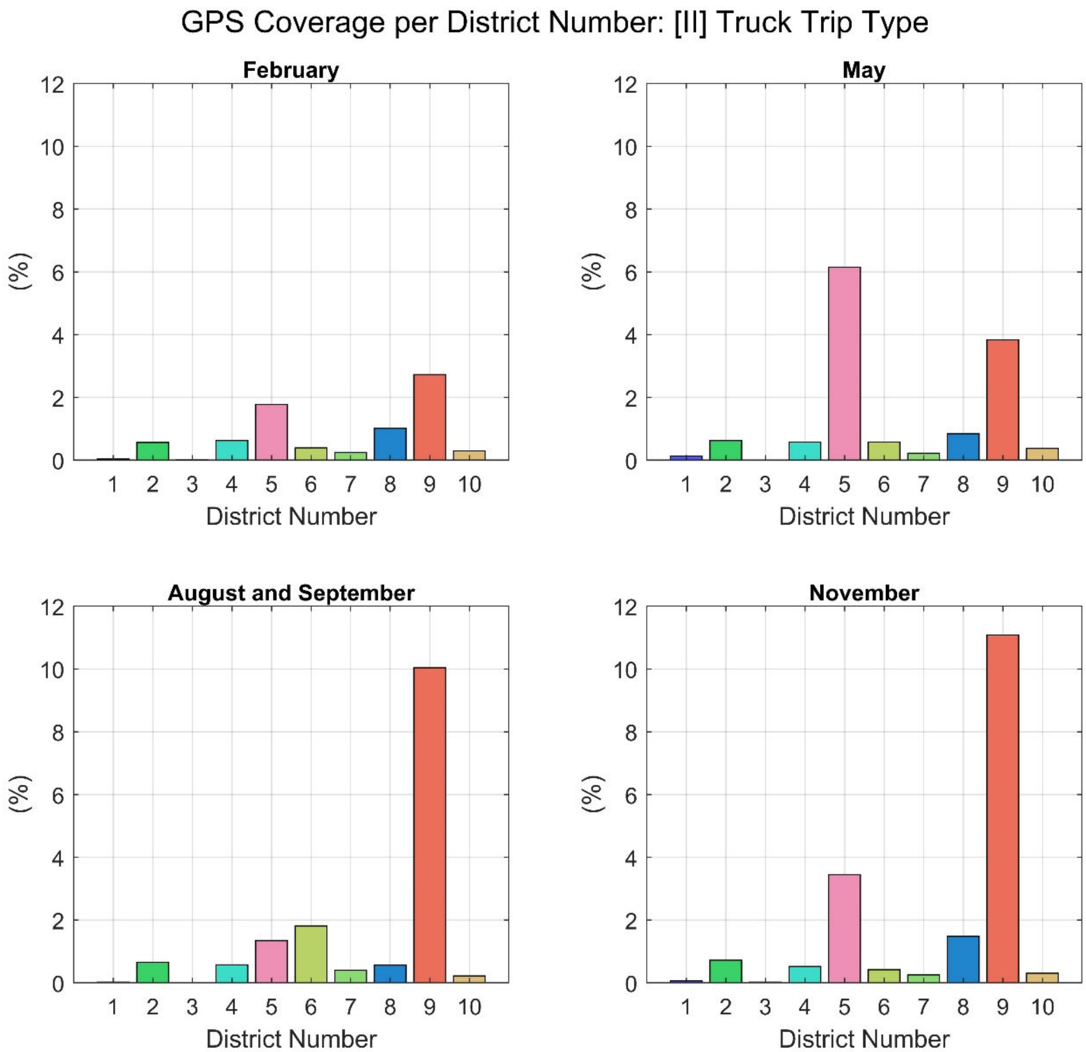


GPS Coverage per Functional Class: [IE-EI-EIE] Truck Trip Type
February
May
August and September
November
(%)
0
2
4
6
8
10
12
1
2
3
Functional Class

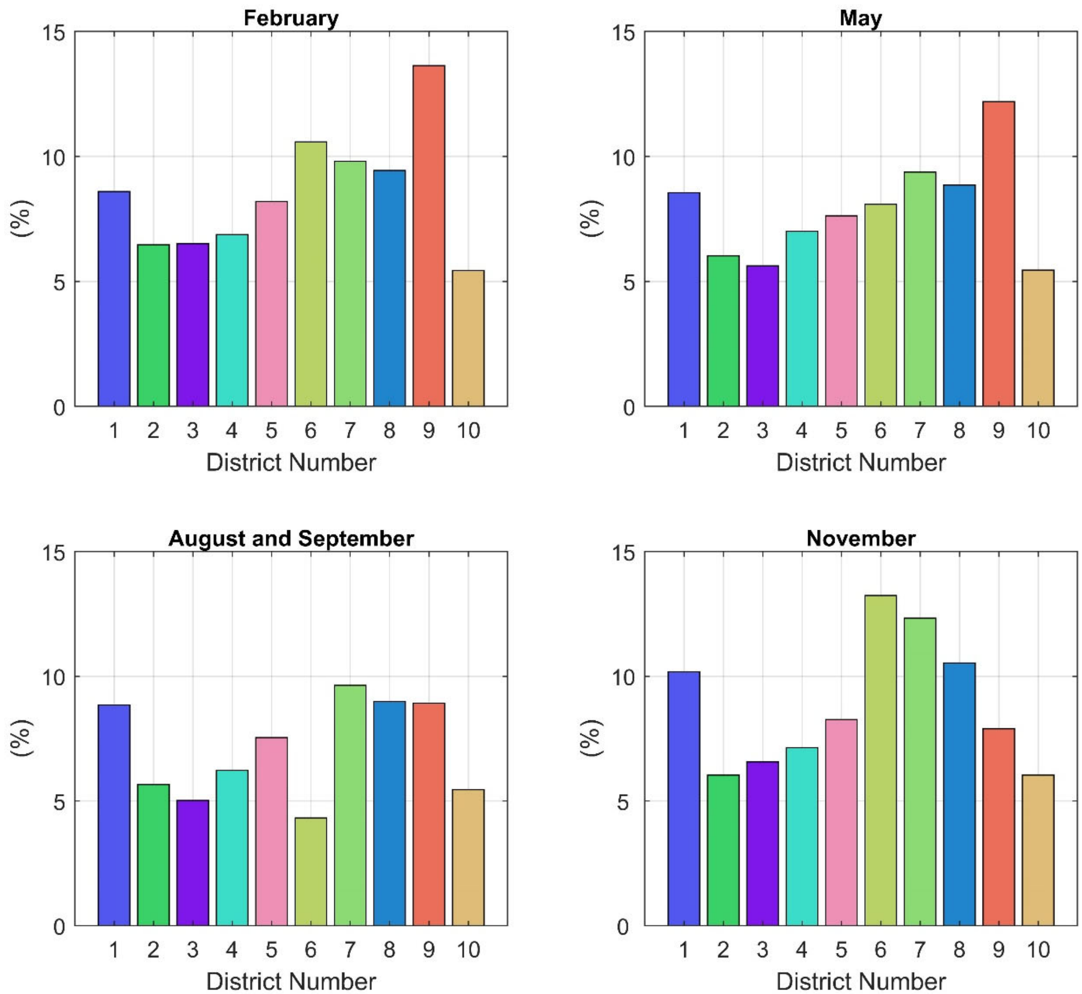
A.3 PROPORTION OF TRUCKS BY ARDOT DISTRICT AND SAMPLE PERIOD



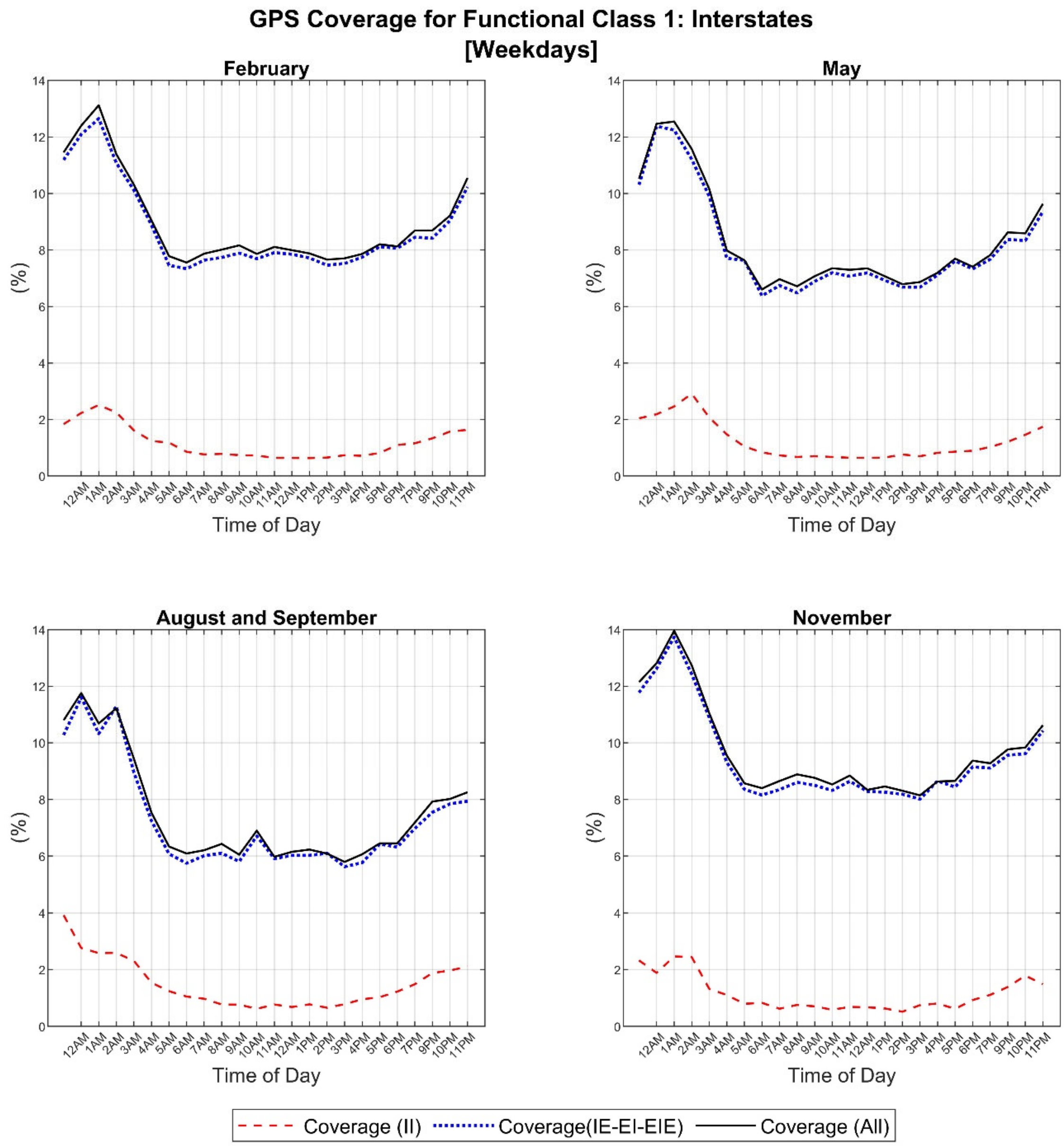
A.4 COVERAGE BY ARDOT DISTRICT AND SAMPLE PERIOD



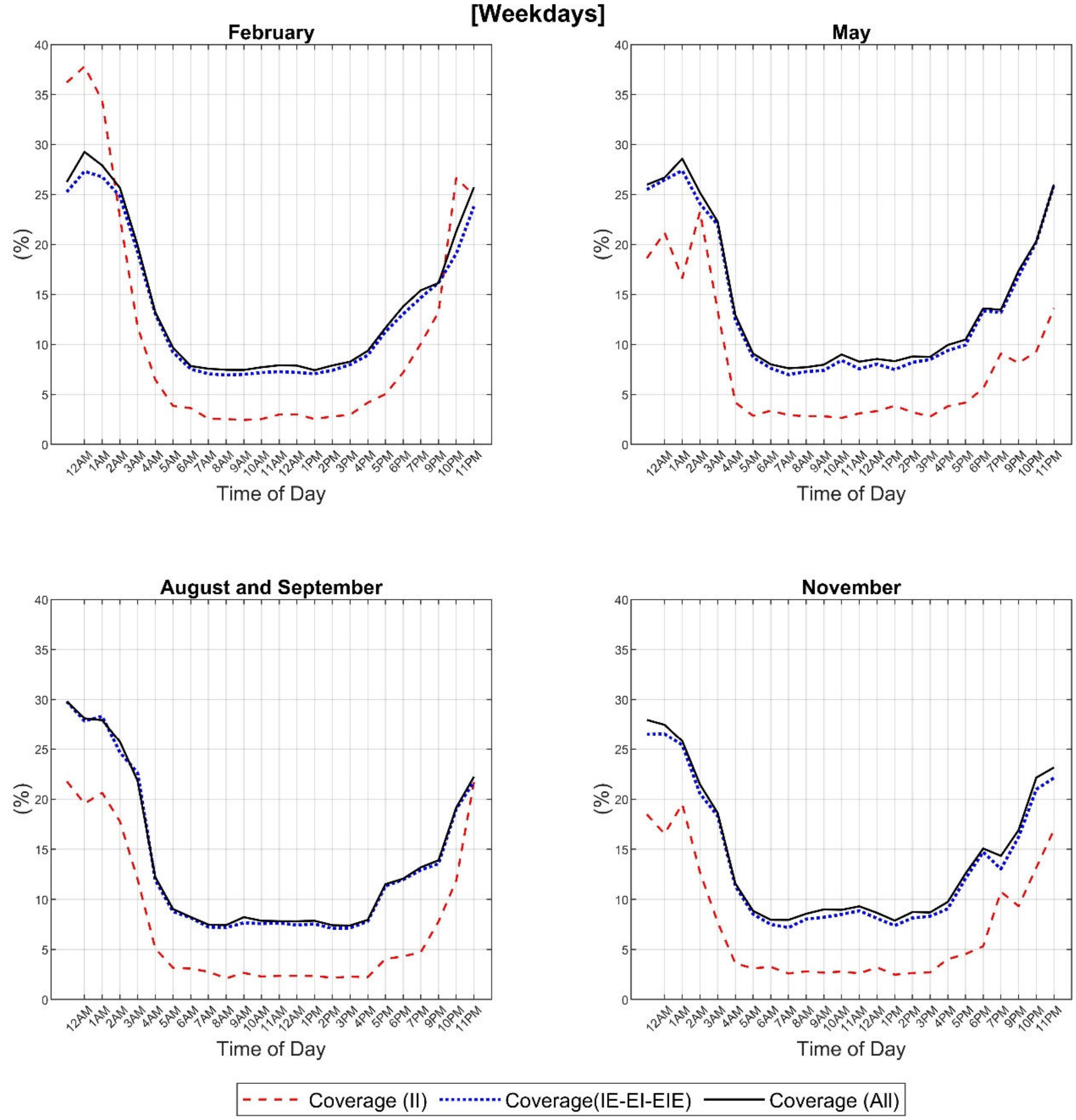
GPS Coverage per District Number:[IE-EI-EIE] Truck Trip Type

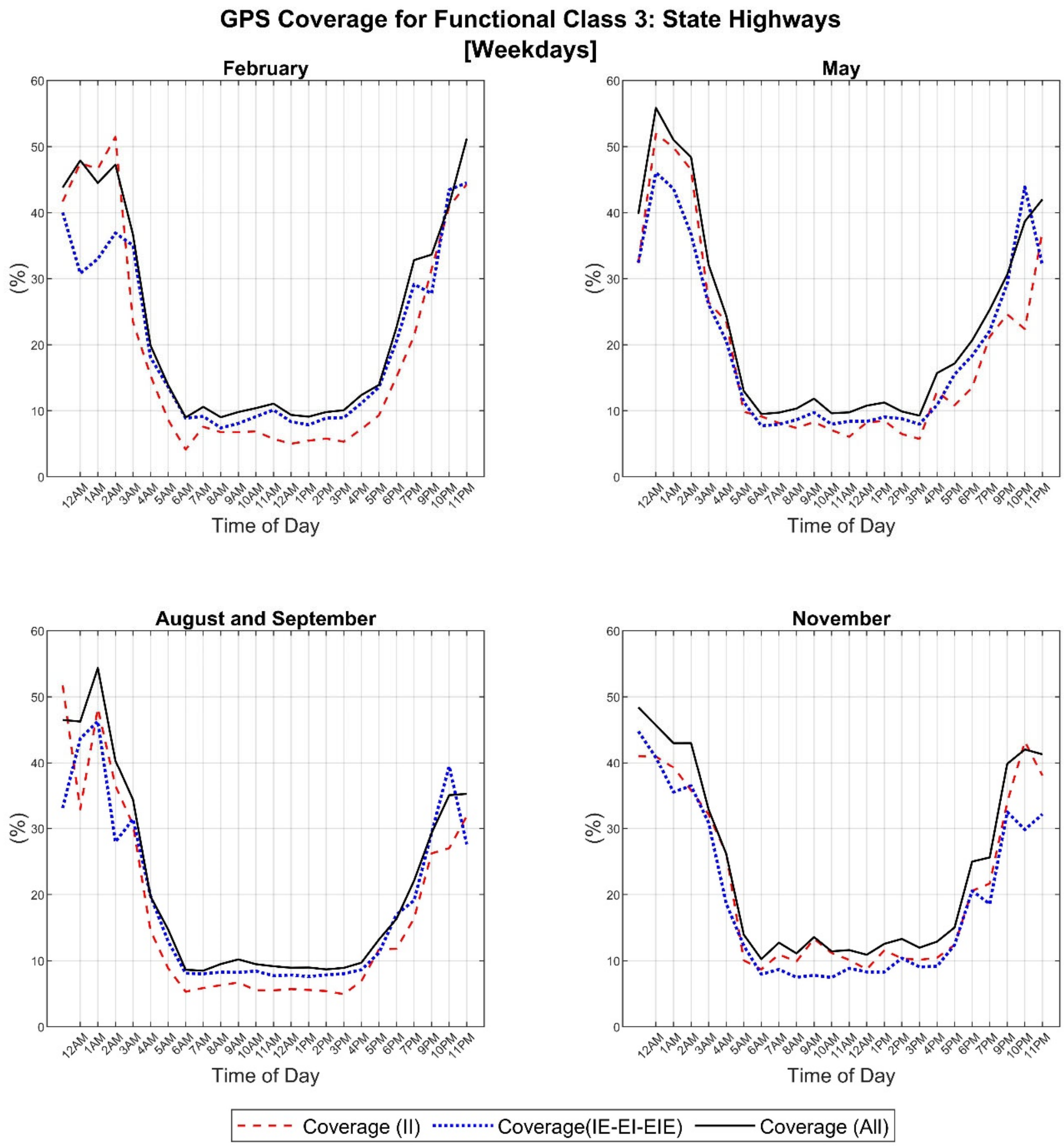


A.5 WEEKDAY COVERAGE BY TIME OF DAY, FUNCTIONAL CLASS, AND SAMPLE PERIOD



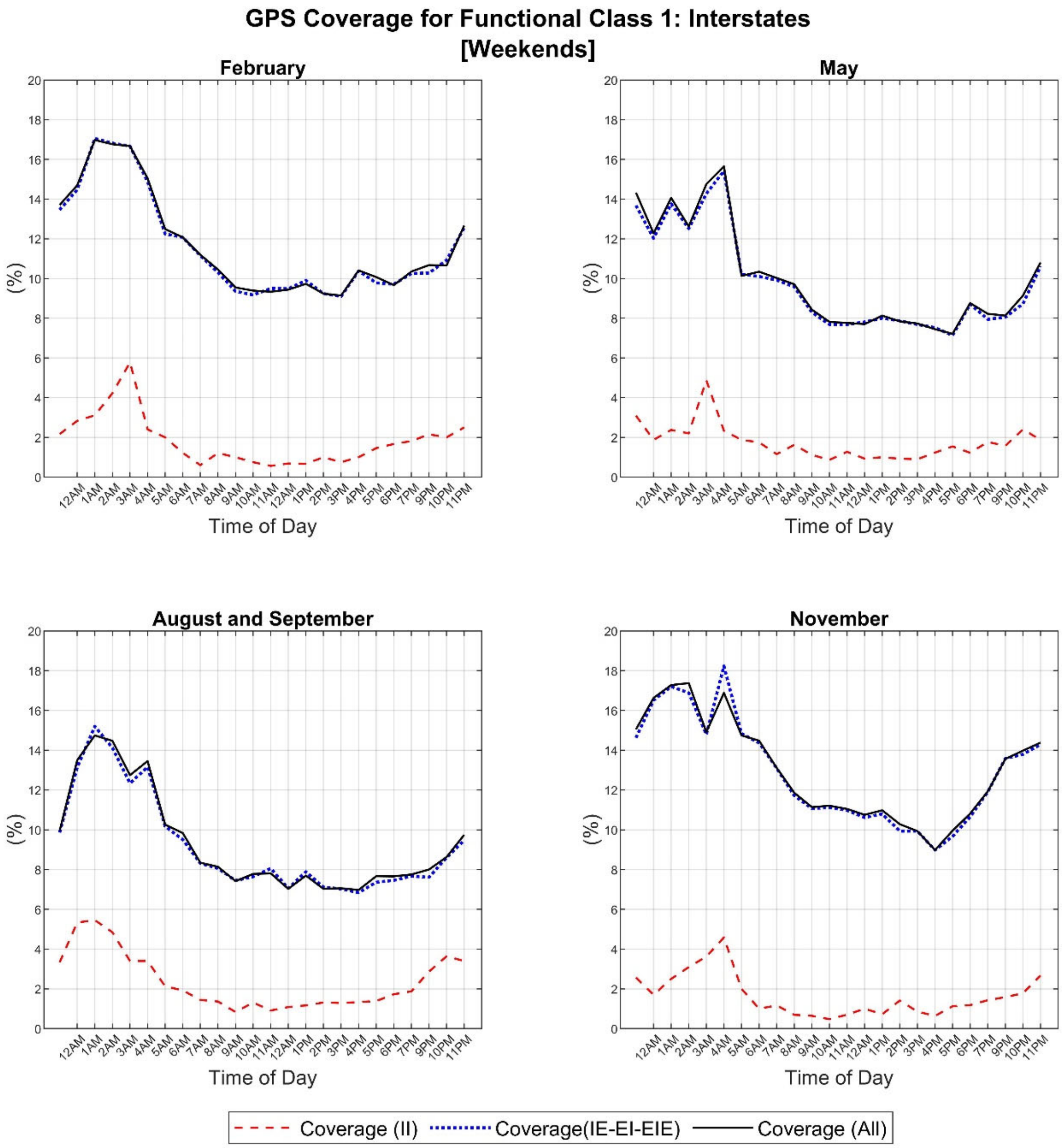
GPS Coverage for Functional Class 2: US Highways [Weekdays]

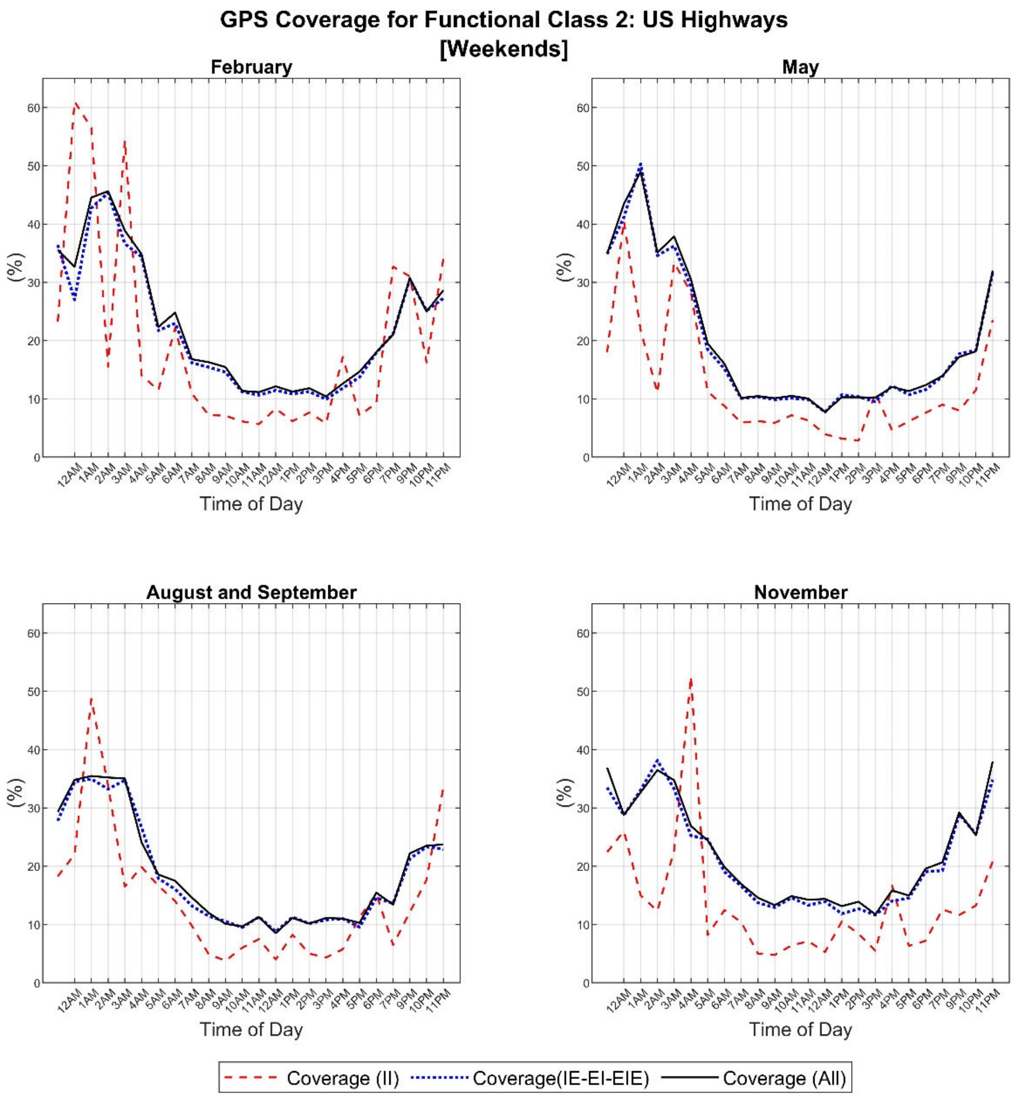


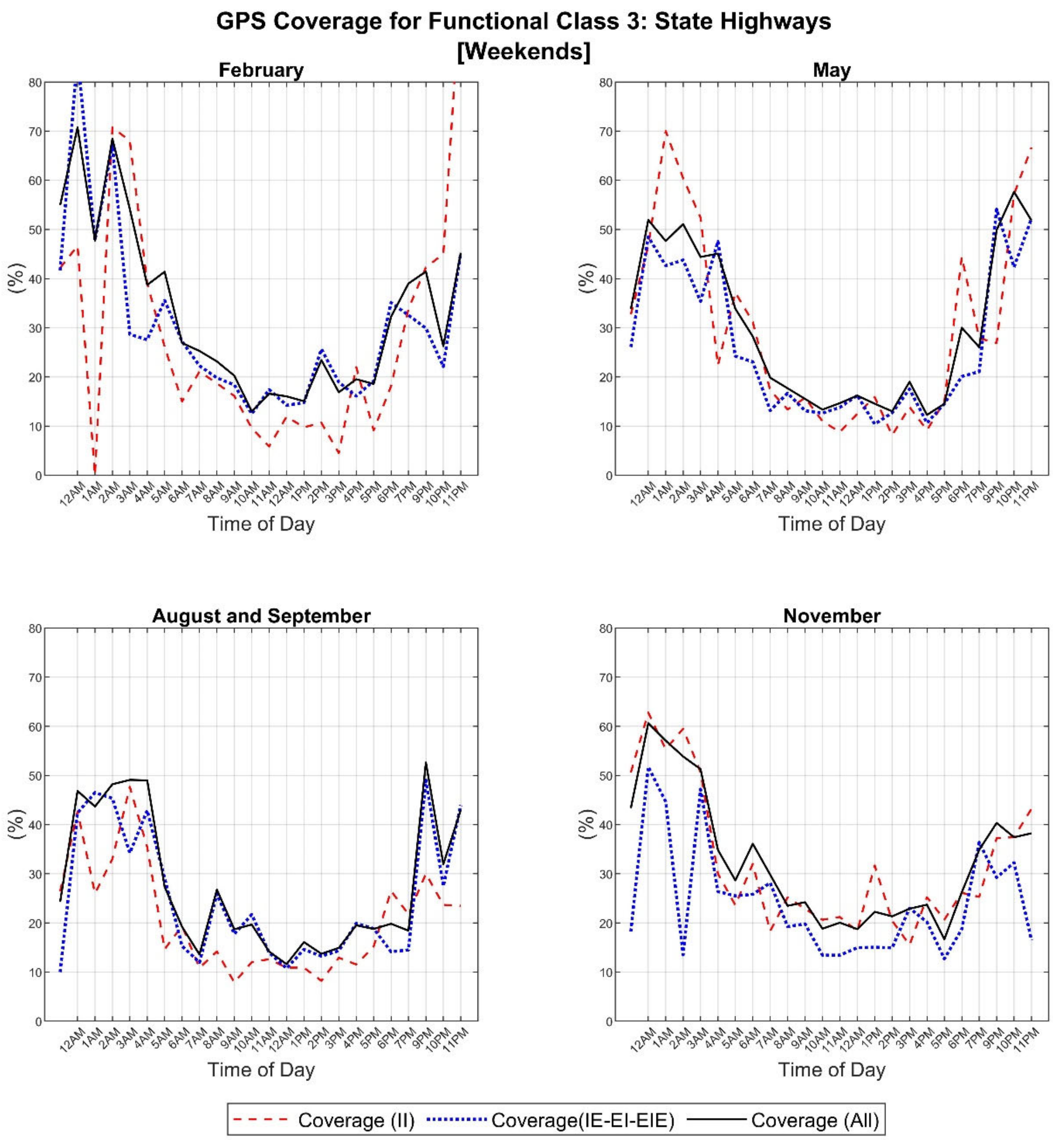


GPS Coverage for Functional Class 3: State Highways
[Weekdays]
February
May
August and September
November
(%)
Time of Day
12AM 1AM 2AM 3AM 4AM 5AM 6AM 7AM 8AM 9AM 10AM 11AM 12AM 1PM 2PM 3PM 4PM 5PM 6PM 7PM 9PM 10PM 11PM
0 10 20 30 40 50 60
Coverage (II)
Coverage(IE-EI-EIE)
Coverage (All)

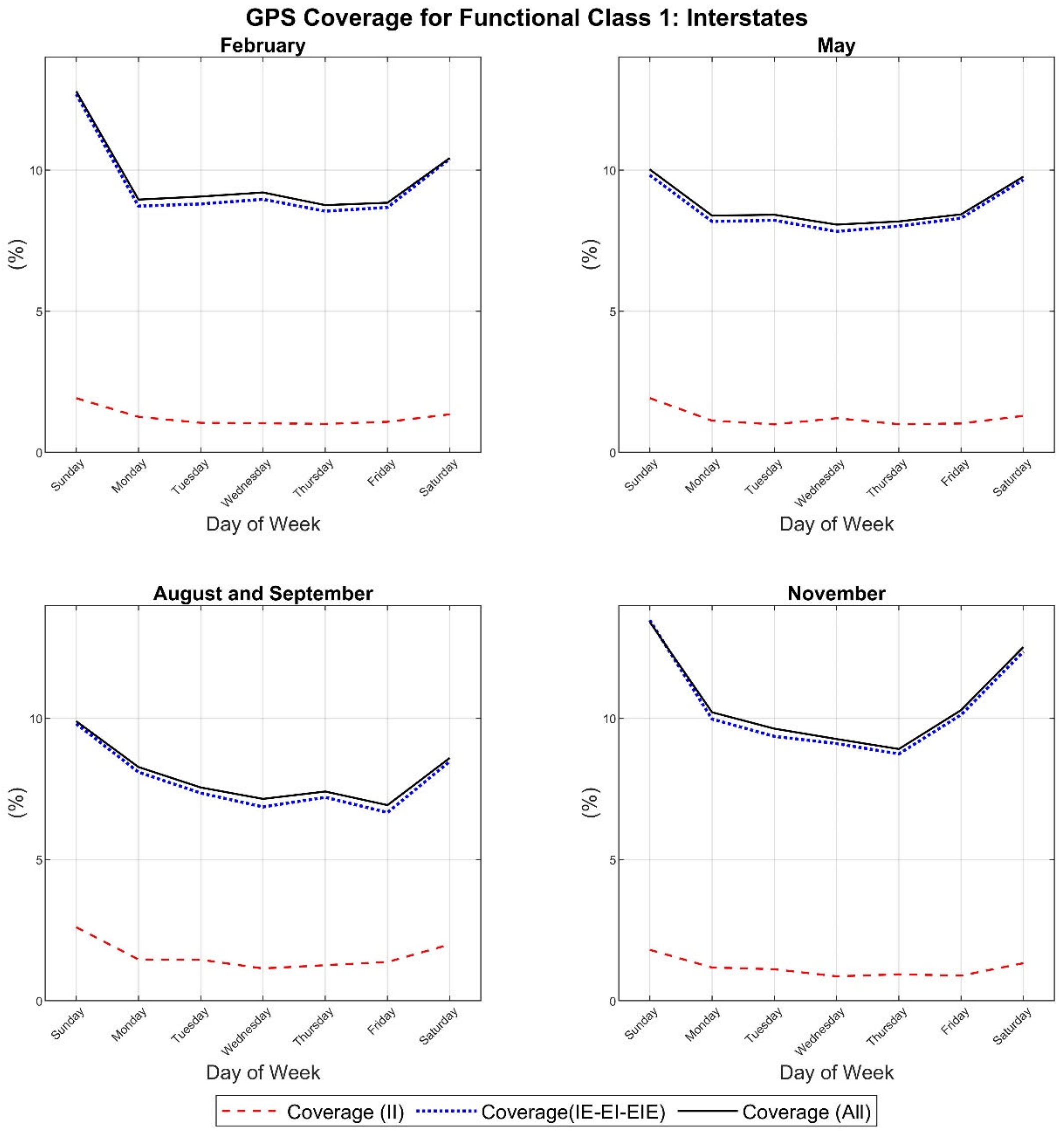
A.6 WEEKEND COVERAGE BY TIME OF DAY, FUNCTIONAL CLASS, AND SAMPLE PERIOD

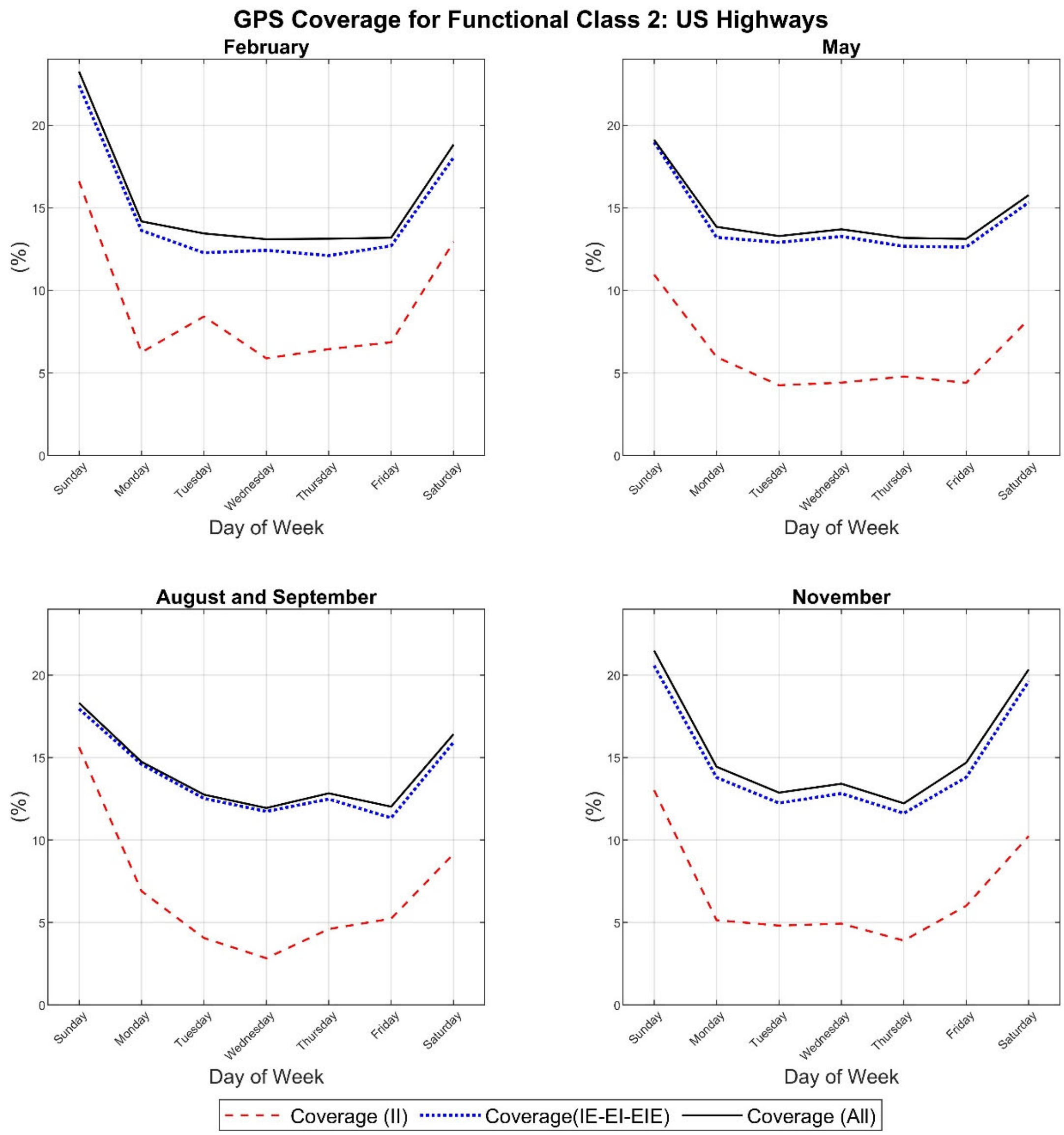



GPS Coverage for Functional Class 2: US Highways
[Weekends]
February
May
August and September
November
(%)
Time of Day
12AM
1AM
2AM
3AM
4AM
5AM
6AM
7AM
8AM
9AM
10AM
11AM
12AM
1PM
2PM
3PM
4PM
5PM
6PM
7PM
9PM
10PM
11PM
Coverage (II)
Coverage(IE-EI-EIE)
Coverage (All)

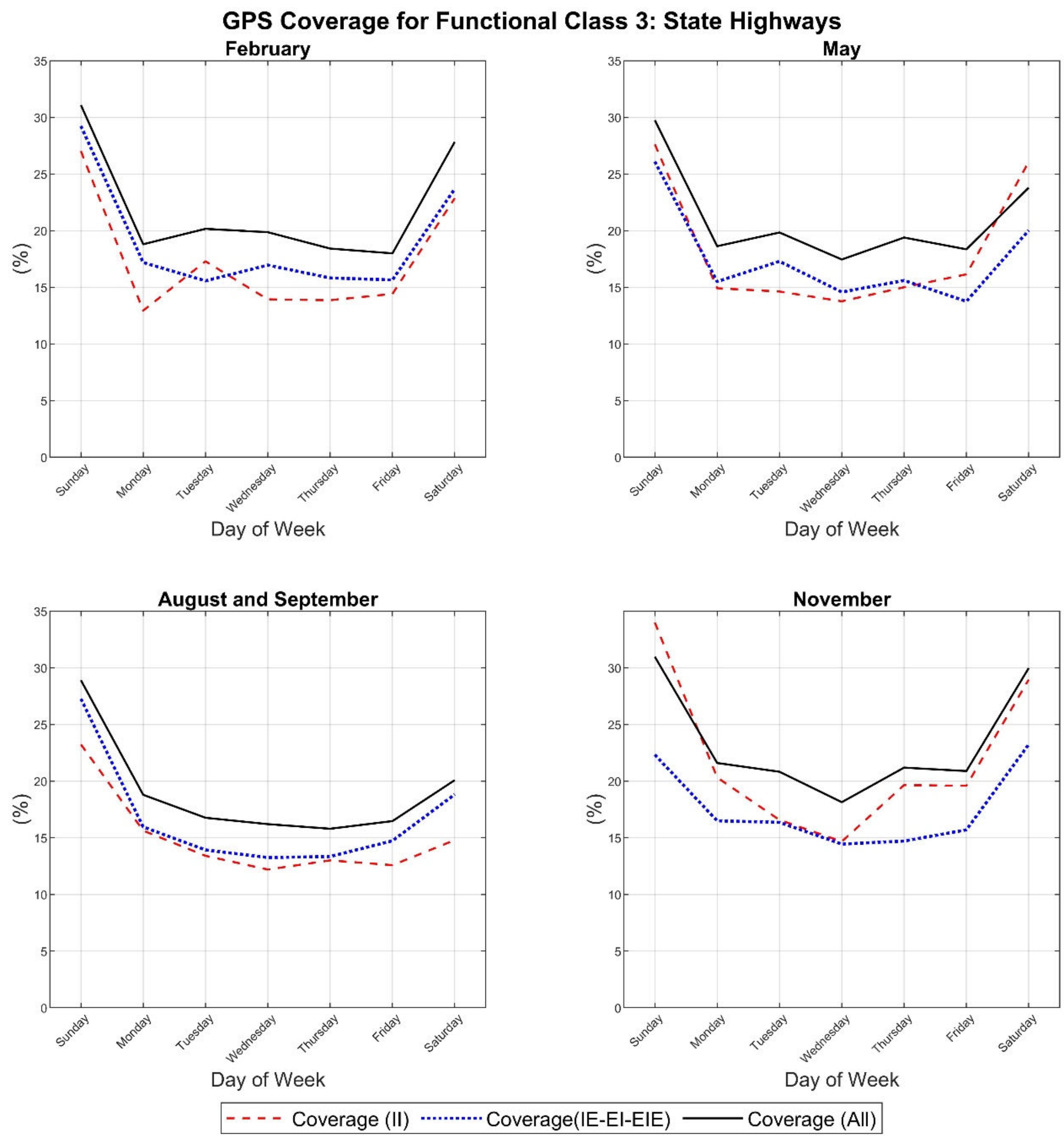

GPS Coverage for Functional Class 3: State Highways
[Weekends]
February
May
August and September
November
(%)
Time of Day
12AM 1AM 2AM 3AM 4AM 5AM 6AM 7AM 8AM 9AM 10AM 11AM 12AM 1PM 2PM 3PM 4PM 5PM 6PM 7PM 9PM 10PM 11PM
0 10 20 30 40 50 60 70 80
Coverage (II)
Coverage(IE-EI-EIE)
Coverage (All)

A.7 WEEKDAY COVERAGE BY DAY OF WEEK, FUNCTIONAL CLASS, AND SAMPLE PERIOD





GPS Coverage for Functional Class 2: US Highways
February
May
August and September
November
(%)
Day of Week
Sunday
Monday
Tuesday
Wednesday
Thursday
Friday
Saturday
0
5
10
15
20
Coverage (II)
Coverage(IE-EI-EIE)
Coverage (All)


GPS Coverage for Functional Class 3: State Highways
February
May
August and September
November
(%)
Day of Week
Sunday
Monday
Tuesday
Wednesday
Thursday
Friday
Saturday
Coverage (II)
Coverage(IE-EI-EIE)
Coverage (All)

A.8 SUMMARY OF WIM SITE AVAILABILITY BY SAMPLE PERIOD

WIM Station Location	February (Q1)	May (Q2)	August (Q3)	November (Q4)
St. Charles	*	*	*	*
Omaha	*	X	*	*
Thornton	X	X	X	X
Berryville	*	*	*	*
Arkadelphia	*	*	*	*
Jonesboro	*	*	*	*
Monette	*	*	*	*
Dora	*	*	*	*
Van Buren	*	*	*	*
Alma	*	*	*	*
Gilmore	*	*	*	*
Monticello	*	*	X	*
Damascus	*	*	*	*
Hot Springs	*	*	*	*
Light	X	*	*	*
Malvern	*	*	*	*
Glen Rose	*	*	X	*
Pine Bluff	*	*	*	*
Lamar	*	*	*	*
Bradley	*	*	*	*
Grady	*	*	*	*
Lonoke	*	X	X	*
Fouke	*	*	*	*
Texarkana	X	*	*	*
Brinkley	*	*	*	*
Rixey	*	*	*	*
Needmore	*	*	*	*
Pindall	*	*	X	X
Fort Smith	*	X	*	*
Cave City	*	*	*	*
El Dorado	*	*	*	*
Fayetteville	*	*	*	*
Pangburn	*	*	*	*
Bald Knob	*	X	*	*
Sunnydale	*	*	*	*
Searcy	*	*	*	*
Patterson	*	*	*	*
Dardanelle	*	*	*	*
Total Number of Stations	***35***	***33***	***33***	***36***

APPENDIX B

*Performance Measures (*Summary of Commonly Used Freight Performance Measures

B.1 MULTIMODAL MOBILITY PERFORMANCE MEASURE SOURCE BOOK (FDOT, 2016)

Type of Performance Measure	Methodology	Reporting Period	Calculation	Sources
Combination Truck Miles Traveled	Determined using combination truck traffic volume and segment length. Combination trucks are defined by FHWA as Classification 8-13.	Daily	$\sum (Segment\ Length\ x\ Combination\ Truck\ Volume)$	▪FDOT Traffic Characteristics Inventory ▪FDOT Roadway Characteristics Inventory
Truck Miles Traveled	The product of a road's vehicle miles traveled and the percentage of vehicles that are trucks. If a road has a daily VMT of 50,000 and an average percentage trucks of 10%, then its daily TMT is 5,000.	Daily	$\sum (Segment\ Length\ x\ Volume\ x\ \%\ Trucks)$	▪FDOT Traffic Characteristics Inventory ▪FDOT Roadway Characteristics Inventory
Combination Truck Tonnage	The Freight Analysis Framework (FAF) tonnage data is interpolated using combination truck miles traveled data to calculate combination truck tonnage.	Yearly	$\sum Combination\ Truck\ Tonnage$	▪Freight Analysis Framework 2012 ▪FDOT Weigh-In-Motion Data
Combination Truck Ton Miles Traveled	Determined using combination truck miles traveled and average weight of the load.	Yearly	$\sum (Average\ Combination\ Truck\ Load\ x\ Combination\ Truck\ Miles\ Traveled)$	▪FDOT Weigh-in-Motion Data ▪FDOT Roadway Characteristics Inventory ▪FDOT Traffic Characteristics Inventory

Type of Performance Measure	Methodology	Reporting Period	Calculation	Sources
Truck Value of Freight	The Freight Analysis Framework (FAF) cargo value data is interpolated using combination truck miles traveled data to calculate combination truck tonnage.	Yearly	$\sum Value\ of\ Combination\ Truck\ Tonnage$	▪Freight Analysis Framework 2012 ▪FDOT Weigh-in-Motion data
Freight Travel Time Reliability	For the seven largest MPOs, freight travel time reliability is defined as the percentage of freeway trips by combination trucks traveling at least 45 mph. For all others, travel time reliability is defined as the percentage of freeway trips by combination trucks traveling at greater than or equal to 5 mph below the posted speed limit. This measure represents the additional time that a shipper should budget to ensure on-time arrival 95% of the time.	7 Largest MPOs: Peak Period and Daily All Others: Peak Hour and Daily	7 Largest MPOs $= \frac{\sum (CTMT \mid Combo\ Truck\ Travel\ Speed \geq 45mph)}{\sum (CTMT)} x100$ All others $= \frac{\sum (CTMT \mid Combo\ Truck\ Travel\ Speed \geq (Speed\ Limit - 5mph))}{\sum (CTMT)} x100$	▪FDOT Traffic Characteristics Inventory ▪HERE Data
Freight Travel Time Variability	Freight travel time variability is defined as 95th percentile travel time index (TTI95). This measure represents the additional time that a	7 Largest MPOs: Peak Period and Daily All Others:	$TTI_{95} = \frac{Travel\ Time_{\ 95th\ percentile}}{Travel\ Time_{\ free\ flow}} x100$	▪FDOT Traffic Characteristics Inventory ▪HERE Data

Type of Performance Measure	Methodology	Reporting Period	Calculation	Sources
	shipper should budget to ensure on-time arrival 95% of the time.	Peak Hour and Daily		
Combination Truck Hours of Delay	Combination truck hours of delay is based on combination truck speed. Delay is calculated as the product of directional hourly volume and the difference between travel time at "threshold" speeds (at LOS B) and travel time at the average speed.	Daily	$\sum(\mathit{Daily\ Combination\ Truck\ Travel\ Time} - \mathit{Travel\ Time\ at\ LOS\ B})$	▪FDOT Traffic Characteristics Inventory ▪FDOT Roadway Characteristics Inventory ▪HERE Data
Combination Truck Average Travel Speed	The calculation of combination truck average travel speed is identical to the methodology for passenger vehicle's average travel speed, except that combination trucks are assumed to have a lower free-flow speed.	Peak Hour and Peak Period	$\frac{\sum(\mathit{CTMT}\ x\ \mathit{Combination\ Truck\ Average\ Travel\ Speed})}{\sum(\mathit{CTMT})}$	▪FDOT Traffic Characteristics Inventory ▪FDOT Roadway Characteristics Inventory ▪HERE Data
Combination Truck Cost of Delay	The monetization of combination truck cost of delay is based on combination truck hours of delay and the marginal cost of truck labor per hour.	Yearly	$\mathit{Combination\ Truck\ Hours\ of\ Delay\ x\ Average}$ $\mathit{of\ Labor\ per\ Hour}$	▪FDOT Traffic Characteristics Inventory ▪FDOT Roadway Characteristics Inventory ▪HERE Speed Data ▪American Transportation Research Institute (ATRI)

Type of Performance Measure	Methodology	Reporting Period	Calculation	Sources
Combination Truck Backhaul Tonnage	The Freight Analysis Framework (FAF) tonnage data is interpolated using combination truck miles traveled data to calculate incoming and outgoing combination truck tonnage. An average capacity to average load ratio is calculated and applied to the difference between incoming and outgoing combination truck tonnage.	Yearly	$\sum \mathit{Combination\ Truck\ Backhaul\ Tonnage}$	▪FDOT Weigh in Motion data ▪Freight Analysis Framework 2012

B.2 MAP-21 PERFORMANCE MEASURE: PERCENT OF THE INTERSTATE SYSTEM MILEAGE UNCONGESTED

Type of Performance Measure	Description	Formula	Variables
PERCENT OF THE INTERSTATE SYSTEM MILEAGE UNCONGESTED	A two-stage process is used to develop the metric. 1st, Average Truck Speed is calculated for **each interstate** reporting segment over the course of a year.	$AverageTruckSpeed_s = \frac{\left[\sum_{b=1}^{T} \frac{SegmentLength_s}{TruckTravelTime_b}\right]}{T} x\ 3600$	*b* = a 5-minute time interval of a travel time reporting segment *s*; *s* = a travel time reporting segment; *T* = total number of time intervals in everyday in a full calendar year; *SegmentLengths* = length of reporting segment *s*, to the nearest one tenth of a mile; *TruckTravelTimeb* = travel time of trucks, for time interval *b* in the Travel Time Data Set, to the nearest second; 3,600 = number of seconds in an hour; and *AverageTruckSpeeds* = average annual speed of trucks traveling through the reporting segment *s*, to the nearest hundredth mile per hour.
	2nd, compute the interstate system wide measure from the Average Truck Speeds developed for the individual reporting segments	$PercentInterstateSystemMileageUncongested = 100x \frac{\sum_{g=1}^{U} SL_g}{\sum_{i=1}^{T} SL_i}$	*g* is an uncongested interstate system reporting segment, defined as a segment that has an average truck speed greater than 50.00 mph; SL_g = segment length, to the nearest hundredth of a mile, of an interstate system reporting segment that has an average truck speed greater than 50.00 mph; *U* = total number of uncongested interstate system reporting segments; *i* is an interstate system reporting segment; and T = total number of interstate system reporting segments.
Additional Information	**Threshold:** A reporting segment is considered uncongested where the Average Truck Speed for the reporting segment is greater than 50.00 mph		

B.3 MAP-21 PERFORMANCE MEASURE: PERCENT OF THE INTERSTATE SYSTEM MILEAGE PROVIDING FOR RELIABLE TRUCK TRAVEL TIME

<table>
<tr><th>Type of Performance Measure</th><th>Description</th><th>Formula</th><th>Variables</th></tr>
<tr><td rowspan="2">PERCENT OF THE INTERSTATE SYSTEM MILEAGE PROVIDING FOR RELIABLE TRUCK TRAVEL TIMES</td><td>A two-stage process is used to develop the metric:

1st, the Truck Travel Time Reliability (TTTR) value is calculated.</td><td>$TTTR = \frac{95^{th} Percentile\ Truck\ Travel\ Time}{50^{th} Percentile\ Tuck\ Travel\ Time}$</td><td>TTTR is the Truck Travel Time Reliability value</td></tr>
<tr><td>2nd, compute the interstate system wide measure from the TTTRs for the individual reporting segments.</td><td>$InterstateTTTR = \frac{\sum_{a=1}^{R} SL_a}{\sum_{t=1}^{T} SL_t} x100$</td><td>InterstateTTTR is the interstate systemwide truck travel time reliability measure
SL_a is the length of an interstate reporting segment a to the nearest hundredth miles where the TTTR value is less than 1.50
SL_t is the length of an interstate reporting segment t that reports a TTTR value, to the nearest hundredth mile
R is the total number of interstate reporting segments where the TTTR value is less than 1.50, to the nearest hundredth mile
T is the total number of interstate reporting segments that report a TTTR value, to the nearest hundredth mile.</td></tr>
<tr><td>Additional Information</td><td colspan="3">Threshold: A reporting segment would provide for reliable truck travel times where the calculated value of the metric is less than 1.50</td></tr>
</table>

APPENDIX C

Use Case Briefs

C.1 USE CHARACTERISTICS OF INTERMODAL CONNECTORS

UNIVERSITY OF ARKANSAS

ARDOT ARKANSAS DEPARTMENT OF TRANSPORTATION

Truck Activity Analysis Using GPS Data:

Use Characteristics of Intermodal Connectors and Ports

Project TRC1702
July 2019

Sarah Hernandez, Ph.D., Taslima Akter, and Karla Diaz-Corro

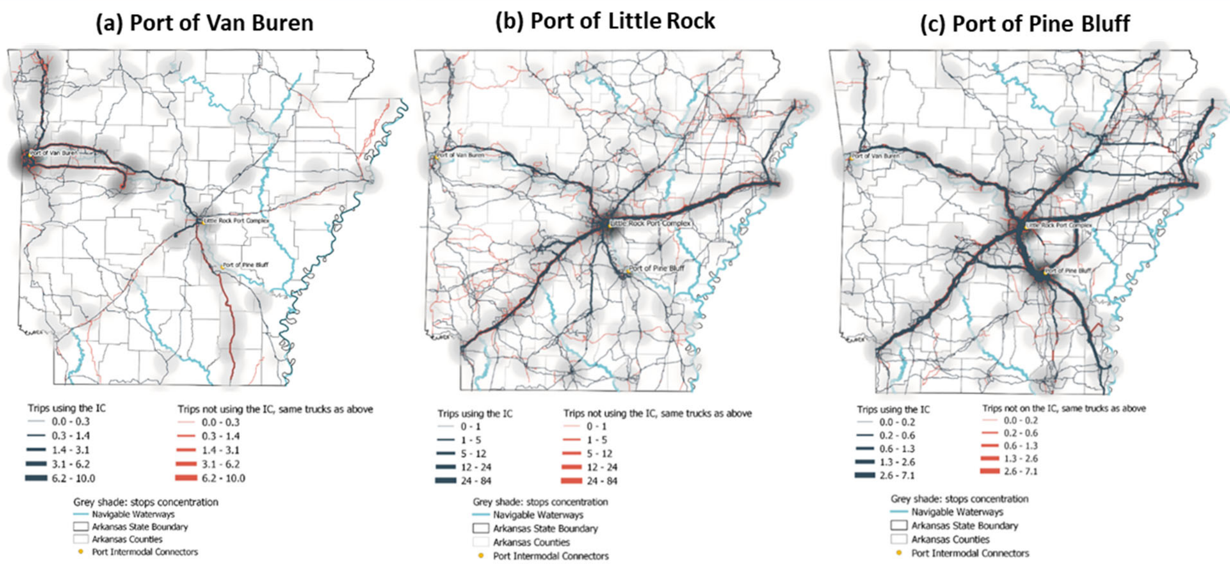


Figure 1. *Catchment Areas for Each Inland Waterway Port Derived from Truck GPS Data*

Truck GPS data can be used to monitor performance of intermodal infrastructure such as inland waterway ports. This use-case identified the in-state routes followed by trucks found at the three port Intermodal Connectors (ICs) in Arkansas, and the location of the stops made along those routes. ICs are short segments of the National Highway System (NHS) that connect intermodal terminals such as ports to the NHS. The study looked at the inland waterway ports, or port areas, in Van Buren, Little Rock, and Pine Bluff. The goal of this case study was to qualitatively and quantitatively describe truck volumes by time of day, season, and region at each of three inland waterway ports.

Study Methods

The number of trucks accessing each inland waterway port was estimated using the results of the Stop Identification and Map Matching algorithms developed in TRC1702. Trucks using the IC and other port access roads were counted from the GPS data via the Map Matching results. The resulting sample was expanded based on coverage factors corresponding to the sample time period (e.g. quarter) and region (e.g. ARDOT district) to produce a daily average truck count for each port for each quarter.

The spatial usage pattern for each port was referred to as a *catchment area*. A catchment area was defined as the geographic extent covered by the set of truck trips, which accessed the port via the port access roads and had an origin or destination at the port. In general, the catchment area represented the landside impacts of the port.

Findings

This use-case identified the usage of roads that serve the inland waterway ports of Van Buren, Little Rock, and Pine Bluff by season and mapped the spatial patterns of trucks accessing each port. Assuming GPS data to be a representative random sample of the total population of trucks moving freight within Arkansas, spatial and temporal patterns of usage identified from the GPS data provide insight into seasonal commodity movements.

Van Buren was the third most active port of the three as measured by estimated daily truck volume, Vehicle Miles Travelled (VMT) and number of stops. Trucks accessing the Port of Van Buren had a high concentration of subsequent stops in Benton/Washington counties, Pulaski county, and Russellville/Dardanelle/Centerville areas Figure 1a). The heaviest concentration of stops was in the Northwest Arkansas region. August saw the lowest activity at the port, with activity spread more evenly across the remaining quarters. The Port of Little Rock was the most active of the three ports with triple the daily volume of Pine Bluff and an order of magnitude greater than Van Buren. Trucks accessing the Little Rock Port Complex had subsequent stops concentrated in the eastern and southern regions of Arkansas. The heaviest concentration of stops was found in Memphis and in cities located along I-30, south of Little Rock. Truck activity peaked in May and declined in February. Trucks accessing the Port of Pine Bluff made subsequent stops in the south-east region of Arkansas. The heaviest concentration of stops was found along I-530 between Pine Bluff and Little Rock. Truck activity declined in February but was evenly spread across the remaining three quarters.

If truck GPS data were also available for a broader region (i.e. adjacent states), this analysis could expand the limits of the state to incorporate out-of-state portions of long-haul trips and allow for analysis of the full region affected by port activities on the landside.

Policy Recommendations

From the catchment area analysis, some truck trips traverse routes that are parallel to navigable waterways, indicating a potential for the cargo to continue by water for a longer stretch than it currently does. Moreover, the GPS data reveals the usage patterns of parallel routes serving the same city pairs. This indicates that truck GPS data could be used to identify and quantify "preferred" routes by carriers. This may be of interest to design detours in cases where roadway infrastructure needs to be temporarily shut down. This seasonality analysis supports several planning and infrastructure decisions.

About the Authors

Dr. Sarah Hernandez is an Assistant Professor in the department of Civil Engineering at the University of Arkansas. *Taslima Akter* is a Ph.D candidate and *Karla Diaz-Corro* is a Masters student, both at the Department of Civil Engineering at the University of Arkansas.

To Learn More

For more details about the study: "Evaluating the Performance of Intermodal Connectors", visit the Maritime Transportation Research and Education Center (MarTREC) website and download the full report: https://martrec.uark.edu/research/infrastructure.php

ARDOT ARKANSAS DEPARTMENT OF TRANSPORTATION

This research was sponsored by the Arkansas Department of Transportation (ARDOT) through their System Information and Research Division. ARDOT's mission is to "provide safe and efficient transportation solutions to support Arkansas' economy and enhance the quality of life for generations to come."

UNIVERSITY OF ARKANSAS

ARDOT ARKANSAS DEPARTMENT OF TRANSPORTATION

Truck Activity Analysis Using GPS Data:
Usage and Capacity Assessment of Truck Parking

Project TRC1702
July 2019

Sarah Hernandez, Ph.D., Taslima Akter, and Karla Diaz-Corro

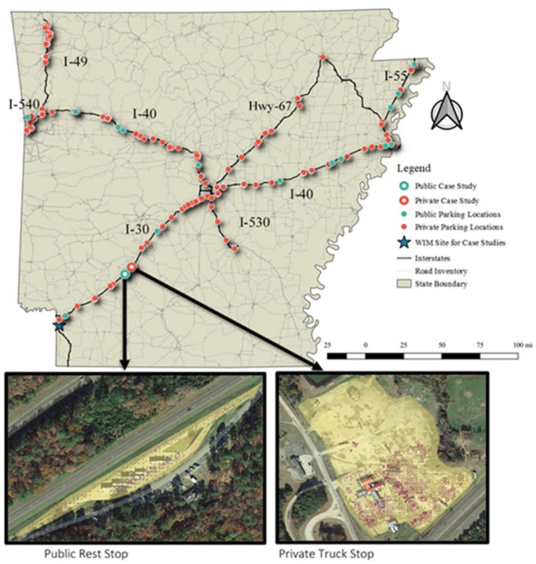


Figure 1. *Public and Private Truck Parking Facility Locations in Arkansas*

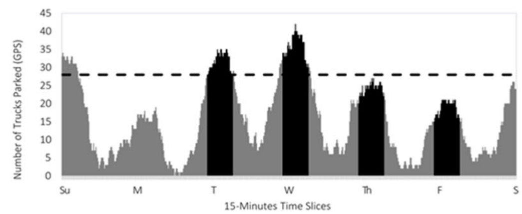


Figure 2. *Fifteen Minute Time Slices for Truck Parking Use Estimation from Truck GPS Data*

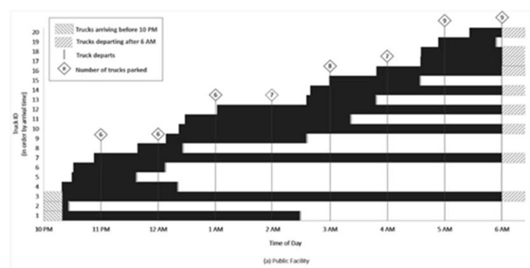


Figure 3. *Method to Count Parked Trucks using Truck GPS Data*

Truck GPS data can be used to replace or supplement ARDOT's Overnight Truck Parking Study to reduce data collection costs and to expand spatial and temporal coverage of the Overnight Study sites. This use-case compared truck parking counts collected through direct observation as part of the ARDOT Overnight Truck Parking Study to those derived from truck GPS data to determine appropriate GPS expansion factors, e.g. ratios of the GPS sample to the truck population, for different facility types. Unlike the ARDOT Overnight Study, truck GPS data provided continuous (e.g. 24/7) estimation of truck parking usage in terms of number of trucks parked and duration of parking for each of 400+ public and private parking facilities in Arkansas.

Study Methods

ARDOT conducts the Overnight Truck Parking Study (referred to as the *Overnight Study*) annually during the first week of September between 10 PM and 6 AM. Teams of observers record the number of trucks parked at each facility by visual inspection including legal and illegal (along on and off ramps and shoulders) truck parking. Observation sites for the study are located at each exit of Interstates I-30, I-40, I-49, I-55, I-440, and I-540, and Highway 67 (Figure 1). Sites include ARDOT facilities where truck parking is permitted (e.g. public rest stops), private truck stops, and private commercial businesses with and without designated truck parking (e.g. Walmart, Home Depot, and restaurants).

This study evaluated 102 of these facilities that pertain to legal and designated parking areas. The goal of the study was to derive expansion factors to apply to the GPS-derived parking counts to estimate population-level parking usage.

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Methods

First, geographic bounding boxes were created for each parking facility. The bounding box defines the parking area so that square footage and number of parking spaces could be estimated. *Second*, for each bounding box, e.g. parking facility, the number of trucks parked during each hour of the day were counted from the GPS data. *Third*, because the exact day and time of the ARDOT Overnight Study observation was not available, a method to match the ARDOT observation to the GPS data was developed as follows. The count of parked trucks derived from the GPS data was sampled at 15-minute time slices during each 10 PM to 6 AM time window between August 29th and September 2nd, 2016.

Findings

Overall, 70% of the 400 study sites were private truck stops, 20% were private commercial properties (like business parking lots), and 10% were public facilities. Private truck stops had the highest capacity of on average 50 parking spaces compared to public rest stops with 27 spaces on average. From the GPS data, the arrival, duration, and departure patterns of the parked trucks for the case study facilities during the time period (10 PM to 6 AM) and day of the Overnight Study are shown in Figure 8. Generally, drivers arriving prior to 10 PM parked for longer, overnight (8+ hour) rest periods, at the private facility while the public rest stop shows longer parking durations throughout the night and early morning periods. Truck parking expansion factors, e.g. ratios of GPS sampled trucks to observed population of parked trucks, ranged from 6.4 at public rest to 4.2 at commercial properties. With these established expansion factors, ARDOT can now use truck GPS data to accurately estimate parking usage 24/7, greatly improving on the resolution provided by the Overnight Study.

Policy Recommendations

With population level estimates of parked trucks derived from GPS data, facility utilization characteristics such as overcrowding by time of day and day of week, arrival rates, and duration patterns can be determined. Such information greatly improves upon what is available through existing observational and driver surveys. While surveys can provide some insight into usage patterns and identify locations of significant congestion, they can be costly to conduct and thus difficult to regularly update. Truck GPS data provides a more repeatable and systematic data source and has the potential to be collected in real-time. This presents opportunities for real-time parking availability applications, if accurate expansion of the GPS samples can be carried out. Moreover, detailed, accurate, and timely illustrations of the truck parking problem can help practitioners relay the importance of funding parking facility improvement projects to the public and funding stakeholders.

About the Authors

Dr. Sarah Hernandez is an Assistant Professor in the department of Civil Engineering at the University of Arkansas. *Taslima Akter* is a Ph.D candidate and *Karla Diaz-Corro* is a Masters student, both at the Department of Civil Engineering at the University of Arkansas.

To Learn More

For more details about the study: "Comparison of Overnight Truck Parking Counts to GPS Derived Counts for Truck Parking Facility Utilization Analysis", download the full report at https://journals.sagepub.com/doi/full/10.1177/0361198119843851

ARDOT ARKANSAS DEPARTMENT OF TRANSPORTATION

This research was sponsored by the Arkansas Department of Transportation (ARDOT) through their System Information and Research Division. ARDOT's mission is to "provide safe and efficient transportation solutions to support Arkansas' economy and enhance the quality of life for generations to come."

C.3 CRASH-INDUCED DELAY FOR TRUCKS

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ARDOT ARKANSAS DEPARTMENT OF TRANSPORTATION

Truck Activity Analysis Using GPS Data:
Crash Induced Delay for Trucks

Project TRC1702
July 2019

Sarah Hernandez, Ph.D., Taslima Akter, and Karla Diaz-Corro

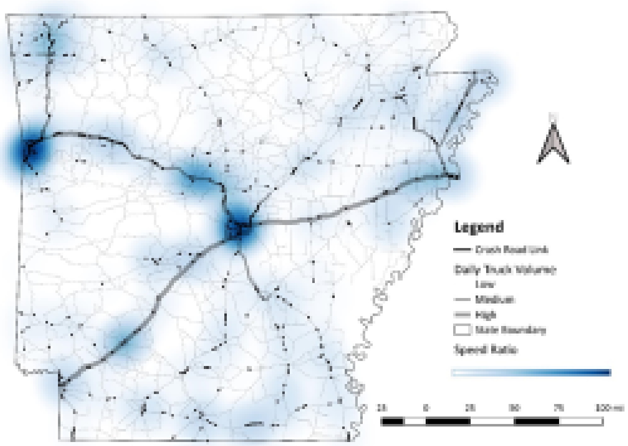


Figure 1. *Crash Locations, Daily Average Truck Volume, and Truck Speed Ratio (TSR)*

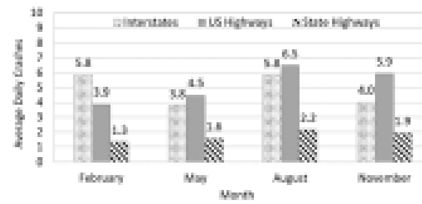


Figure 2. *Daily Average Crashes by Functional Class and Sample Period*

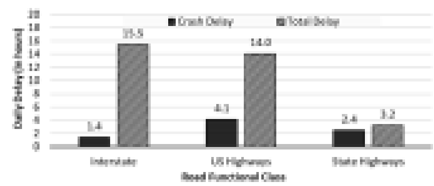


Figure 3. *Total Delay and Crash Related Delay by Functional Class*

Truck GPS data in combination with location and timestamped crash records can be used to estimate crash induced delay. Truck GPS data was used to estimate Daily Delay. Daily Delay includes delay due to recurring congestion and nonrecurring congestion induced by accidents, weather, and construction, among others. For this case study, crash records indexed by time and location collected by the Arkansas State Police (ASP) were merged with the truck GPS data. The goals were to determine the effects of crashes on truck travel speeds and to identify corridors that experience a higher proportion of crash induced delays.

Study Methods

ASP crash records contain location (e.g. latitude-longitude), time of incident, roadway index, and crash severity. Crashes occurring during the GPS sample periods were mapped to the nearest ARNOLD network link. All crashes were considered in the analysis regardless of severity or truck-involvement.

From the GPS data, hourly average truck speeds were estimated for each link associated with a crash for an hour before the crash and the hour of the crash. A Truck Speed Ratio (TSR) was then estimated to represent the effect of the crash on hourly average truck speeds (Eq. 1).

$$TSR = \frac{Speed_{During\ Crash}}{Speed_{After\ Crash}} \qquad \text{Eq. 1}$$

Where

TSR is the Truck Speed Ratio (unit less)

$Speed_{During\ Crash}$ is the estimated hourly average truck speed in the hour during the crash (mph)

$Speed_{After\ Crash}$ is the estimated hourly average truck speed in the hour after the crash (mph)

Findings

The Average Daily Crashes estimated from the ASP Crash Data varied by sample period and roadway functional class (Figure 2). US Highways experienced the highest proportion of crashes in all sample periods except February, and overall had the highest average daily crashes. Note that Average Daily Crashes is not the same as a crash rate as it was not indexed by traffic volume or vehicle miles travelled. To add some context, approximately 2,000 miles of Interstate, 5,000 miles of US Highways, and 14,000 miles of State Highways were represented in the ARNOLD network. State highways had the lowest average daily crashes despite having the highest mileage. As expected, crashes resulted in decreased truck traffic speeds as represented by the TSR. A higher TSR represented minimal delay effects due to crashes while a lower TSR represented more sever effects. The greatest impacts of crashes on TSR occurred in the Ft. Smith/Van Buren (Northwest Arkansas), Conway count (Central Arkansas), and Little Rock (Central Arkansas) (Figure 1).

The impact of crashes on traffic speed tend to vary between interstates and state highways. The number and impact of crashes are noticeably higher in and around intersection points of interstates (Figure 1). The impact of traffic crashes on traffic speed is significantly high for the area near the intersection of I-49 and I-540. Similar scenario is observed in Pulaski where several interstates meet.

In comparing total and crash induced delays, crash induced delays accounted for around 9% (=1.4/15.5) of total delay for Interstates, 29% of total delay for US Highways, and 76% for State Highways (Figure 31). Thus, crash related delay was the main component of total delay for trucks on State Highways. This was in heavy contrast to the causes of delay for Interstates and US Highways.

Policy Recommendations

Critical corridors identified in the study of crash induced delay for trucks can be added to prioritization criteria for roadway safety improvement projects. Identified hotspots could be investigated further to have a better understanding of the potential issues, for instance, road geometric design, long response time after primary accident and poor operational management, contributing to reduced traffic speed due to crash.

About the Authors

Dr. Sarah Hernandez is an Assistant Professor in the Department of Civil Engineering at the University of Arkansas. *Taslima Akter* is a Ph.D candidate and *Karla Diaz-Corro* is a Masters student, both at the Department of Civil Engineering at the University of Arkansas.

To Learn More

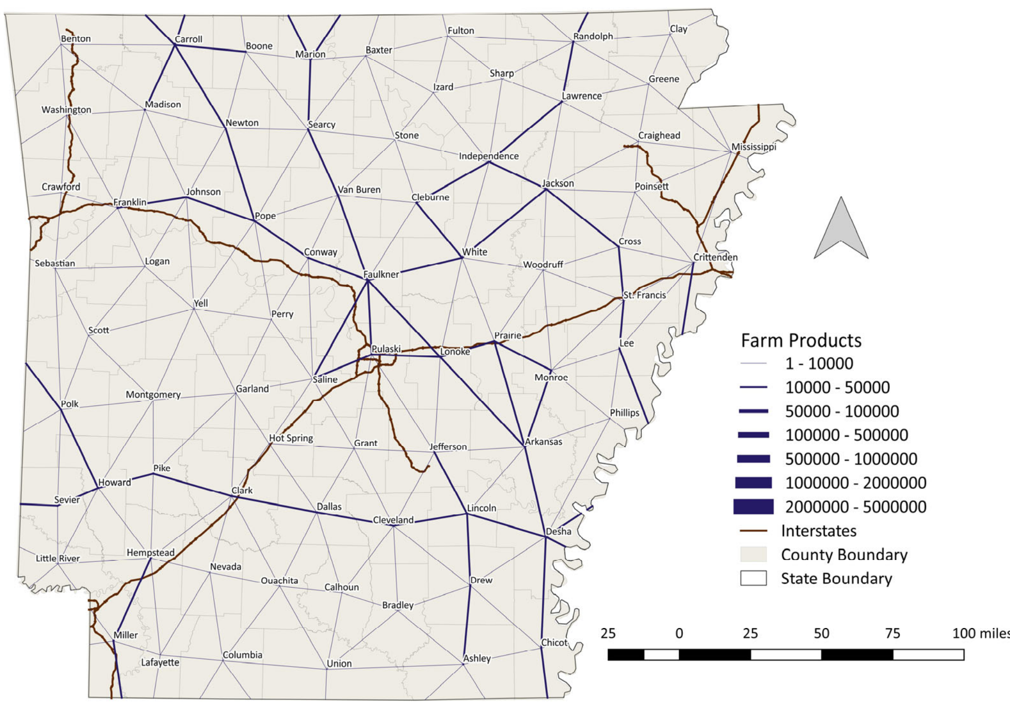
For more details about the study, please visit https://sites.uark.edu/sarahvh/research for a copy of the Final Report for TRC1702 Truck Activity Analysis Using GPS Data

This research was sponsored by the Arkansas Department of Transportation (ARDOT) through their System Information and Research Division. ARDOT's mission is to "provide safe and efficient transportation solutions to support Arkansas' economy and enhance the quality of life for generations to come."

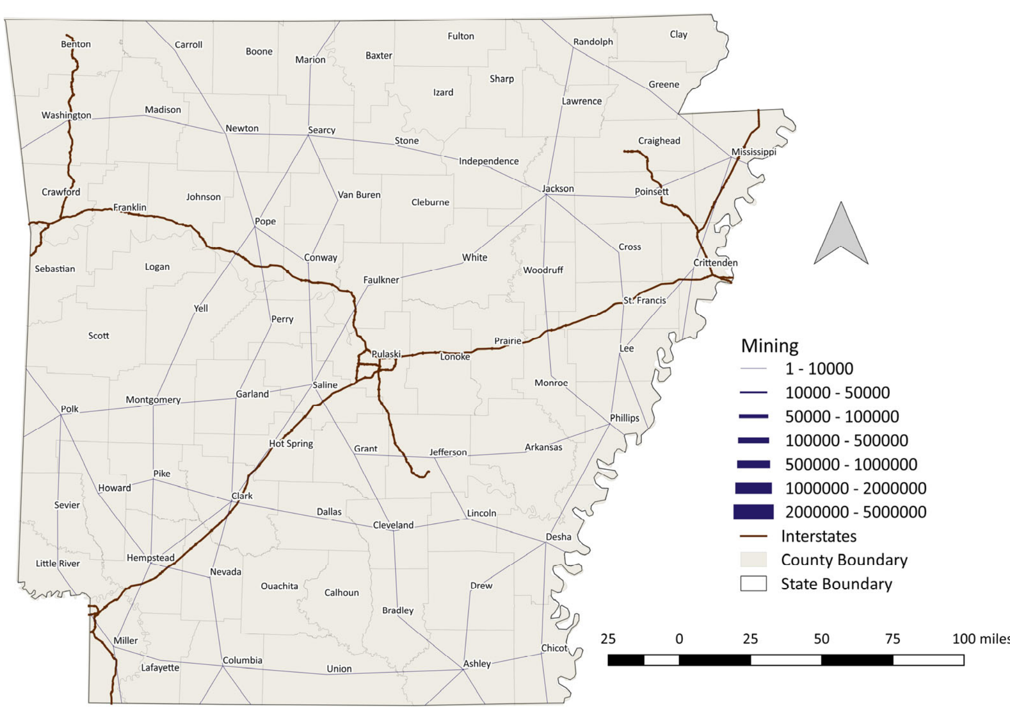
APPENDIX D

Annual Origin-Destination (OD) Flows

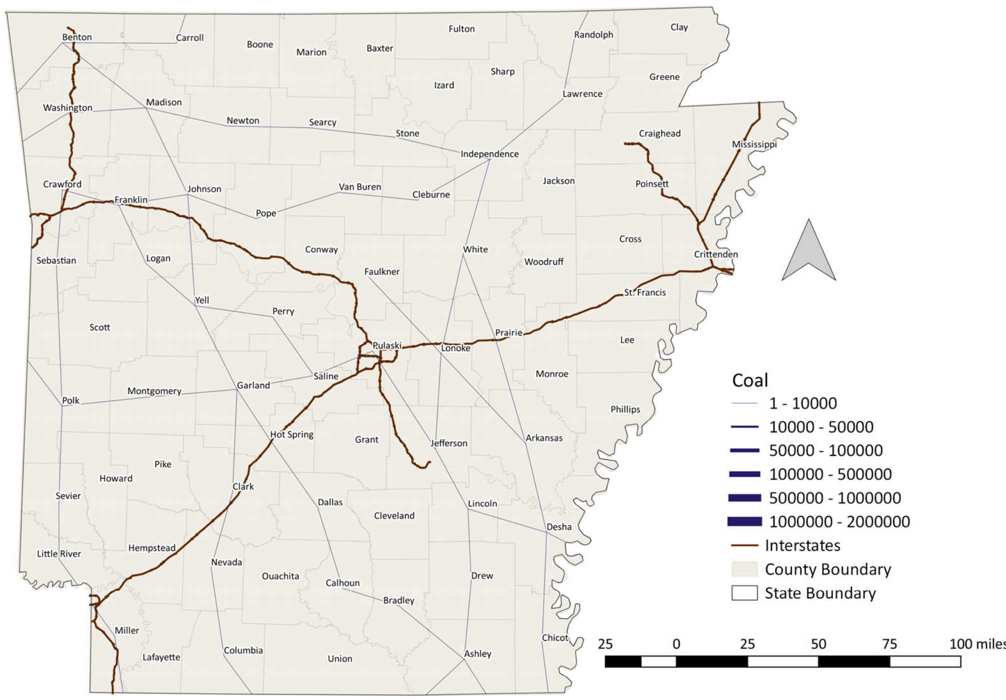
D.1 ANNUAL OD FLOWS OF FARM PRODUCTS IN ARKANSAS



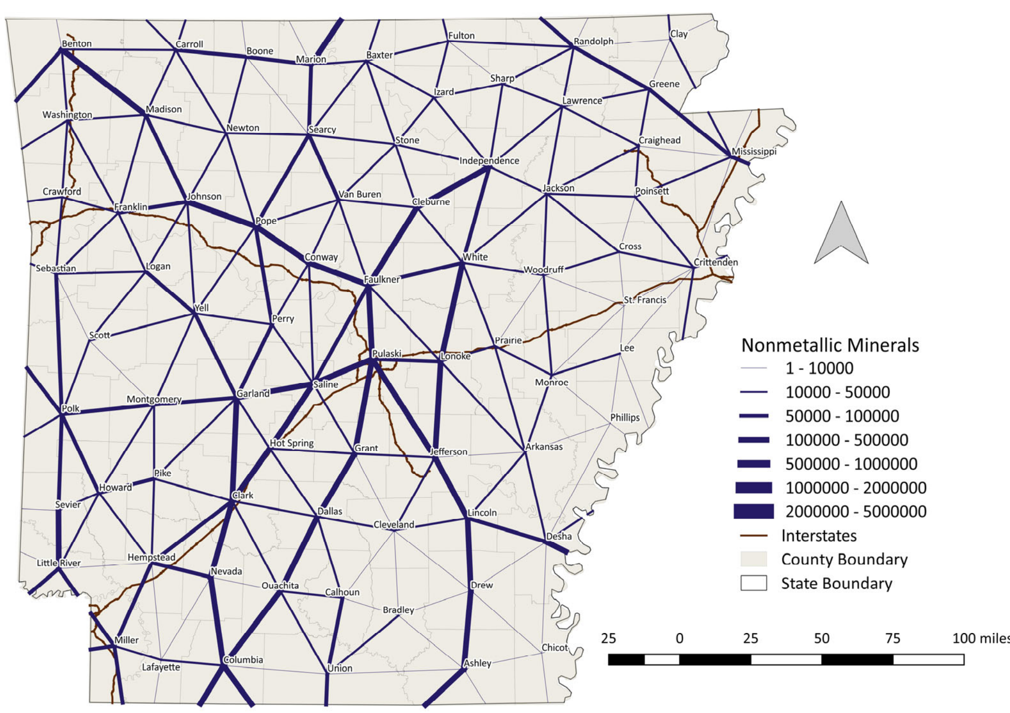
D.2 ANNUAL OD FLOWS OF MINING IN ARKANSAS



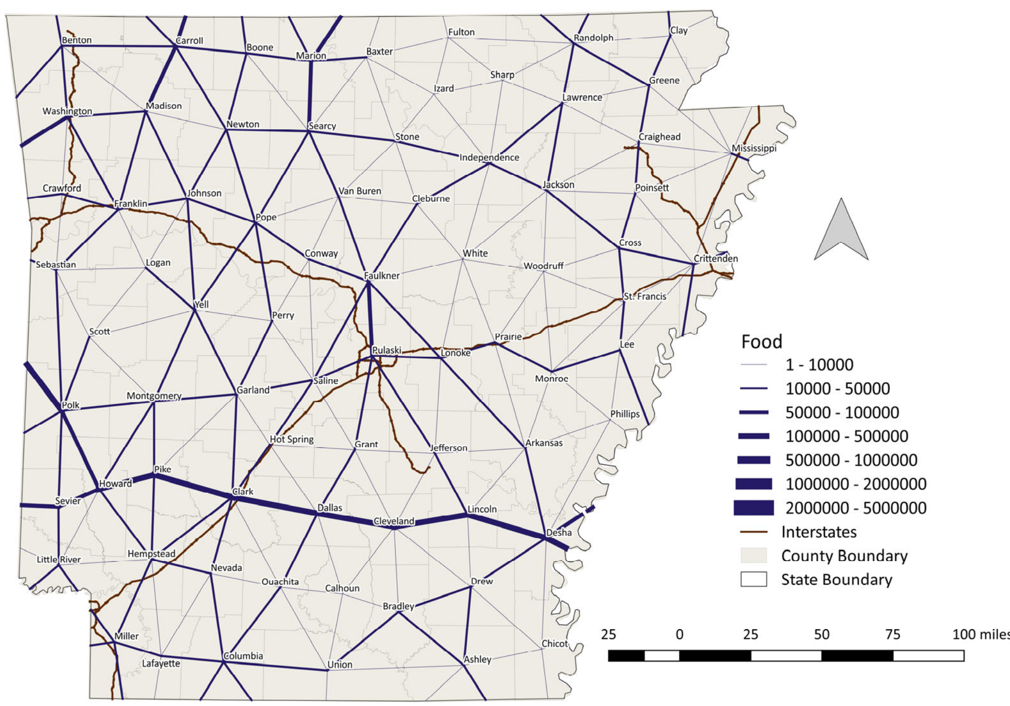
D.3 ANNUAL OD FLOWS OF COAL IN ARKANSAS



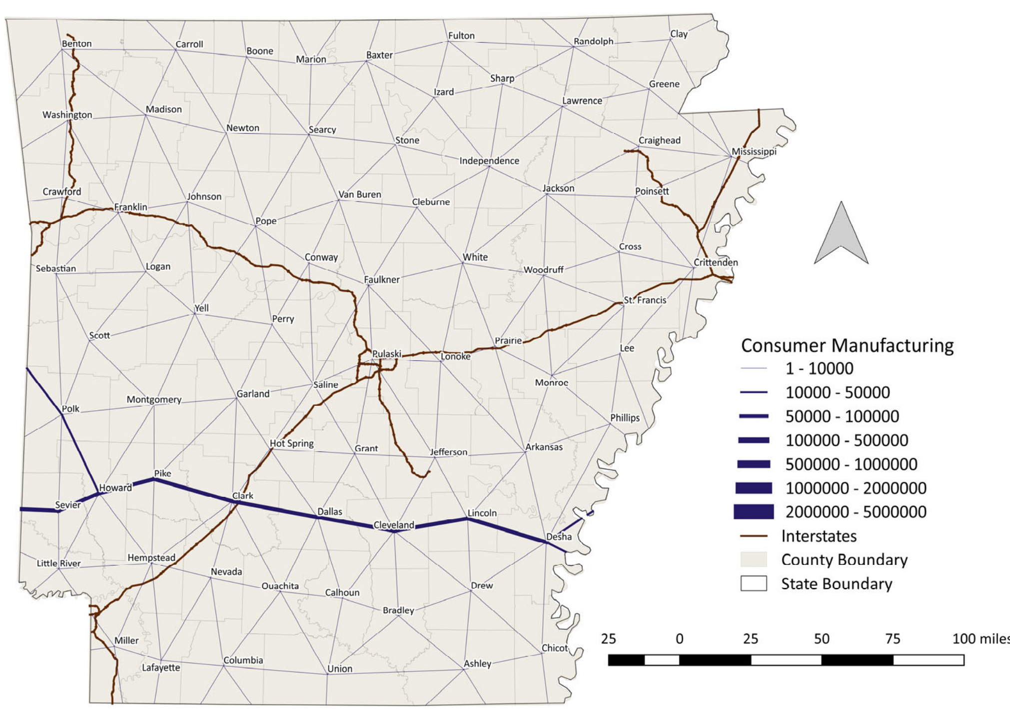
D.4 ANNUAL OD FLOWS OF NONMETALLIC MINERALS IN ARKANSAS



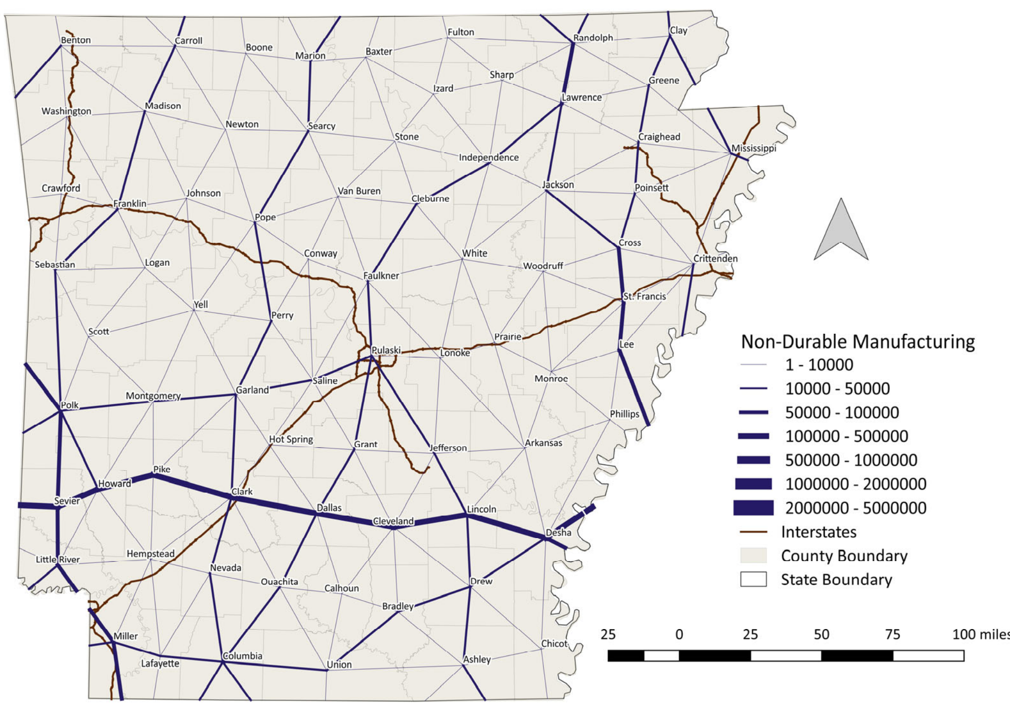
D.5 ANNUAL OD FLOWS OF FOOD IN ARKANSAS



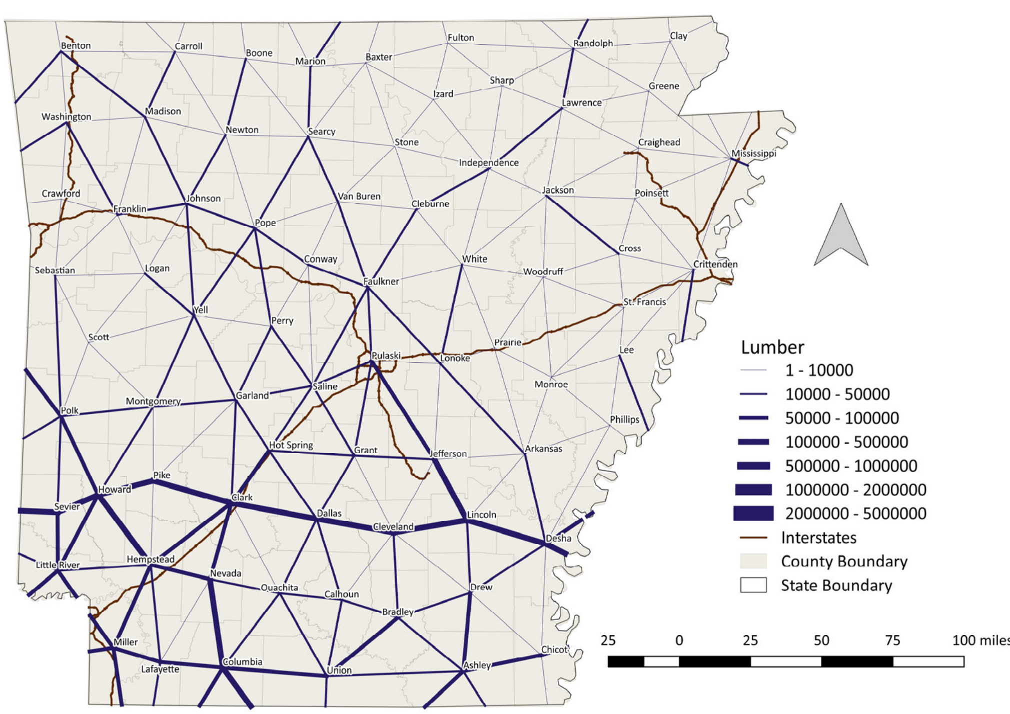
D.6 ANNUAL OD FLOWS OF CONSUMER MANUFACTURING IN ARKANSAS



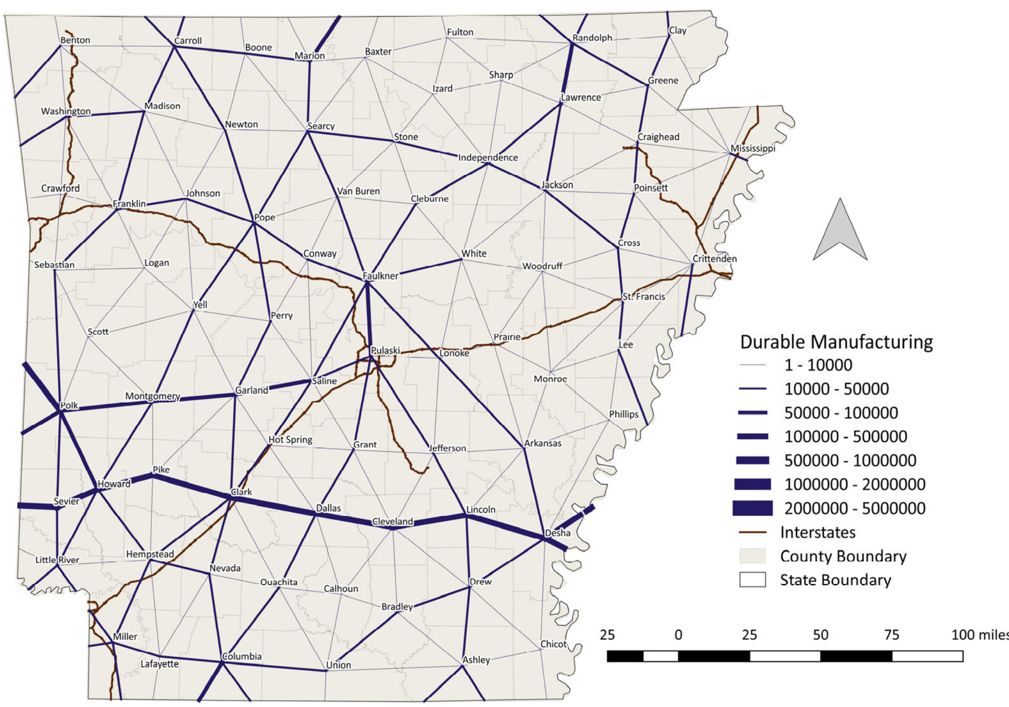
D.7 ANNUAL OD FLOWS OF NON-DURABLE MANUFACTURING IN ARKANSAS



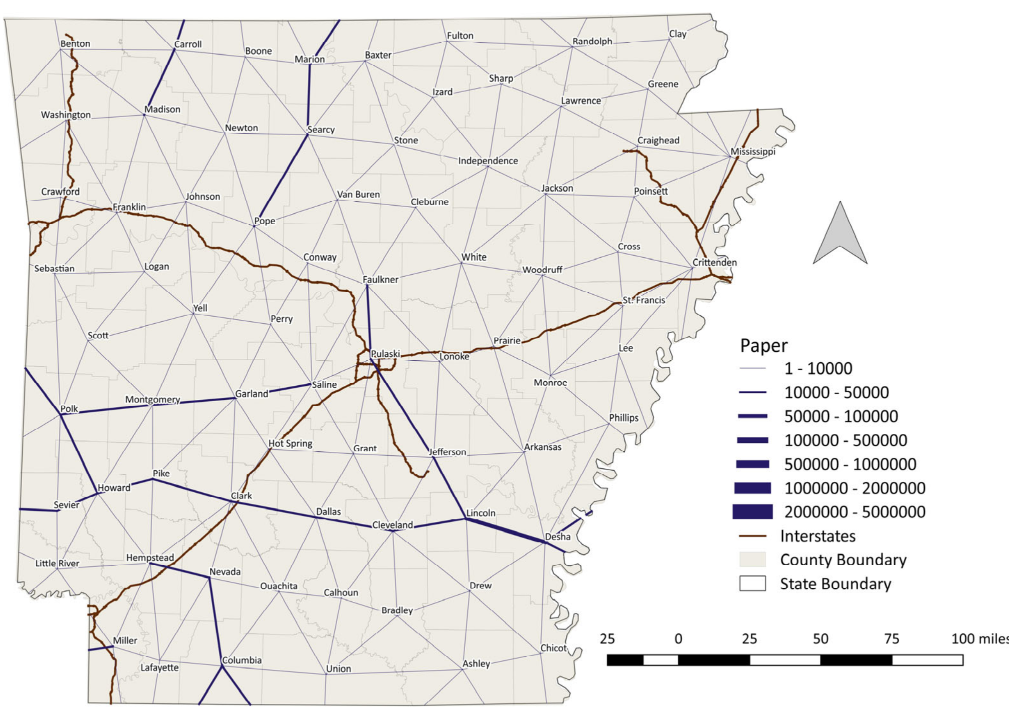
D.8 ANNUAL OD FLOWS OF LUMBER IN ARKANSAS



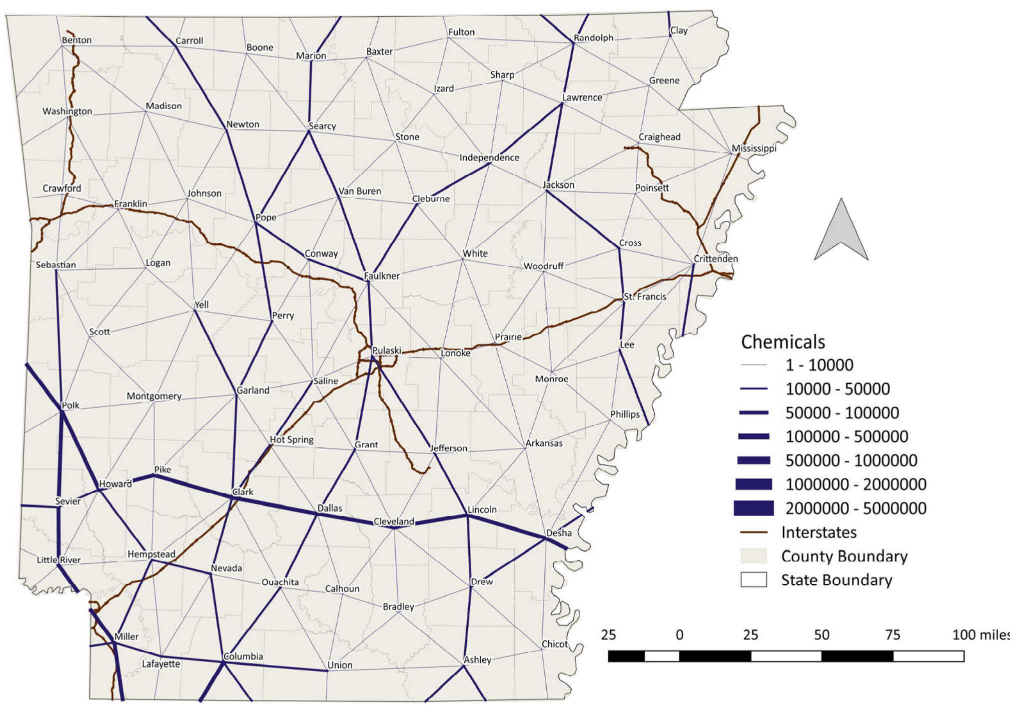
D.9 ANNUAL OD FLOWS OF DURABLE MANUFACTURING IN ARKANSAS



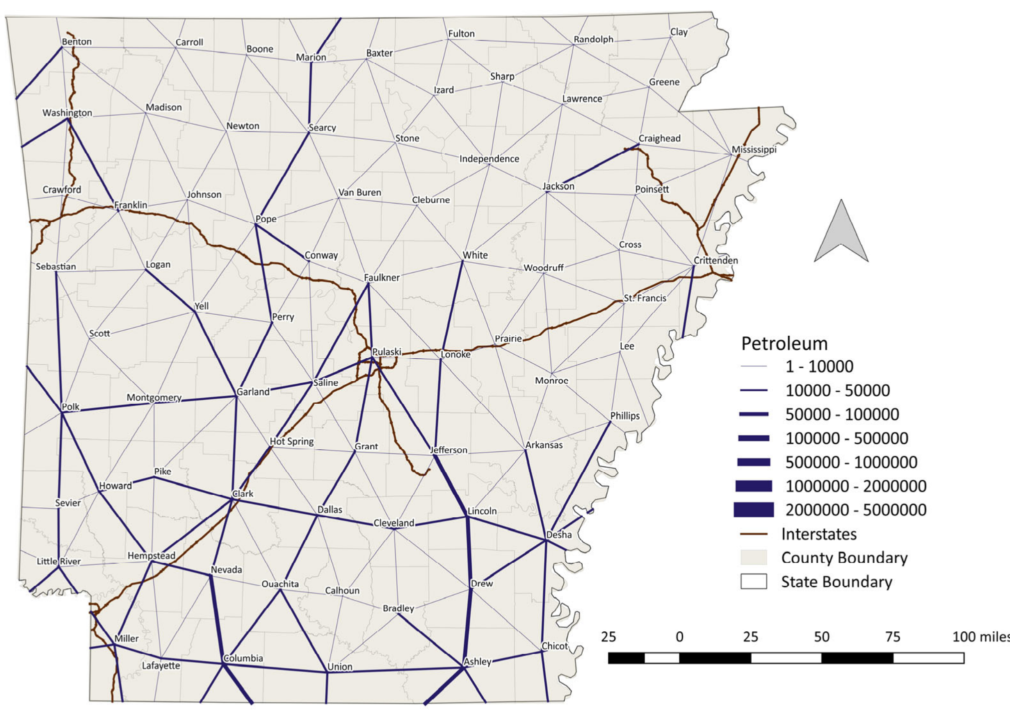
D.10 ANNUAL OD FLOWS OF PAPER IN ARKANSAS



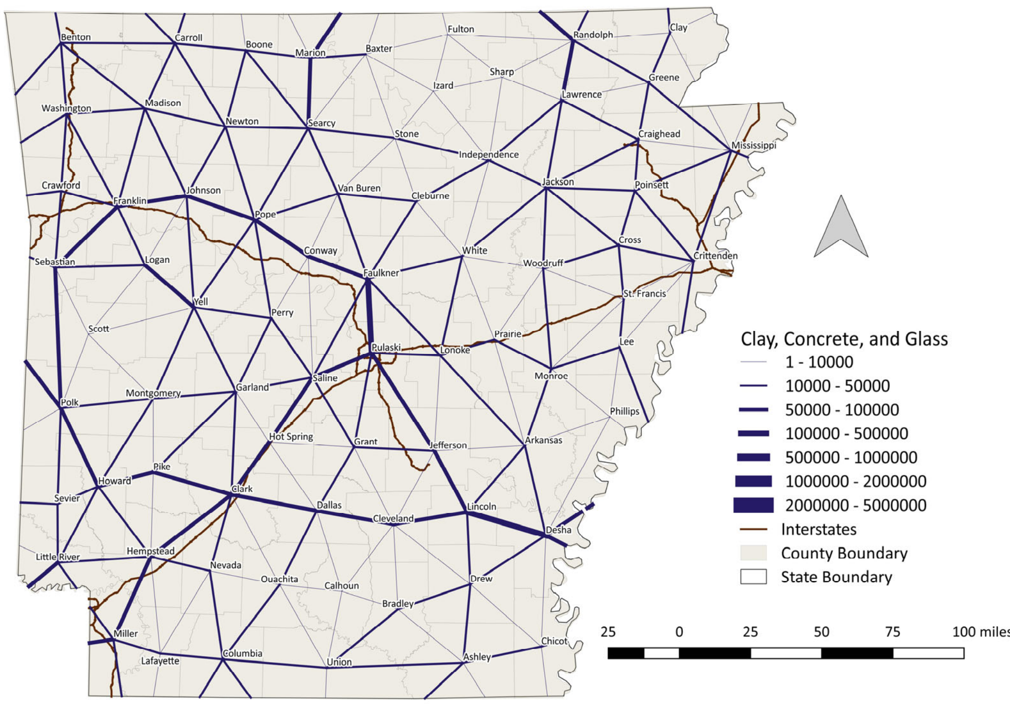
D.11 ANNUAL OD FLOWS OF CHEMICALS IN ARKANSAS



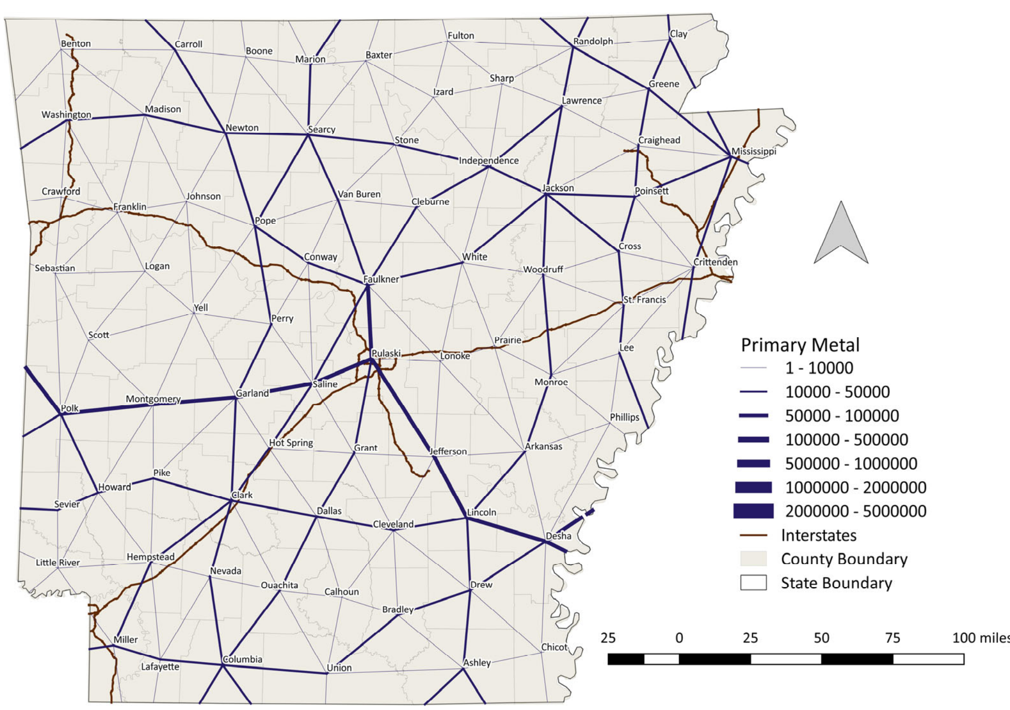
D.12 ANNUAL OD FLOWS OF PETROLEUM IN ARKANSAS



D.13 ANNUAL OD FLOWS OF CLAY, CONCRETE, AND GLASS IN ARKANSAS



D.14 ANNUAL OD FLOWS OF PRIMARY METAL IN ARKANSAS



D.15 ANNUAL OD FLOWS OF MISCELLANEOUS MIXED IN ARKANSAS