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Evaluating the Performance of Intermodal Connectors in Arkansas

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1 Project Description

1.1 Project Overview and Objectives

The purpose of this project is to evaluate the performance and usage of Intermodal Connectors (ICs) in Arkansas using data-driven methods. ICs serve as the critical 'first and last mile' segments of the National Highway System (NHS) by connecting airports, marine and river ports, and intermodal facilities to the NHS. ICs play a critical role in the movement of multi-modal freight such that congestion on the IC can have cascading effects on the reliability multi-modal supply chain. ICs are officially designated by state Departments of Transportation (DOT) and Metropolitan Planning Organizations (MPO) based on federal criteria. Designation implies eligibility for federal funds to support improvement projects.

Unfortunately, considering the significant impact ICs have on efficient multi-modal freight movements, ICs are not currently well monitored, nor is their performance well understood. This limits the transportation planning and programming efforts for ICs. Adding to the lack of understanding are the limited tools available for collecting data on these links. Commonly used data collection tools which rely on intrusive sensors (i.e. those that must be installed in the paved travelled lanes) do not work well for ICs which tend to have poor pavement quality due to heavy truck volumes. With the increasing availability and affordability of non-obtrusive technologies such as Lidar sensors, Bluetooth tracking devices, and truck Global Positioning Systems (GPS), the ability to collect comprehensive data on ICs is increasingly possible.

In this context, this study identifies options for improving the quality and amount of data available for freight transportation planning on ICs by focusing on advanced data collection methods. The objectives of this study are: (1) to determine an ideal data collection technology platform for characterizing the usage and performance of intermodal connectors, (2) to deploy and evaluate the technology on an IC in Arkansas, and (3) to demonstrate through case studies how usage and performance of ICs can be monitored through advanced detection technologies.

To achieve these objectives, the research team developed a non-intrusive, low-cost traffic sensor bundle that is capable of providing high quality data for ICs including truck travel times, and truck characteristics such as commodity carried or industry served. To do this, various non-intrusive sensor technologies were compared, and truck classification algorithms were developed and tested on the IC which connects the Port of Van Buren, on the Arkansas River, to the NHS at Interstate I-540. Moreover, GPS data collected at the three port ICs in Arkansas (located at Van Buren, Little Rock and Pine Bluff) was used for case studies to highlight the unique performance and usage patterns found on ICs. Additionally, GPS data was used to evaluate the performance of routes used to access intermodal port facilities that are not officially designated as ICs.

1.2 Background

1.2.1 Motivation

ICs are the critical "first and last mile" roadways that tie intermodal freight facilities such as maritime ports to the NHS. Often less than 2 miles in length, ICs account for less than 1% of NHS mileage, but are critical for timely and efficient multimodal freight movements. ICs are in relatively poor condition compared to the NHS as a whole. For example, 56% of ICs are reported to have mediocre or poor pavement conditions (FHWA, 2017). This has cascading effects on the reliability of multimodal freight operations- a one or two hour delay in a drayage movement along the IC can result in a 24-hour holdup in a domestic multimodal shipment (A. Strauss-Wieder, Inc. , 1999). Continued economic growth and reliance on intermodal supply chains will further strain intermodal connectors if freight planning efforts do not effectively consider the use and performance of these critical network links. Without timely and comprehensive usage and performance data for ICs, transportation agencies tasked with statewide planning, programming, and forecasting efforts are faced with a poor understanding of the impacts ICs have on an efficient multi-modal freight transportation network.

Compounding the issues for ICs are the limited data collection tools that can be applied to gather comprehensive and timely usage and performance data on these uniquely situated links. Most states rely on simple estimates of annual average daily traffic (AADT) and annual average daily truck traffic (AADTT) gathered from one-week counts using tube counters. Not only are tube counters known to provide inaccurate measurements of truck volumes, given the seasonality of freight movements, one week counts may not accurately represent annual truck flows. In terms of the type of data collected, at best, current practices provide vehicle volumes stratified by axle configuration to determine the number of trucks. This has little value when trying to estimate the impact of IC usage for different industries. It would be much more valuable to estimate truck volumes by commodity carried or industry served. Moreover, measures such as AADTT are not available for all ICs. The Highway Performance Measurement System (HPMS), the federal data reporting platform used to distribute funds provided by Moving Ahead for Progress in the 21st Century (MAP-21) and the Fixing Americas Surface Transportation (FAST) Act, captures 88% of ICs. Performance measures such as travel times and facility turn times are even less readily available. For example, national travel time data sets such as the National Performance Measurement Research Dataset (NPMRDS) (e.g. truck GPS) are only able to capture 52% of the ICs.

As a remedy, this project focuses on developing a sensor system to monitor the performance of Intermodal Connectors (IC). The sensor system was deployed to a designated NHS IC in Arkansas to gather comprehensive usage and performance characteristics. This project is timely given a recent assessment by the FHWA's Office of Freight Operations and Management and MARAD which identified a number of shortcomings in current data collection methods, data availability and a lack of understanding in how IC performance affects local, regional and national freight movements (FHWA, 2017).

1.2.2 Intermodal Connectors

The first inventory and assessment of ICs was performed by the FHWA in 2000 (FHWA, 2000). This report found deficiencies related to pavement quality, geometric design, and investment. In fact, the study reported that ICs to ports had twice the percent of mileage with pavement deficiencies when compared to non-interstate NHS routes (FHWA, 2000). A more recent study conducted by the FHWA and MARAD (FHWA, 2017) noted that the number of designated ICs have increased since 2000 due to tripled intermodal volumes at ports. Based on stakeholder surveys, the study found that over two-thirds of ICs experience congestion and that many local roads not designated as ICs are used by trucks to avoid congested conditions on the ICs. The report found that existing data and tools (e.g. HPMS) are not widely used due to their inaccuracies and lack of comprehensive data, which has lead DOTs and MPOs to collect new data for planning projects or to leave ICs out of the calibration/validation process for travel demand modelling.

ICs are designated in cooperation with State DOTs and MPOs in line with the criteria established by the FHWA (FHWA, 2000). As an example, the criteria related to freight to designate ICs are (RPC, 2010):

- provide access to container terminals that handle more than 50,000 Twenty-foot Equivalent Units (TEUs) per year or more than 100 large single unit or combination trucks per day per direction,
- provide access to bulk commodity terminals (e.g. Transload) that handle more than 500,000 tons per year or 100 trucks per day per direction.

This report focuses on freight related ICs connecting inland river ports to the NHS. These facilities are typically low capacity, two-lane roadways with an average 1 mile in length. There are a total of 13 freight ICs in AR, three of which are port terminals located at the Little Rock Port Complex, Port of Pine Bluff, and Port of Van Buren (FHWA, n.d.). The characteristics of these port ICs are summarized in Table 1. The location of these ICs is shown in Figures 1 and 3.

Table 1 Description of Port ICs in Arkansas

Facility	Intermodal Connector Description	Length (miles)	ID
Little Rock Port Complex	From I-440 (exit 5): S 0.27 mile on Fourche Dam Pike, NE 0.76 mile on Lindsey Rd, E 0.43 mile on Industrial Harbor Dr, S 0.20 mile on Slackwater Harbor Dr, E 0.40 mile on Intermodal Loop Dr to entrance to road to facility.	2.06	AR10P
Port of Pine Bluff	(AR12R) From US 65B access ramps: E 0.10 mile on 2nd Ave, N 0.11 mile on Nebraska Ave, NE 3.04 miles on Port Rd, NE 0.30 mile on Emmett Sanders Rd.	3.55 (AR12R)	AR15P
Port of Van Buren	From I-540 (EX 3): SE 0.48 mile on SH 59, S 0.15 mile on Port Rd.	0.63	AR17P

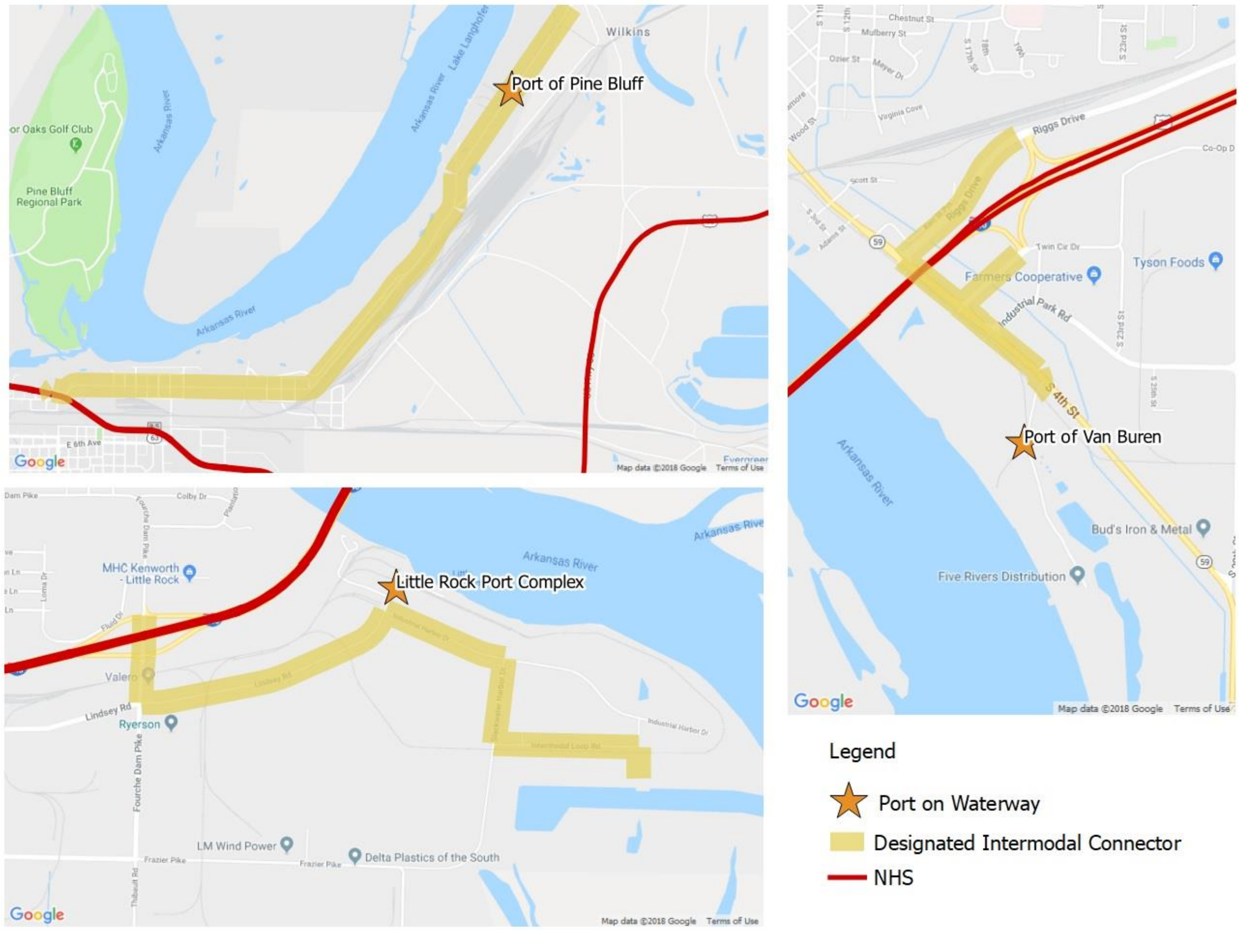


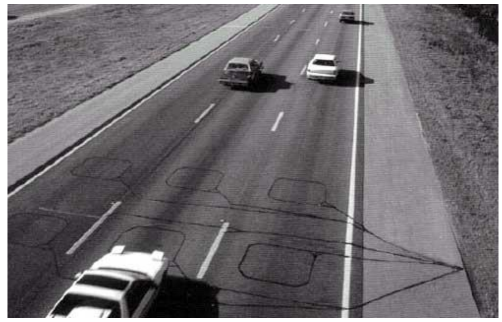
Figure 1 Detail of Port ICs in Arkansas

1.2.3 Data Collection Approaches

IC usage and performance data are critical inputs for infrastructure design, pavement maintenance programs, and the calibration/validation of long range freight transportation planning models. However, as identified in previous stakeholder surveys, there is a lack of quality data available for ICs. Desirable data needed to fully characterize ICs include (1) truck volumes by industry and commodity, (2) truck weights, (3) link speeds and travel times, and (4) pavement conditions. Also, it is important to gather this data on routes used as ICs but not designated as such, i.e. alternate NHS access routes.

A variety of traffic detection technologies exist for data collection and performance monitoring. The environmental conditions under which the detector will be placed dictate the type of sensor that is needed. Environmental factors refer to short term vs. permanent count stations, low vs. high traffic and/or truck volumes, pavement conditions, and the application (e.g. planning, design, etc.) for which the collected data is needed. For example, an important consideration in selecting a sensor is the ability of the sensor to withstand harsh roadway environments like extreme temperatures, moisture, dirt, and power instability.

In general, traffic detection technologies can be divided into two groups: intrusive and non-intrusive sensors. Intrusive sensors are embedded in the travelled lanes while non-intrusive sensors are typically mounted along the right of way of the travelled lanes in a side-fire configuration as shown in Figure 2. Examples of both technologies are included in Table 2.



(right) Intrusive (*FHWA, 2003*)

(left) Non-Intrusive (*Kotzenmacher et al., 2005*)

Figure 2 Example of intrusive (right) and non-intrusive (left) traffic detection installations.

Under ideal pavement quality conditions, intrusive sensors show excellent performance due to their close location to the vehicle and insensitivity to inclement weather (i.e. high and low temperatures) (FHWA, 2003). However, there are several disadvantages of intrusive sensors including: (1) safety issues to place the sensor in the lane if there are heavy traffic volumes, (2) high costs related to traffic control during installation and maintenance activity, (3) shortened lifespan and data quality issues when the pavement condition has deteriorated. Non-intrusive sensors are easier to install and maintain than intrusive sensors and are not affected by pavement quality. Some types of non-intrusive sensors, such as video cameras, can be affected by inclement weather (i.e. snow, fog, wind, etc.) and in a side-fire configuration, occlusion can be a major issue. Due to their steady use by heavy duty trucks, the pavement quality on intermodal connectors can be quite poor. Thus, non-intrusive detection methods are necessary for intermodal connectors to overcome pavement quality issues.

In addition to considering the environmental factors in selection of a traffic sensor, it is also necessary to consider the type of data that needs to be collected, as not all sensors are capable of gathering a full array of measurements. Truck volumes classified by vehicle configuration, weight, industry served or commodity carried, speed, and travel time are desirable performance measures for ICs. While previous studies provide ranges of data accuracy from various sensors for common vehicle classification schemes (e.g. FHWA's 13 class axle based classification scheme), none have evaluated the potential for highly detailed truck classification (Yu, Prevedouros, & Sulijoadikusumo, 2010) (Banks, 2008). Freight transportation planners, need a more detailed, commodity-oriented classification, which is not provided by the commonly used axle-based classification schemes.

Even though most sensors can capture vehicle volumes and speeds, of the non-intrusive detection technologies, only microwave radar, active infrared, and video detection are capable of some form of classification (Table 2). Ideally the classification scheme should encompass both axle, length, and body-class schemes to fully characterize the truck so that it can be related to an industry or commodity carried. For example, body types of five-axle tractor-trailer trucks can include tanks, enclosed vans, or hoppers. Each of these body types is associated with a particular commodity movement, time-of-day travel pattern, and routing behavior. None of the existing non-intrusive sensors have been used for truck body-type classification. In the next subsections a discussion of the sensor selection for truck characterization including (1) classification and (2) route identification is presented.

Table 2 Sensor Comparison (Adapted from the Traffic Detector Handbook (FHWA, 2006))

	Sensor Technology	Type of Output Data					Purchase Cost
		Volume	Speed	Vehicle Classification			
				Axle-based	Length-based	Body-type	
Intrusive Detectors	Inductive Loop	X	X	X	X	X[(3)]	Low
	Magnetometer	X	X		X		Moderate
	Weigh-in-Motion (WIM)	X	X	X			Moderate to high
Non-Intrusive Detectors	Microwave Radar	X	X	X	X		Low to Moderate
	Active Infrared	X	X	X			Moderate to High
	Acoustic Array	X	X				Moderate
	Lidar	X	X		X		Moderate to High
	Video Detection	X	X	X	X		Moderate to High
	Global Positioning System (GPS)[1]		X		X		Moderate to High
	Cell Phone[1]		X		X		Moderate to High
	Bluetooth[2]		X		X		Low to Moderate
	Radio Frequency ID (RFID)[2]		X		X		Moderate to High

1. Mobile sensors; 2. Point based tracking sensors; 3. Existing research by Hernandez et.al. (2016) distinguished more than 50 truck body types.

1.2.3.1 Sensor Selection for Detailed Truck Classification

None of the existing non-intrusive sensor technologies shown in Table 2 have yet to be explored for truck body-type classification. Based on previous work by Hernandez et al. (2016), body-type detection is possible if the sensor has the ability to output features indicative of the tractor and/or trailer configuration of the vehicle. For example, using inductive loop sensors (an intrusive detection technology), Hernandez et al. (2016) developed a model to distinguish 50+ truck body types based on the high frequency inductance outputs, or signature, produced by the sensor. An inductive loop sensor captures the ferrous components of the vehicle which differ by body type and thus it is possible to distinguish body types.

The closest attempt to determining body-type using non-intrusive sensors found in the literature was performed by Lee and Coifman (2012) in which scanning Lidar sensors were used. Lee and Coifman developed a prototype side-fire, vertical-scanning Lidar sensor bundle capable of classifying vehicles into six broad categories: motorcycle, passenger vehicle, passenger vehicle pulling a trailer, single-unit truck, single-unit truck pulling a trailer, and multi-unit truck (Lee & Coifman, 2012). By adopting a decision tree classification algorithm, 99.5% of non-occluded vehicles were correctly classified. The algorithm's features are vehicle's length and height at different points of each vehicle. These features were collected by deploying two vertical planar Lidar sensors on the side of the road, separated 4.6ft apart. Each sensor scanned a vertical plane across the highway, detecting the front and rear of each vehicle as it crossed each plane. The dataset consisted of over 23,000 non-occluded vehicles, 90% of which were passenger vehicles.

Two significant improvements to this approach were evaluated in this project: 1) use of low cost Lidar sensors, and 2) expansion of the truck classification to body-type categories. First, as confirmed by quotations provided by Lidar sensor vendors in the U.S., scanning vertical planes (such as the one used in the study by Lee and Coifman (2012)) instead of simple horizontal beams considerably increases the sensor cost. Expensive planar Lidar sensor bundles existing on the market provide a 3D scan of the vehicles traversing each plane and are typically mounted on overhead gantries. The overhead placement allows the Lidar to scan the top of a vehicle and eliminates occlusion, but it further increases the bundle cost, by requiring an additional structure to be built along the roadway. This type of sensor is offered for axle-based vehicle classification, and are commonly used for tolling enforcement purposes (SICK, n.d.) (Vitronic, n.d.). Therefore, this work explored the use of a single-beam Lidar sensor for truck-body type classification, as a low-cost alternative to vertical scanning. Second, the classification scheme and subsequent data set used for model development presented by Lee and Coifman (2012) focused mostly on passenger vehicles. Therefore, this work expands the classification scheme to include truck body classes and collected a data set representative of trucks on the ICs in Arkansas.

1.2.3.2 Sensor Selection for Truck Routing

Another important consideration is the ability of a sensor to track vehicles over space and time so that alternate routes and travel times can be measured. For this type of data, more advanced methodologies are needed to adapt existing point-based sensors such as radar or video detectors to collect vehicle tracking data.

Alternatively, new sensor technologies that can track vehicles are becoming increasingly cost effective and widely deployed. Point based tracking systems require installations of road-side readers to capture uniquely identifiable information from each passing vehicle. Point based detectors used for vehicle tracking include Bluetooth and Radio Frequency ID (RFID). Mobile sensors do not require physical infrastructure installations; rather, data are collected via on-board devices that are transmitted to a central data processing center. Examples of mobile sensors include Global Positioning System (GPS) and cell phone tracking systems. Tracking capable sensors can be considered as non-intrusive detector technologies and thus share the same advantages previously mentioned. Since not all vehicles possess on-board sensors, the types of tracking sensors mentioned above provide samples of trajectories rather than counts of the total population. Studies have shown that the national GPS dataset maintained by the American Transportation Research Institute (ATRI) captures around 10% of the total truck population (Pinjari, et al., 2014), for example. Thus, none of the existing tracking capable sensors provide traffic count or vehicle classification data directly.

This work explores two technologies for vehicle tracking: (1) Bluetooth sensors and (2) GPS data. Bluetooth sensors were chosen for this study because they are low cost, easily implementable, and have been shown to be capable of tracking vehicles and measuring travel times. GPS data was chosen because it is the only current source of data that can provide information on the routing behavior of trucks. GPS data is available from several vendors, and provides coverage across the US. In particular, in a study for the Arkansas Department of Transportation (ARDOT), PI Hernandez explored the representativeness and use of American Transportation Research Institute (ATRI) truck GPS data in Arkansas. Overall, the ATRI GPS data provided adequate coverage in Arkansas for estimating link travel times and origin-destination patterns. The same data used in the ARDOT study is used in this project.

1.3 Contribution

This project provides a means to increase both the spatial coverage, temporal coverage, and comprehensiveness of data that is collected on ICs. The current state-of-the-practice for gathering IC performance and usage data is extremely limited in terms of timeliness, accuracy, detail, and scope (FHWA, 2017). While many data collection technologies exist for general data collection, little to no emphasis has been placed on the complicated data collection needs and environmental setting for effective data collection on ICs. While previous studies are useful in determining data accuracy from various sensors, with the exception of advanced inductive loop detectors, none have evaluated the potential for highly detailed truck body-type classification (Kotzenmacher, Minge, & Ho, 2005) (French Engineering LLC, 2006) (Banks, 2008) (Yu, Prevedouros, & Sulijoadikusumo, 2010).

A combination of point-based and tracking capable non-intrusive detector technologies would provide the apt solution for IC usage and performance monitoring. This work develops a point based sensor bundle, consisting of a single beam Lidar sensor to detect truck body configuration, and the exploration of Bluetooth readers to track vehicles across multiple locations. This sensor bundle was placed at the Van Buren IC, closest to the intermodal facility (port access road), with only a Bluetooth reader placed at the end closest to the NHS. In this way, the travel time of the vehicle is measured while also providing data on the truck body configuration. As an added benefit, vehicles could be tracked as they enter and exit the intermodal facility by matching their MAC addresses to provide data on facility turn times which has been proposed as a performance measures for a port. In parallel, truck GPS data is analyzed to monitor truck travel times on ICs and alternate routes. This work investigates an ideal sensor bundle and develops necessary methods to pair multi-sensor data in order to derive performance measures. Previous studies have yet to evaluate multi-sensor systems that combine non-intrusive point based detectors with tracking based detectors to provide a full array of useful performance measure data.

With more detailed data on the usage and performance of ICs the state can potentially improve the quality of its long range planning models and provide more robust performance data to support grants for IC improvement projects under the new FAST Act, FASTLANE grants programs. The Florida DOT, for instance, used comprehensive intermodal connector data to support funding of just under $7 million in 2014 for improvements that included auxiliary lanes, exit ramp improvements, adding new lanes, developing turn lanes, and resurfacing an intersection using concrete.

An additional benefit, not specific to ICs, is the development of a framework for a detailed truck classification and tracking algorithm based on non-intrusive technologies. In previous work, PI Hernandez developed a comprehensive truck body classification algorithm using data from intrusive detectors (Hernandez, Tok, & Ritchie, 2016). This report extends such work to non-intrusive detectors so that the same level of data could be collected on roadways that do not permit installation of pavement intrusive technologies like loop detectors.

2 Methodological Approach

This section explains the methodology developed in this work. First, three existing databases to collect IC data are briefly synthetized, focusing on their suitability to evaluate IC performance. Second, the development of two additional sources of data are described including: (a) a single-beam Lidar sensor to estimate the volume of trucks traveling on a network link by industry served, and (b) Bluetooth sensors to collect travel times on ICs. Third, truck GPS data is analyzed to study IC usage patterns and identify potential alternative routes, currently not designated as ICs. The results and discussion of findings, and implementation examples are summarized in Chapters 3 and 4, respectively.

2.1 Data Assessment for ICs

This section analyzes the characteristics of data collected for ICs that serve inland waterway ports in Arkansas, focusing on their suitability to evaluate IC performance. As discussed, ideal data to evaluate IC usage includes truck volumes by commodity carried, truck weight, speed and travel time. The assessment provided in the subsequent sections includes spatial and temporal coverage of three datasets:

- Average Annual Daily Truck Traffic (AADTT) data,
- Weigh-in-Motion (WIM) data, and
- Truck GPS data from ATRI.

The main characteristics of the three datasets discussed above are summarized in Table 3. The spatial coverage in Arkansas of the three datasets is shown in Figure 3, and Figure 4 for the detailed zones where the three port ICs are located.

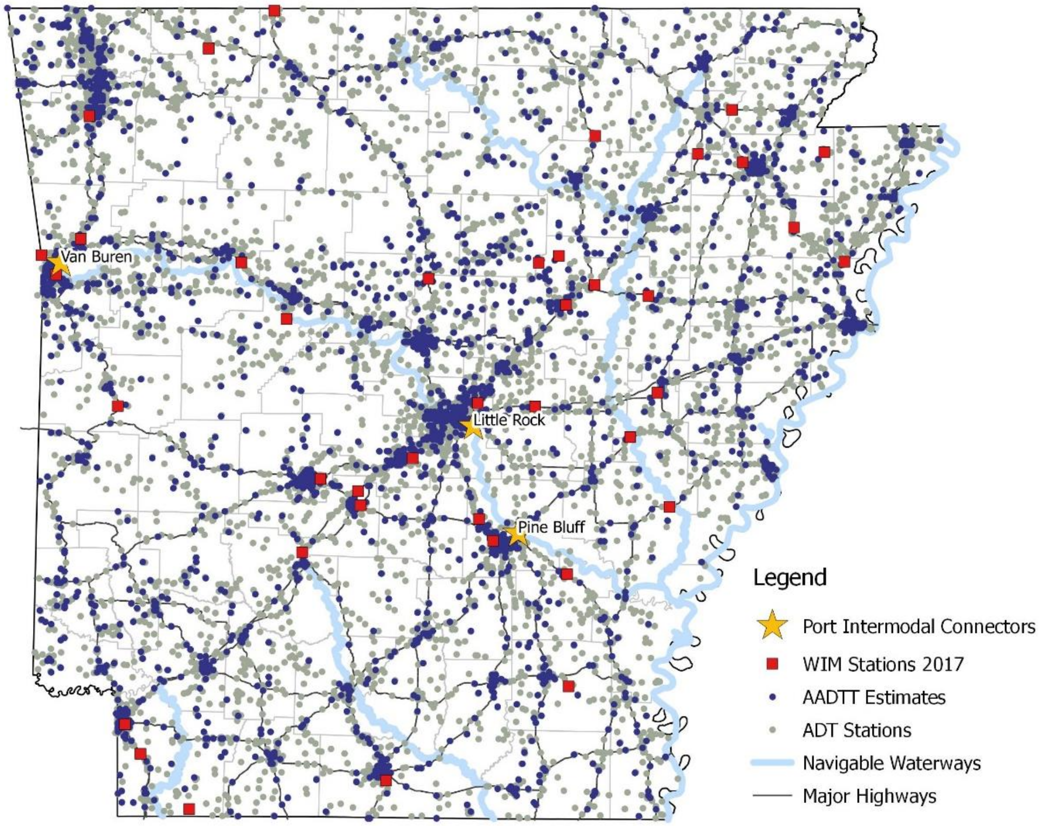


Figure 3 Location of ICs, WIM, ADT, and AADTT stations in Arkansas

Table 3 Database suitability to evaluate the performance of ICs

Characteristics	AADT/AADTT	WIM	Truck GPS
Data elements	Annual average daily traffic and truck traffic.	Travel speed, lane, time and date, wheel load, axle load, axle group load, gross vehicle weight, individual axle spacings, overall vehicle length, and axle-based vehicle classification.	Position of trucks (latitude and longitude). Allows for routing, speed, and time-of-day evaluation.
Spatial resolution	Point sensors located on several network links. Poor coverage of ICs.	Point sensors located on few network links. Inadequate coverage of ICs.	All U.S. territory, including Arkansas.
Temporal coverage	Annual.	Continuous.	Continuous.
Cost	Free	Free for research purposes.	Moderate to High.
Format	Tabular and GIS-based files; available online.	Tabular and provided upon request.	Tabular converted to GIS-based files; provided at a cost.
Main limitations	Spatial coverage. Lack of routing, weight, speed, industry served.	Spatial coverage. Lack of routing, and industry served.	Potential bias to exclude small truck fleets. Lack of industry served.

2.1.1 Average Annual Daily Truck Traffic (AADTT) Data

The FHWA defines the Annual Average Daily Truck Traffic (AADTT) as the volume of truck traffic for one day (24 hour period) during a data reporting year (FHWA, n.d.). In Arkansas, the Traffic Information Systems Section of the Arkansas Department of Transportation (ARDOT) is responsible for collecting, processing, and storing traffic data. Figure 3 shows the locations where AADTT is available in Arkansas for 2017, and Figure 4 focuses on AADTT availability within the three port ICs in Arkansas. AADTT constitutes a sub-set of the Annual Average Daily Traffic (AADT), which does not discriminate trucks from general traffic. AADTT is typically referred to as a percentage of the AADT.

There are two methods to collect AADT data: permanent and portable traffic monitoring. Permanent count stations continuously (24 hours a day) collected traffic data from sensors, while portable traffic monitoring sites include installed temporarily on the road. Data collected at permanent sites permits the analysis of variations of traffic flow throughout seasons, months of the year, days of the week, and time of day. The traffic information collected by permanent and short duration sites are used to calculate the AADT. The sensor technology utilized by ARDOT to collect data at permanent count stations are Automatic Traffic Recorders (ATRs) (Arkansas State Highway and Transportation Department, 2013). ATRs include some combination of inductive loops and axle sensors to classify vehicles (axle-based classification). Portable traffic count sites typically consist of rubber tubes deployed on top of the pavement, perpendicular to the direction of traffic, during 48-hour periods. These sensors are easily transportable and secured to telephone poles, sing posts, trees, etc. The simplest temporary sensors are only able to count axles, requiring the application of seasonal factors to calculate Average Daily Traffic (ADT). More sophisticated vehicle counters utilize an algorithm to classify vehicles based on their axle configuration. These units require a special software to download and process the data collected (Arkansas State Highway and Transportation Department, 2013).

The database with Arkansas' AADTT and AADT is available for free from the Arkansas GIS Office and can be downloaded as GIS files, i.e. spatial data files (Arkansas GIS Office, 2018).

AADTT data may be suitable to evaluate truck count at ICs, but unsuitable to consider industry served, truck weight, speed or routing. Moreover, the spatial coverage of AADTT or ADT counts is inadequate to understand the performance of all port ICs in Arkansas as it is unlikely that the AADTT counters are provided for the ICs. For example, as observed in Figure 4.a, there are no classification stations located on Little Rock IC. Notably, there is one classification station in a potential alternative IC route, which counts 320 trucks per day (5% of total traffic volume at the site). In addition, the ADT stations on Little Rock IC are located along the IC segment closest to the NHS, capturing traffic from nearby areas, not exclusively travelling on the IC. In contrast, Figure 4.c shows that the Pine Bluff IC does have two classification stations along its corridor, with an AADTT of 147 trucks per day (in 2017) near the port access road -constituting 21% of total traffic; 340 trucks per day on the port access road near the NHS; and 630 trucks per day at the closest station to the NHS. As for Van Buren IC, Figure 4.b. shows that there is one classification station along the IC. This station collects data on trucks traveling on the IC, both accessing the Port of Van Buren and passing through. At this count station, the volume of trucks (AADTT) on Van Buren IC in 2017 was 1,320 –representing 12% of total traffic volume. A second station (not able to classify trucks from general traffic) is located at the port entrance, capturing 130 vehicles per day (in average). The analysis of data captured by these two stations indicates that most truck traffic travelling on the IC passes through the IC, instead of accessing the port.

Overall, in order to understand IC performance, there is a need to complement the spatial and temporal coverage of the AADTT counts and, moreover, to provide more robust truck classification information.

Figure 4.a ADT and ADTT at Little Rock Port IC

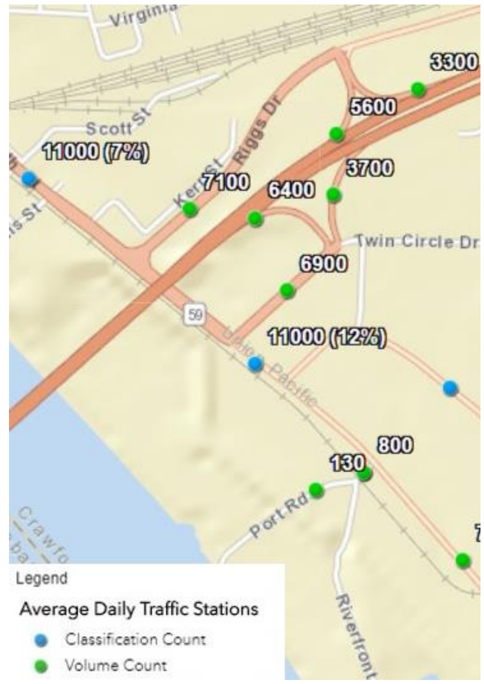


Figure 4.b ADT and ADTT at Van Buren Port IC

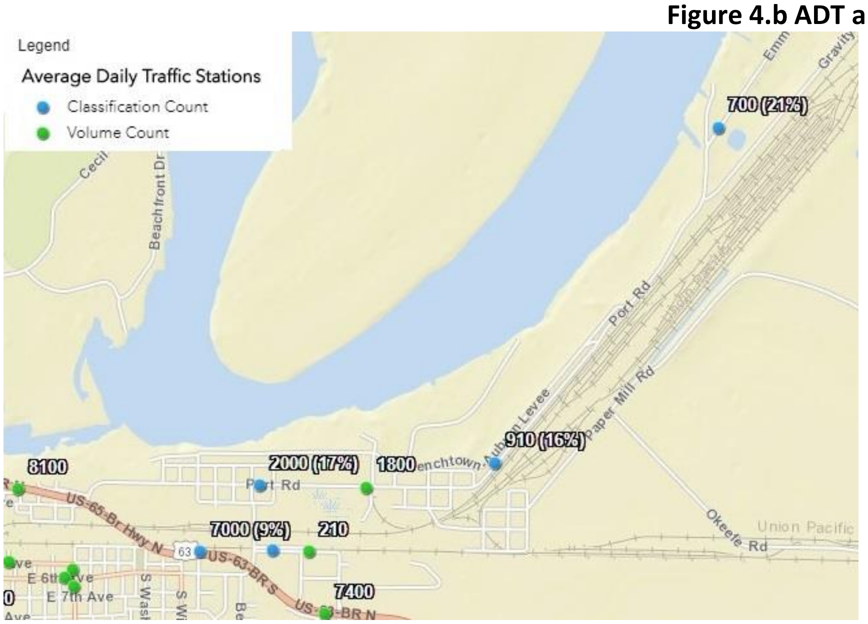


Figure 4.c ADT and ADTT at Pine Bluff Port IC

Figure 4 WIM, ADT and AADTT stations near port ICs in Arkansas, 2017.

2.1.2 Weigh-in-Motion (WIM) data

In the U.S., efforts to collect weight data of moving trucks started in the early 1950s. Technology has evolved since, but the operational principle remains the same. Weigh-in-Motion (WIM) sensors measure axle loads of vehicles moving at normal highway speed, through signals recorded by devices typically embedded in the road surface. Data collected at WIM sites is utilized to derive the following information pertaining to each vehicle: speed, lane, time and date, wheel load, axle load, axle group load, gross vehicle weight, individual inter-axle spacings, overall vehicle length, and axle-based vehicle classification (FHWA, 2010). For research purposes, WIM data is available upon request to the state DOT, free of charge.

In Arkansas, WIM data is collected continuously by ARDOT. These sensors consist of a single inductive loop to detect and count traffic, with two weight sensors either straddling the loops or sandwiched between two loops. Weight sensors can be piezoelectric systems (polymeric, ceramic, and quartz), bending plates or load cells (Arkansas State Highway and Transportation Department, 2013). Figure 3 shows the location of WIM stations within Arkansas. There are no WIM stations located on port ICs (Figure 4). The characteristics and data collected at WIM stations closest to Arkansas port ICs are summarized in Table 4. However, these stations are too far from port ICs and primarily capture vehicles that are travelling on the interstate/highway and not stopping at the port. Thus, WIM data in Arkansas is not suitable to directly evaluate the performance of ICs. No routing or commodity information is provided by WIM data. It is possible that in the future, WIM sensors can be strategically placed along ICs to collect continuous truck configuration and weight data.

Table 4 Characteristics of WIM Stations closest to port ICs in Arkansas

WIM station number	Closest Port IC	Port/WIM distance (miles)	WIM AADT (2016)	WIM AADTT (2016)	Year of installation	Road	Pavement type / condition	Speed limit (mph)
170053	Van Buren	3.7	16,000	15%	1986	I-530	Asphalt / Fair	45
600870	Little Rock	8.3	21,000	16%	2003	I-440	Concrete / Fair	70
350314	Pine Bluff	8.9	26,000	14%	1986	US- 64	Concrete / Good	65

2.1.3 Truck GPS data

Truck GPS data consists of vehicle positioning data (latitude and longitude) emitted by GPS devices onboard a truck. The spatial coverage in the US is almost ubiquitous (Turnbull, 2014). Private truck fleets typically record positioning data of their own trucks, for security and route tracking purposes, fuel cost and other operational optimization analysis. The American Transport Research Institute (ATRI), part of the American Trucking Association, gathers anonymous truck GPS data from a number of private fleets. In cooperation with FHWA, truck GPS data gathered by ATRI is used for diverse purposes, such as bottleneck identification, travel time analysis, border crossings, truck parking and hours of services tracking, rerouting, etc. (Turnbull, 2014). Truck GPS data can be purchased from ATRI for a fee.

Truck GPS data is a valuable source of truck routing, time-of-day corridor usage, volume and speed data, which serves the needs of IC performance evaluation. For reference, GPS data in Arkansas provided by ATRI represents about 35 million raw data points per week corresponding to approximate

40,000 unique trucks. Because current sources of truck GPS data are samples of the total truck population, it is important to evaluate the spatial and temporal coverage for each application, such as performance and usage evaluation of ICs. Analysis of GPS data in this project focused on time-of-day usage patterns, in-state mileage travelled by trucks using the ICs, routes travelled and stops made by trucks accessing the ICs, and identification of potential alternative routes between the port and the NHS. In this way, the representativeness of the truck GPS data was evaluated for IC performance evaluation. The results of this analysis are presented in Chapter 4.

The spatial and temporal analysis based on truck GPS data has several advantages over WIM or AADTT data. The main advantage is the broad spatial and temporal coverage of truck GPS data. From a spatial coverage point of view, truck GPS data covers every single road in the statewide network, while AADTT is restricted to fixed and few counting stations (Figure 3). Even though the information derived from truck GPS data is comprehensive, it lacks the commodity carried or industry served by trucks and thus is a good compliment to the data derived from the Lidar sensor developed in this work.

2.1.4 Summary of Findings

As discussed, from existing data collection technologies it is possible to evaluate traffic volumes, speeds, and routing for trucks travelling on Arkansas ICs.

Notably, truck GPS data has yet to be implemented as a comprehensive data collection scheme by state DOTs, potentially due to the cost of acquiring such data. Another limiting factor for the use of truck GPS data its potential lack of representativeness of small to medium size trucking companies, as it is biased toward major truck fleets (Turnbull, 2014). This is a concern for ICs in Arkansas which serve ports along the inland waterway network which is used to transport non-containerized goods, e.g. bulk and break-bulk goods including agricultural products, lumber, etc.. The transport of these types of goods may be handled by smaller trucking companies and thus not represented in the ATRI data. The limitations of the GPS data coupled with the limited spatial coverage of WIM and AADTT data do not permit a comprehensive performance evaluation of ICs. The main data gap identified to fully evaluate the performance of ICs is an understanding of the commodities carried on ICs. Thus, this report focuses on the development of a sensor bundle to fill such gap.

2.2 Sensor Development

This section presents the sensor developed to collect data to address the main data gap found on ICs: the industry served by trucks travelling on a network link with mediocre or poor pavement conditions. Because of such conditions, it is required that the sensor is non-intrusive.

2.2.1 Technology Selection

Conceptually, the prototype sensor presented in this paper identifies different truck body-types by associating them with the sensor output, or “signature”, generated by each moving vehicle. The signature generally represents the shape of the vehicle body. For example, all enclosed vans have a similar physical shape and sensor signature, which are different than those of livestock trailers or platforms (Figure 5). Of all non-intrusive technologies (Table 2), Lidar and video detection can identify the shape of an object. For example, on automated vehicles, Lidar sensors have been shown to be better suited than radar and cameras to estimate the shape of surrounding moving objects (Magnier, Gruyer, & Godelle, 2017). Moreover, unlike video detection, Lidar operation is not limited by inclement weather conditions or glare caused by sunlight. For these reasons, Lidar technology presents an apt platform for robust, high resolution truck body-type identification.

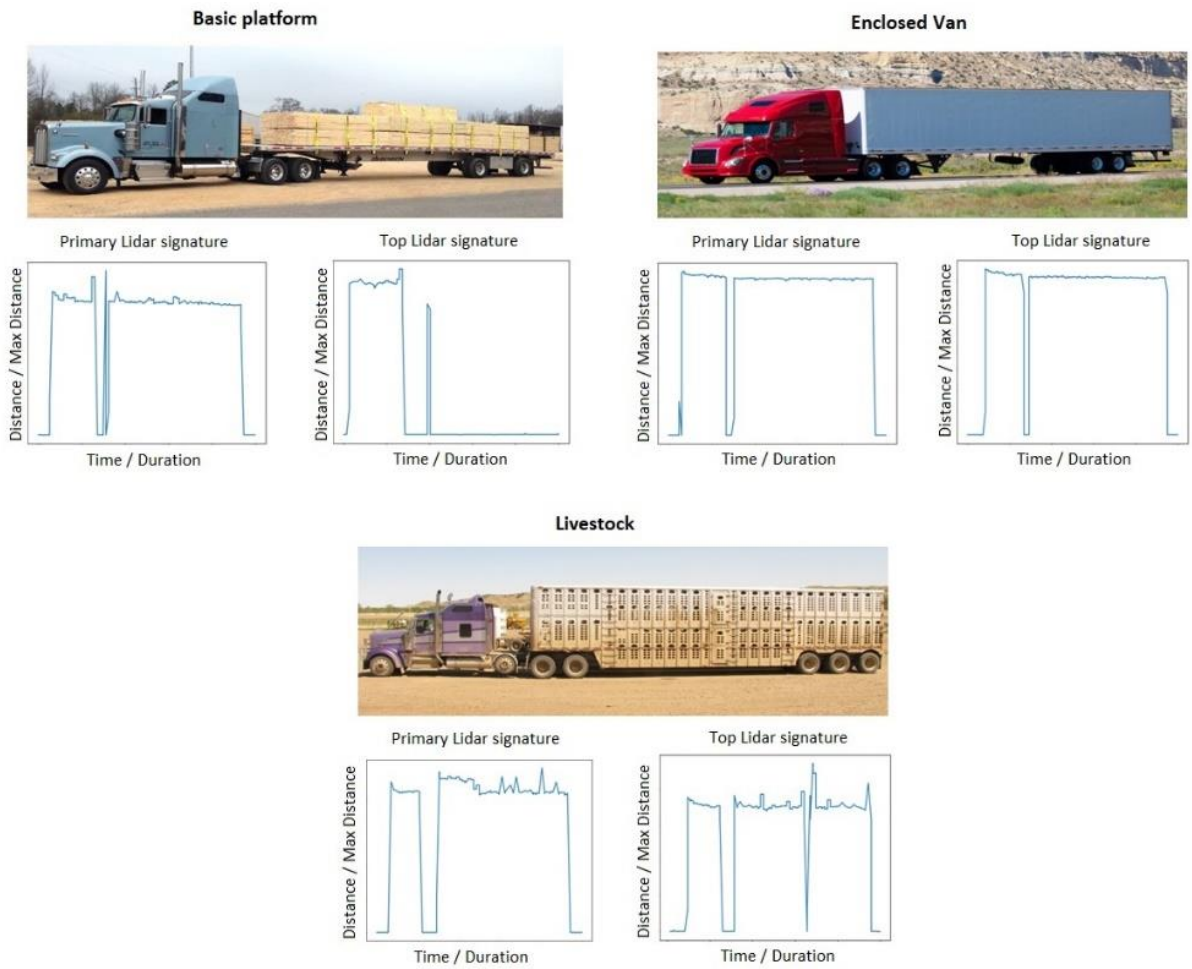


Figure 5 Lidar signatures of different truck-body-types

2.2.2 Sensor Design

The Lidar sensor developed for this work is a low cost (<$1,000), optical distance measurement Lidar sensor with two single-stripe laser transmitters that have a range of approximately 130ft. On site, the sensor is deployed on the road shoulder, in a side-fire configuration, with the lower Lidar unit ("primary Lidar") placed approximately 4ft above the ground, and the upper unit ("top Lidar") placed 1.5ft above the lower unit (Figure 6). Each Lidar unit (Figure 7) emits a single laser beam, perpendicular to traffic. The sensors are attached to a portable box that contains a battery-powered, low-cost processing computer. The Lidar units take continuous distance measurements with a frequency of 200 measurements per second. The distance measure is equivalent to the distance at which an object (vehicle) passing in front of the sensor is detected. The raw sensor readings and timestamp of each measurement are recorded.

This prototype sensor could easily be made deployable as it has the advantage of being low cost and requiring minimal power consumption- two characteristics that improve upon previous work.

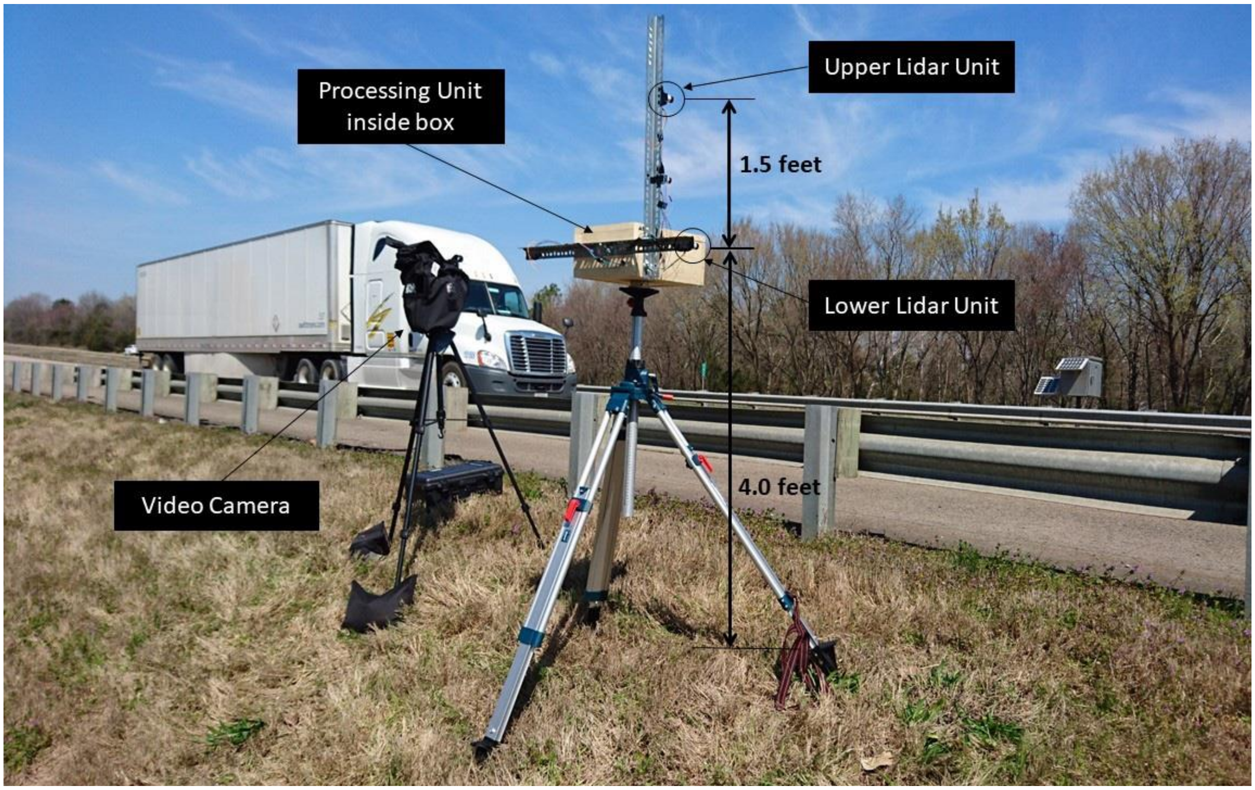


Figure 6 Sensor deployment for field test

Figure 7 Lidar optical unit detail

2.2.3 Field Evaluations

2.2.3.1 Site Selection

From the three port ICs in Arkansas, Van Buren was chosen to deploy and test the sensor bundle. The selection criteria is based on its proximity to the University of Arkansas, Fayetteville campus, where the project office is located. An analysis of Google Earth images allowed for the pre-selection of three zones (A, B, C) on Van Buren IC where to potentially locate the sensor (Figure 8).

A preliminary trip to the Van Buren Port took place on November 7, 2017. The purpose of this trip was to evaluate the site and serve as basis to develop the Field Data Collection Plan (Appendix II). During the first portion of this site visit, the project team drove through the IC and identified the three zones where to potentially deploy the sensor bundle. Later, the team spent approximately 20 minutes in each of these locations and observed the number of trucks, the variety of truck body types, site topographic characteristics, and nearby industries / business. The site visit report is available in Appendix I. An overview of the sensor set-up implemented for Van Buren is shown in Figure 8.

Figure 8 Overview of Van Buren sensor set-up

2.2.3.2 Sensor Deployment

The sensor was deployed at two locations: (a) a low speed, low volume IC referred to as the Van Buren site and (b) a high speed, high volume interstate location referred to as the Lamar site.

The Van Buren site connects the Port of Van Buren with the NHS at Interstate I-540, in Arkansas. The Lidar sensor bundle was deployed on South 4th Street, an undivided roadway with a speed limit of 45 mph. The sensor was deployed behind the shoulder, approximately 15ft from the outermost lane where traffic flows at near constant speeds. The lower Lidar unit was placed approximately 4ft above the ground. Data was collected on Monday, February 26, 2018, from 9:00AM to 4:30PM. Originally, Data collection was schedule for Wednesday, February 21st. However, the trip had to be postponed due to weather conditions that would have disrupted video data collected for groundtruth purposes. Traffic conditions were uncongested. A total of 1,188 vehicles were observed across all lanes, of which 234 were five-axle freight trucks.

In synergy with a concurrent project, a second location was chosen to collect more samples of unique truck types, and evaluate sensor transferability by testing it at a high-speed location. The sensor was deployed on Interstate I-40, 7.6 miles east of Lamar, Arkansas. At the site, I-40 is a 4-lane (2 lanes in each direction) road with a center median. The sensor was located on the right shoulder. Because of the wide median, only traffic travelling in the eastbound direction lanes was considered. Data was collected during uncongested conditions. The posted speed limit was 70 mph. The data was collected on Thursday, March 15th, 2018, between 9:00AM and 6:00PM. The Lamar dataset contains 3,423 records, with 1,656 corresponding to unobstructed, five-axle freight trucks.

2.2.4 Data Preparation

Data preparation consists of: (1) vehicle identification, (2) development of Lidar signatures, (3) data ground-truth, and (4) feature extraction. Both the data preparation code and the code to control the Lidar were developed using Python 2.7. The following libraries were used: Opencv, Matplotlib, and Numpy. The processing code was self-developed while the code to control the Lidar was adapted from manufacturer provided code.

2.2.4.1 Vehicle Identification

Individual vehicles are detected from the primary Lidar sensor data stream by identifying the presence of a vehicle and the lane a vehicle is travelling in, based on the average distance measurements for each lane. Conceptually, a Lidar measurement (Li) corresponds to a potential vehicle in a given lane if said measurement is greater than the distance from the sensor to the inside lane edge (d_{inside}) and less than the distance to the outside lane edge $(d_{outside})$.

Following an initial distance measurement (L1) between d_{inside} and $d_{outside}$, a vehicle (V) is identified if more than n measurements within the first 10 recorded measurements are between d_{inside} and $d_{outside}$. The next N consecutive measurements are associated with this new vehicle until m consecutive points are outside the lane distance boundaries. Thus, each vehicle is represented as:

$$V = \{ L_i \mid d_{inside} \leq L_i \leq d_{outside} \},\ i \in \{1 \ldots N\text{-}m\}$$

Both n and m are calibrated for road conditions (i.e. traffic volume and speed). The overall process of vehicle identification is shown in Figure 9a-b. As distance measurements are relative to the site configuration and sensor placement (i.e. number of lanes, lane and shoulder width, presence of median, etc.) it is necessary to adjust these parameters. The variables adopted for our case study are:

Van Buren:	$n = 5$	$m = 5$
Lamar:	$n = 8$	$m = 15$

2.2.4.2 Lidar Signature Detection

Once individual vehicles are identified, raw measurements for each of the two Lidar units are grouped into *vehicle signatures*. Each signature consists of sensor distance measurements over time such that the time spans the duration that the vehicle is in front of the sensor. As discussed, the signatures are characteristic of each vehicle body-type (Figure 5). Distance measurements outside the lane boundaries are considered outliers and removed from the signature (Figure 9c). Later, during the feature extraction process, the raw signatures are reduced and normalized to generate a representative set of features.

2.2.4.3 Feature Extraction

For each vehicle, the following features are extracted from each of the two Lidar sensor signatures: (i) *duration*, and (ii) an array of normalized *vehicle-body-points*. The overall process of feature extraction is shown in Figure 9.

Duration is the time elapsed while the vehicle is in front of the sensor. If all vehicles travel at approximately the same speed such as during uncongested traffic conditions, *duration* is an indication of the length of the vehicle. A future sensor improvement is to add a second Lidar sensor, separated approximately 5ft away from the first sensor, at the same height, i.e. a speed trap configuration. This second unit would allow for a detailed calculation of vehicle speed and length.

The array of distance-time measurement pairs obtained from the signature are used to calculate the *vehicle-body-points*. *Vehicle-body-points* capture the shape of the signature and thus the body-shape of each vehicle. To obtain a discrete number of *vehicle-body-points,* every $\boldsymbol{j}^{\mathbf{th}}$ distance measurement is extracted from the normalized Lidar signature. The signature is normalized by dividing each time measurement by the *duration* and each distance measurement by the max distance measurement after removing outliers. The first set of *vehicle-body-points* represents normalized distance measures at discrete points along the signature, and are called the *discrete vehicle-body-points*. A second set of *vehicle-body-points* is derived by taking the difference between each pair of *discrete vehicle-body-points,* these are called the *difference vehicle-body-points*, and are intended to further capture the shape of the signature. The variable $\boldsymbol{j}$ is calibrated based on the average travelling speed on the link where the sensor is deployed, to obtain approximately 70 *discrete vehicle-body-points* for each vehicle. For our case study, we adopted:

Van Buren: j = 5; Lamar: j = 2

Considering the presence of multi-unit tractor-trailers such as FHWA Class 9 five-axle tractor-trailers or '3S2' trucks, the *discrete vehicle-body-points* are separated into two sub-groups broadly corresponding to the tractor and trailer portions of the signature. The first 30% of the *vehicle-body-points* approximate the length of the tractor, while the remaining 70% correspond to the trailer. An additional feature is calculated as (iii) the standard deviation of the *discrete vehicle-body-points* for each of these sub-groups.

The feature extraction process explained above is applied to both signatures from the upper and lower Lidar units, totaling 291 features per vehicle.

2.2.4.4 Ground-Truth Data Development

For model development, video was collected concurrently with sensor measurements and broken into frames that coincide with sensor actuations, i.e. a vehicle passing in front of the Lidar sensor. The raw sensor readings, along with images derived from the video footage, are processed to manually classify vehicles that passed in front of the sensor using a specially designed Visual Basic interface (Figure 10).

Using the interface, vehicles identified by the sensor are labeled as per their body-type classes. In this way, each vehicle detection is matched to a Lidar sensor reading and a video image.

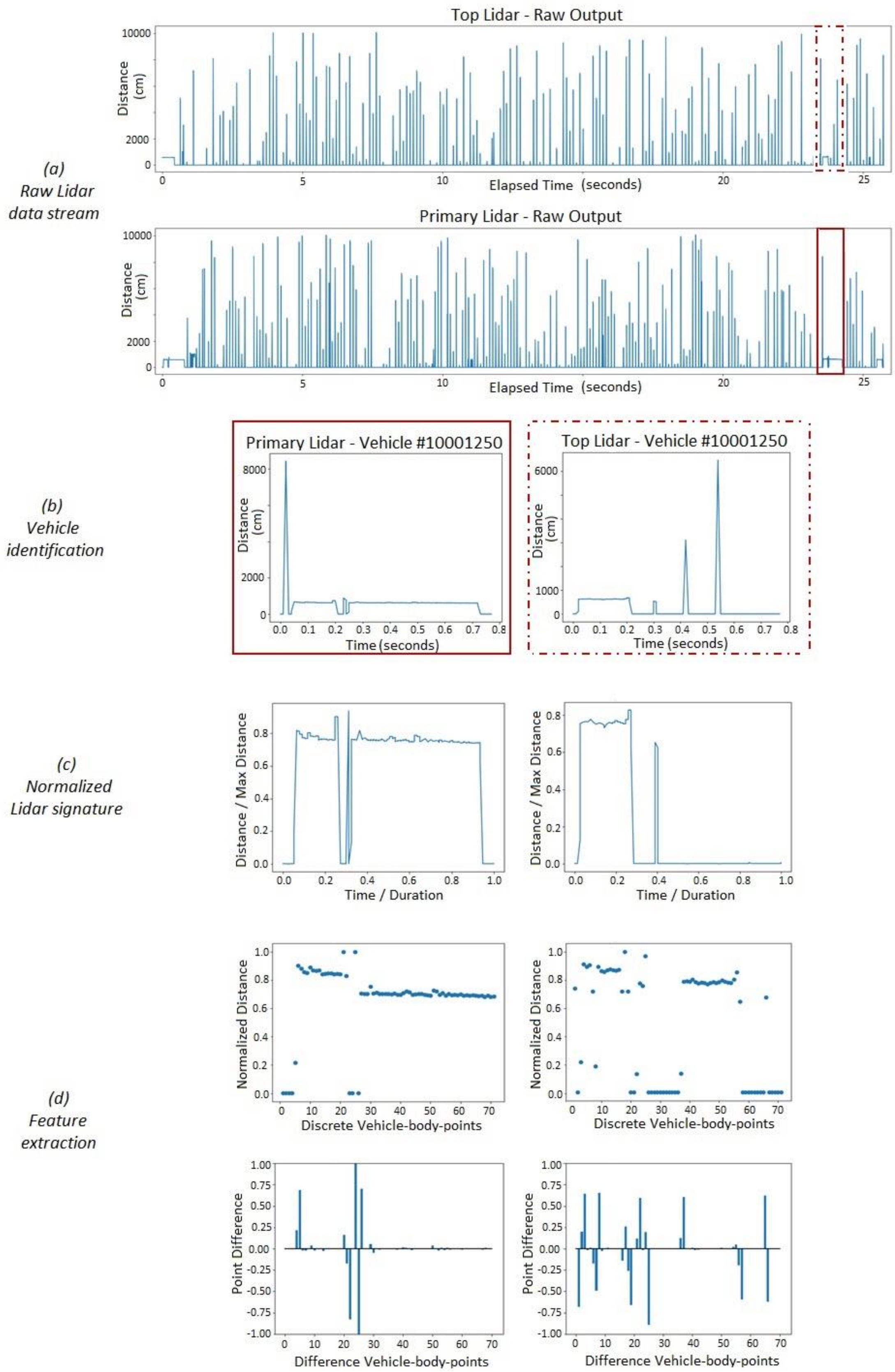


Figure 9 Raw Lidar to feature process

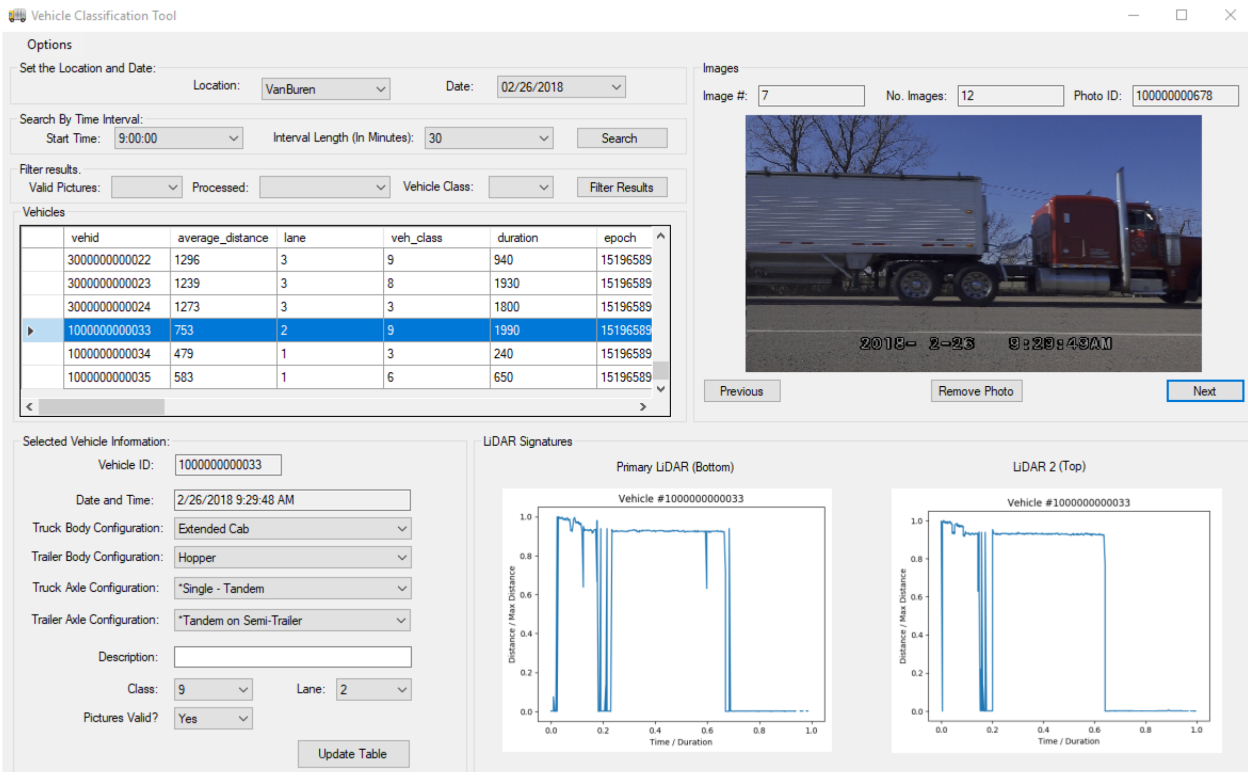


Figure 10 Visual Basic user interface for data ground-truth process

2.2.5 Classification Model Development

The classification model developed for this work distinguishes the trailer-body type of five-axle tractor-trailer trucks, or '3-S2' axle configurations (e.g. three axle tractor and two axle semi-trailer, or "FHWA Class 9"). These larger trucks tend to be tied to freight related movements, as opposed to service or passenger movements, and thus relate to the intended applications of this work, e.g. freight IC performance and planning. It should be noted that for full deployment and operation of the proposed methodology, a classification model to distinguish tractor-trailers from general traffic will need to be developed using the Lidar data. However, as the purpose of this work is to demonstrate a novel, proof-of-concept approach to vehicle body-type classification from non-obtrusive sensors, the model developed here focuses on five-axle tractor trailers exclusively.

The body-type classification models are based on a multiple classifier scheme using a Naïve Bayes method to fuse the predictions of each individual classifier. The selection of the base classifiers and explanation of the ensemble approach is described in the following paragraphs.

2.2.5.1 Selection of Machine Learning Classifiers

Machine learning (ML) methods used for classification purposes are mainly supervised algorithms, which require a dataset labeled with known, pre-established categories. From the many ML techniques available, examples of supervised methods include: Support Vector Machines (SVM), Artificial Neural Networks (ANN), Naïve Bayes (NB), Decision Trees (DT), and ensembles (such as Random Forest). Among their many benefits, most ML methods are well suited to deal with large datasets, containing massive amounts of multi-dimensional data. Large datasets usually contain erroneous or missing information and require nonlinear, flexible and intelligent models (Hand, 2000). Most ML tools have the ability to deal with noisy, missing data, and with multi-collinearity, because they do not require a specific functional form (Karlaftis & Vlahogianni, 2011).

With the objective to improve the classification ability of the model, the preselected ML methods constitute base classifiers in an ensemble classification scheme (ECS). Thus, the pre-selected methods need to be complementary and heterogeneous. Such heterogeneity is achieved by selecting classifiers from multiple and diverse categories, which produce different decision boundaries for each feature. Hernandez et al. developed an advanced truck classification method based on ensemble classification to identify over 50 truck-body configurations. The ensemble's base classifiers included: NB, DT, SVM, and two types of ANNs. The ensemble increased the accuracy of minority classes and achieved a correct classification rate of over 80% (Hernandez, Tok, & Ritchie, 2016).

Because of the proven transferability of Hernandez et al. method, we opt to apply the same classification model architecture, calibrated to our specific datasets. Several ML methods and specifications for those models were evaluated. The set of classifiers used are chosen based on their ability to perform multi-category classification and on data characteristics (i.e. numeric data, which may be correlated, and presence of class imbalance). Within each ML method, only the specification for the model with the highest True Positive Rate (TPR) on the test data is selected as a base classifier, and combined in the ECS. The following base classifiers are used:

1. **Decision Tree (DT)** - Rule based classifier; Classification and regression tree (CART C4.5); Gini index used for pruning.
2. **Multilayer Feedforward Neural Network (MLFF)** - ANN architecture; 3 hidden layers with 12-18 neurons.
3. **Support Vector Machine (SVM)** - Multi-class SVM with radial basis kernel function, sigma of 1.5-2.0.
4. **Naïve Bayes (NB)** - Statistical method; Gaussian distribution.
5. **Probabilistic Neural Network (PNN)** - ANN architecture with test records used as prototypes.

2.2.5.2 Model Evaluation

The evaluation and comparison of ML models is made by assessing both qualitative (e.g. efficiency, robustness, interpretability and compactness) and quantitative model characteristics. The main quantitative metrics used to evaluate models are (Han, Kamber, & Pei, 2012):

Accuracy	$\frac{TP+TN}{P+N}$
Precision	$\frac{TP}{TP+FP}$
Error rate	$\frac{FP+FN}{P+N}$
Sensitivity	$\frac{TP}{P}$
Specificity	$\frac{TN}{N}$

Where:
TP = amount of test set samples that the model correctly classified as positives (True Positives),
TN = amount of samples correctly classified as negatives (True Negatives),
FP = amount of samples incorrectly classified as positives (False Positives),
FN = amount of samples incorrectly classified as negatives (False Negatives),
P = amount of actual positive test set samples (Positives), and
N = amount of actual negative test set samples (Negatives).

The *sensitivity* and *specificity* metrics are typically used when there is class imbalance (i.e. the dataset has a clear majority of elements of one class over the others, as is the case for truck-body-class data where most trailers are of the enclosed van configuration). The most broadly used metric for model evaluation and comparison is the *accuracy*. However, when TN is very high, a high accuracy may be masking poor classification results. Similarly, when FP is very low, a high precision may not truly represent the classification ability of the model. In such cases, and if misclassification does not constitute a severe issue, the *sensitivity*, also called *True Positive Rate* (TPR), is a better indication of the true classification ability of the model. TPR is adopted in this work to evaluate and compare class-specific and overall model classification ability.

2.2.5.3 Ensemble Classification Scheme (ECS)

Different base classifiers identify different output classes with a broad range of TPRs. The objective of the ECS is to improve the overall classification scheme ability, by taking advantage of the best results of all the base classifiers. The simplest ensemble method constitutes a majority vote using the predictions of each base classifier. The main limitation is that all classifiers are given the same weight, regardless of the predictive accuracy of each classifier. To overcome this issue, a Bayesian Combined Predictor (BCP) in which base models are weighted as per Bayesian posterior probabilities generated by the base classifiers is introduced (Petridis, et al., 2001). Each individual model provides an estimated *value of support* (μ_k) calculated for each class ($k=1\ldots c$). The class with the highest value of support is assigned as the resulting ensemble prediction ($\hat{C}$) (Petridis, et al., 2001). Even though the BCP is presented for time series, it is transferable to classification problems (Hernandez, Tok, & Ritchie, 2016).

From the several strategies to combine classifiers, we adopt the architecture successfully implemented for detailed truck-body-classification by Hernandez et al. (Figure 11). The hybrid ensemble first trains individual classifiers (i), producing individual predictions s^i. Then, the corresponding cross-classification matrices of each method (cm^i) are obtained, and used as evidence to calculate joint probabilities for each class ($cm^i_{k,s}$). Later, the joint probabilities feed the calculation of values of support for each class (μ_k), from which the final ensemble prediction ($\hat{C}$) is made.

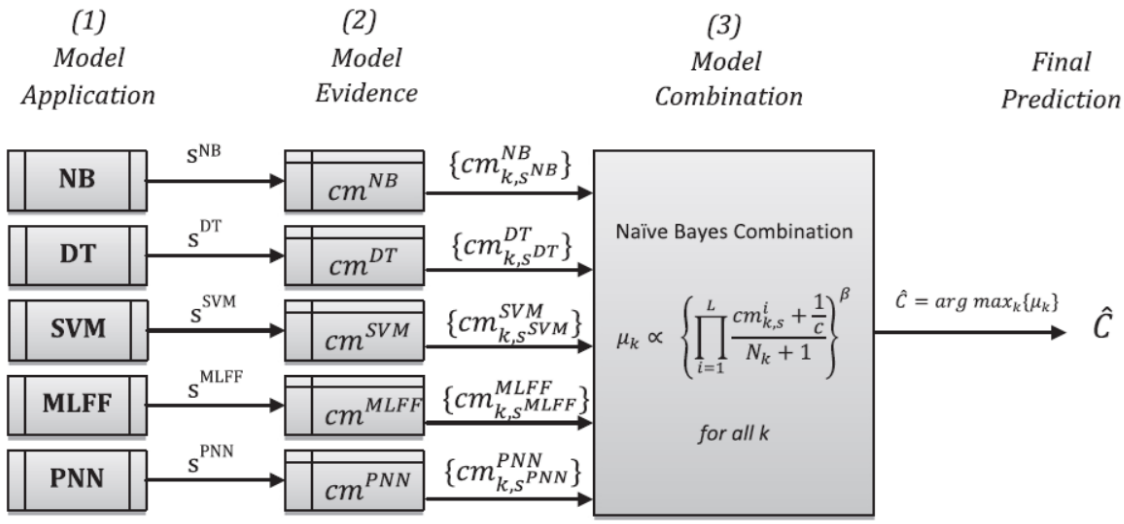


Figure 11 Classification model architecture (Hernandez, Tok, & Ritchie, 2016)

The results of the classification model trained, validated, and tested with the single-beam Lidar sensor data are presented and discussed in Section 3 of this report.

2.3 Bluetooth Sensor

In addition to collecting and analyzing data from the single-beam Lidar sensor, this work explores the use of Bluetooth sensors, another non-intrusive technology. Two sensors were placed along the Van Buren IC route: one on 'South 4th Street', next to the Lidar sensor, and another on 'Twin Cir Drive', leading to I-540 access ramp (Figure 8). The field test was designed with the purpose of identifying the route followed by vehicles travelling on the IC, and estimating the time-of-day usage and travel time along the IC.

Each Bluetooth sensor detects and records unique MAC addresses with timestamps from Bluetooth devices in vehicles travelling in the close proximity to the sensor. The MAC addresses collected at each of the two locations can then be compared to identify potential matches. If a match were found, the travel time along the IC could be calculated as the difference in the recorded timestamps.

In practice, Bluetooth detection in limited by its penetration rate, i.e. the number of vehicles with a Bluetooth device relative to the total population of vehicles. Previous studies have shown that the penetration rate can vary from 2 to 5% along highway locations with significant volumes of passenger vehicles. With lower volumes of total vehicles and a high percent of trucks expected along ICs, it was anticipated that very few MAC addressed would be recorded.

As expected, the data collection in Van Buren resulted in a very small number of recorded MAC addresses. Approximately 10 MAC addresses were recorded at the port access location, and 20 at the position near the NHS. No matching MAC addresses were found by comparing the data collected at these two locations. Thus, the sample size was too small to draw conclusions about time-of-day usage, and not suitable to calculate travel time along the IC.

2.4 Truck GPS Data Analysis

The following section details truck GPS dataset used for this study, the data preparation efforts, and methodology followed. Findings and benefits of implementing this methodology to Arkansas GPS truck data are presented in Chapter 4.

The analysis is performed with Truck GPS data purchased from ATRI. The dataset includes all truck GPS location "pings" (latitude and longitude), and its corresponding timestamps, emitted within Arkansas and a buffer zone of 10 miles. The data was collected during four, two-week periods in 2016:

- First quarter (Q1): January 31 to February 15
- Second quarter (Q2): April 30 to May 15
- Third quarter (Q3): August 27 to September 11
- Fourth quarter (Q4): October 31 to November 15

The temporally continuous nature of the GPS data allows for robust time-of-day usage analysis. In addition, the selected periods are suitable to analyze day-of-week and seasonal patterns. Note that each of the two-week periods contain a different amount of weekdays and weekends. To account for this difference, the average number of trucks was calculated for each day of a typical week (Sunday to Saturday) by averaging daily volumes for the same day of the week.

Previous studies show that GPS data is a sample of roughly 10% of the total population of trucks travelling on the roads (Pinjari, et al., 2014). This was confirmed for the Arkansas data sample by comparing the volume of trucks on the GPS dataset at WIM stations, with the volume of trucks counted at those WIM stations in Arkansas (Hernandez, Akter, & Diaz, 2018) . A further detailed percentage of coverage was calculated for each quarter of the year at WIM stations close to port ICs in Arkansas, as follows:

$$DCC_{q,y} = \frac{V_{\ WIM,q,y}}{V_{\ GPS,q,y}}$$

Where,
DCC = Data Coverage Coefficient for Quarter q = *1,…,4* at IC *y*
$V_{\ WIM,q,y}$ = volume of trucks of FHWA class 8 to 13 observed at the WIM station closest to IC y during the two-week period corresponding to the GPS data sample, during quarter q
$V_{\ GPS,q,y}$ = volume of trucks in the GPS dataset found at the location where the WIM station above is located, during the two-week period corresponding to the GPS data sample, during quarter q.

The resulting percentages of coverage of such analysis are used in this report, considering the WIM stations closest to each IC (Table 5).

Table 5 GPS Data Coverage Coefficients (DCC)

Quarter	Van Buren	Little Rock	Pine Bluff
Q1	15.69	16.58	11.76
Q2	14.02	9.91	11.12
Q3	14.53	10.39	10.45
Q4	16.74	13.28	13.00
Average	***15.25***	***12.54***	***11.11***

The raw GPS "pings" are converted to truck trips (i.e. a series of pings between stops) and assigned to network links by using an algorithm developed for a concurrent project, in which the stops made by trucks are also identified in time and space (Hernandez, Akter, & Diaz, 2018). The data attributes (spatial and non-spatial) for these trips and stops are stored in a relational database, which can be queried to extract the trips and stops corresponding to IC links. For this project, several maps were developed from the trips and stops derived from the GPS data to show time-of-day, seasonal, and spatial patterns for each IC in Arkansas. The software utilized for this methodology is open source (PGAdmin and QGIS).

The number of trips of trucks on the network links shown in the maps presented in Appendix III represents a Daily Average Truck Volume per quarter, and it is calculated as:

$$Daily\ Average_{y,q} = \frac{\sum T_{y,q}}{N} \times DCC_{y,q}$$

Where,

$Daily\ Average_{y,q}$ = estimated daily truck volume per quarter, *q*, at IC, *y*

T = number of trips made by trucks found at IC y, during quarter q,

N = number of days included in each quarter's the sample (e.g. 15 days), and

DCC = Data Coverage Coefficient corresponding to IC y, and quarter q (Table 5),

The number truck-trips on the network links shown in the maps presented in Chapter 4 represents an Annual Daily Average Truck Volume (i.e. considering all four quarters), and it is calculated as:

$$Annual\ Daily\ Average_y = \frac{\sum_q \left(\sum T_{y,q} \times DCC_{y,q}\right)}{N}$$

Where,

$Annual\ Daily\ Average_y$ = estimated annual daily average truck volume for IC *y*

T = number of trips made by trucks found at IC y, during quarter q,

N = number of days included in the sample (e.g. 60 days), and

DCC = Data Coverage Coefficient corresponding to IC y, and quarter q (Table 5),

3 Sensor Evaluation

This section presents the results of the Lidar sensor field data collection exercise, and the classification models trained, validated, and tested for five-axle tractor-trailer trucks, or '3-S2' axle configurations, which constitute the majority class in the dataset (48% records).

3.1 Summary of Processed Field Data

The data collected at the Van Buren and Lamar sites is shown in Table 6, together with the class aggregation adopted for trailer body-type classification. The data is imbalanced in that it contains a significantly different number of vehicles of each body-type, with the majority class being enclosed vans. Two measures are adopted to minimize this class imbalance issue on the ensemble classifier: i) a stratified sampling partitioning scheme, where the training set contains 40% of the records, the validation set contains 20%, and the test set contains the remaining 40%; and ii) a 10-fold cross-validation scheme for training base classifiers. In spite of these measures, classes with less than 25 total records are not expected to be identified by the classifiers. Future development of this work may explore additional disaggregation of the classes, such as differentiating refrigerated and non-refrigerated enclosed vans.

Table 6 Dataset Characteristics

Five-axle freight trucks	Lamar dataset records				Van Buren dataset records			
Trailer-body class (*)	Training	Validation	Testing	*Total*	Training	Validation	Testing	*Total*
Enclosed Van	460	227	457	*1144*	24	13	24	*61*
Basic Platform	84	42	84	*210*	17	8	17	*42*
Low Boy Platform	36	18	36	*90*	4	2	4	*10*
Tank	36	17	36	*89*	15	7	15	*37*
Hopper	23	12	24	*59*	9	4	9	*22*
Livestock	7	3	7	*17*	16	8	16	*40*
40ft (2 TEU) Box Container	6	3	6	*15*	0	0	0	*0*
Pole/ Logging/ Pipe	5	1	3	*9*	1	1	1	*3*
53ft Box Container	3	2	4	*9*	1	0	0	*1*
End Dump	3	2	3	*8*	7	4	7	*18*
20ft (1 TEU) Box Container	3	1	2	*6*	0	0	0	*0*
Total	***666***	***328***	***662***	***1656***	***94***	***47***	***93***	***234***
(*) The order of trailer-body-class categories is based on the volume recorded at Lamar.								

3.2 Classification Model Results

First, Lamar data is subject to an SVM classifier, which identifies trucks carrying a trailer. This classification is made by applying a Radial Basis Function as a kernel (sigma=0.9). Because of the distinct features of vehicles carrying small or no trailers when compared to truck carrying trailers, using only 50% of the data for training purposes, and testing the classifier on the remaining 50%, results in a TPR of 100%. This demonstrates the ability of classifying vehicles as large, tractor trailers prior to further distinguishing them by body-type.

Table 7 summarizes the results of two ensemble models on the test dataset: Naïve-Bayes Ensemble (NBE) and Majority Vote (MVE), and serves to compare and contrast the results of the individual base classifiers. The remaining classes shown in Table 6 (but not in Table 7) were used for models' training, validation, and testing, but were not distinguished by the NBE and therefore not shown in Table 7.

Table 7 Model Results on Lamar and Van Buren data. Metric: True Positive Rate (TPR)

a. Lamar data	**Ensembles**		**Individual Classifiers**				
Trailer body-class	**NBE**	**MVE**	**DT**	**MLP**	**SVM**	**NB**	**PNN**
Enclosed Van	95%	97%	94%	93%	**99%**	88%	97%
Basic Platform	63%	60%	54%	**64%**	57%	60%	0%
Low Boy Platform	53%	30%	33%	23%	10%	**67%**	37%
Tank	33%	28%	25%	31%	0%	**36%**	25%
Hopper	**29%**	4%	4%	**29%**	13%	0%	4%
Average class TPR	**55%**	44%	42%	48%	36%	50%	33%
Overall model TPR	**79%**	78%	75%	77%	76%	73%	70%
b. Van Buren data	**Ensembles**		**Individual Classifiers**				
Trailer body-class	**NBE**	**MVE**	**DT**	**MLP**	**SVM**	**NB**	**PNN**
Enclosed Van	71%	**79%**	**79%**	42%	54%	71%	63%
Basic Platform	18%	18%	12%	24%	18%	6%	**29%**
Tank	27%	27%	20%	13%	33%	**73%**	7%
Livestock	**56%**	38%	44%	50%	44%	0%	38%
End Dump	**29%**	0%	0%	**29%**	0%	0%	0%
Average class TPR	**37%**	22%	21%	31%	26%	24%	15%
Overall model TPR	**38%**	36%	36%	29%	30%	32%	30%

(*) The order of trailer-body-class categories is based on the volume recorded at Lamar.
Bold indicates highest TPR for each class or evaluation metric.

3.3 Discussion of Results

The last column of Table 6 shows the volume and industry served by five-axle trucks travelling on Van Buren IC, based on the proposed single-beam Lidar sensor output. As expected, most of the trucks travelling are Enclosed vans (26%), although there is a relatively high percentage of Platforms (22%), Livestock (17%), Tanks (16%) carrying chemicals or food grade liquids, and Hoppers (9%) carrying mineral or agricultural products.

With features extracted exclusively from sensor data, a series of ML classifiers were trained, validated and tested. The results of the ML classification model (Table 7.b) show that the NBE classifier identifies five distinct five-axle tractor-trailer body types travelling on Van Buren IC, namely: Enclosed vans, Basic platforms, Tanks, Livestock Vans, and End Dumps. Only one of the base classifiers (MLP) identifies the same number of classes as the ensembles, but with lower class-specific TPR. Building upon individual classifiers' class-specific TPR, Table 7 shows the importance of selecting heterogeneous methods to build the ensemble: while NB has the lowest performance to classify Basic platforms, no other classifiers perform as well to identify Tanks. Moreover, NBE outperforms the base classifiers and MVE in terms of average class TPR and overall model TPR, making it preferable over MVE. Given the limited data available for this site, it is not expected that the classifiers perform well in terms of TPR. In addition, we observe that classes with less than 25 total dataset records (Table 6) are not identified by any classifier (Table 7).

An insight provided by the NBE cross-classification matrix for Lamar data indicates that 54% of Hoppers are misclassified as Enclosed Vans, explaining the relatively low class-specific TRP for Hoppers (Table 7). Hoppers and Enclosed Vans share a common body type but are distinguished by the bottom of the trailer where the hopper funnels are located. Moreover, it was not possible to discriminate Refrigerated from Standard Enclosed Vans with the current sensor data. The main distinction between the two is the refrigeration unit on the front of the trailer. These two limitations may be caused by a less-than-optimal vertical sensor positioning during data collection, indicating there is room for improvement.

An analysis of the 291 features selected to perform the machine-learning classification indicates the importance to adopt both top and primary Lidar features: the overall NBE model TPR improved by 5% when the top Lidar features were incorporated (versus considering only features extracted from the primary Lidar). Further tests indicated that considering vehicles travelling on all lanes is preferable to limiting the analysis to a single lane. This indicates the sensor is capable of monitoring several travel lanes, and highlights the importance of normalizing the Lidar signatures. Although some of the abovementioned issues may be caused by the relatively small number of records in the dataset, in general, the model was able to distinguish several dominate classes.

The transferability of the proposed data collection and body-type-classification is assessed by applying the proposed methods to Lamar data. Following the same data collection, feature extraction, and modelling procedures, five distinct body-types are identified by the NBE classifier (Table 6b). In contrast to the Van Buren model, the Lamar model was able to distinguish Hoppers and Low boy platform trailers due to the higher number of sample records available for model training, but unable to distinguish Livestock and End Dumps due to the lower number of sample records (Table 5). We conclude that the framework is transferable to sites with different traffic characteristics (i.e. volume and speed), provided a proper calibration of the sensor's vehicle detection code and model implementation is made. Overall, the two models show that it is possible to distinguish at least seven unique trailer body classes from single-beam Lidar data.

4 Evaluation of IC Usage and Performance in Arkansas

This section exemplifies the implementation of truck GPS and Lidar sensor data analysis to the three inland waterway port ICs located in Arkansas. Time-of-day and seasonal volume of trip trucks on each of the three port ICs is compared. The findings of this section may serve to make recommendations on IC monitoring, maintenance, and designation.

When possible, within the area where each IC is located, three locations are considered in the analysis of truck GPS data: (i) an intersection near the port access road labeled as 'Port Access', (ii) an intersection near the NHS at the terminus of the IC labeled as 'Near NHS', and (iii) an intersection on a potential Alternative Route (AR) to access the NHS from the port area that is not currently designated as an IC. The spatial and temporal analysis of IC usage is based on the trucks included in the GPS dataset, and observed at the locations identified in Figure 12.

The first portion of this section discusses temporal patterns (i.e. time-of-day, day-of-week, and seasonal) of IC usage based on Truck GPS data, further disaggregated per industry served based on Lidar sensor data. Next, we evaluate the impact of port ICs within the state, by observing the routes travelled and stops made by trucks found on port ICs. To conclude, we search for potential alternative routes followed by trucks to connect the port and the NHS which are not currently designated as ICs.

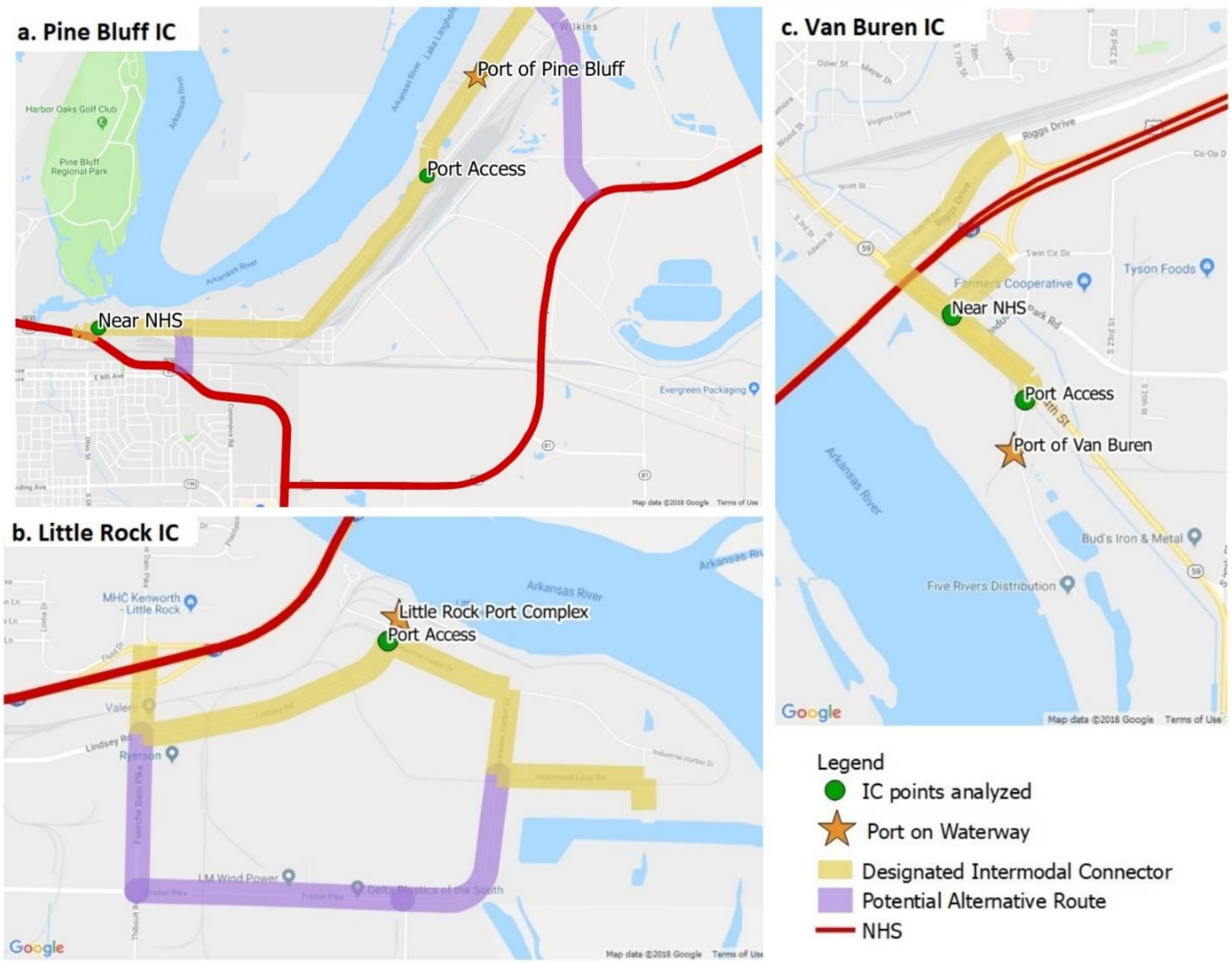


Figure 12 Location of potential alternative routes and points analyzed on each IC.

4.1 Temporal Patterns of IC usage

This section analyzes the time of day, weekly, and seasonal usage of ICs, and compares the traffic found at different points along each IC corridor, based on truck GPS data. Time-of-day findings are disaggregated per industry served by trucks found on Van Buren IC, based on data from the Lidar sensor developed for this work.

4.1.1 Van Buren IC

The usage of the Van Buren IC is analyzed at two intersections along its corridor, one near port access and another one near the NHS (Figure 12.c). The intersection near port access captures all trucks within the GPS dataset which access the port. On the other hand, the intersection near NHS captures not only trucks accessing the port, but also trucks which “pass through” the IC but not accessing the port. Figure 12 shows the distribution of time-of-day usage of the two different types of truck trips, indicating: (i) a more evenly distributed time-of-day pattern of trucks passing through versus trucks accessing the port, and (ii) a reflection of the operation hours (6AM to 3PM) highlighted by a peak in volume on the port access road mid-day.

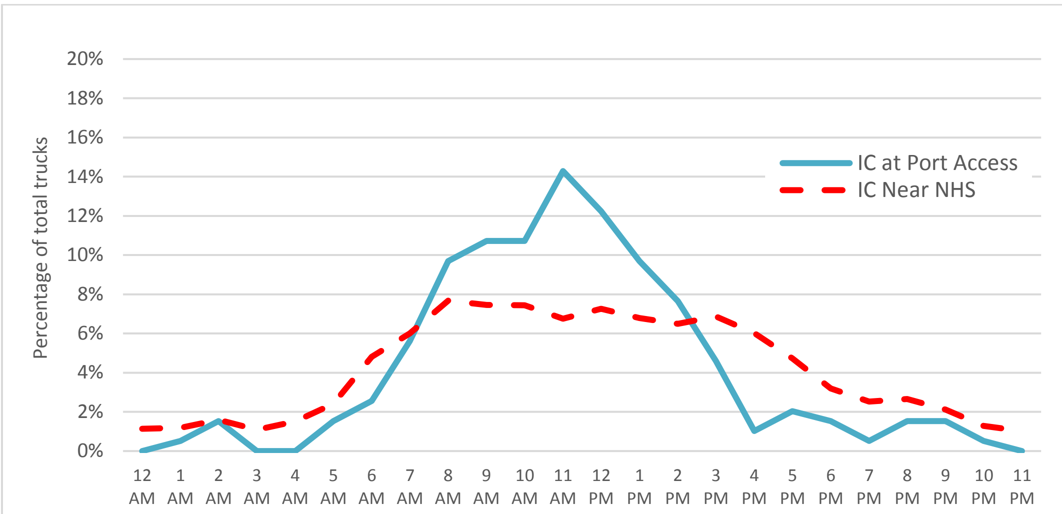


Figure 13 Time-of-day usage at two locations on Van Buren IC

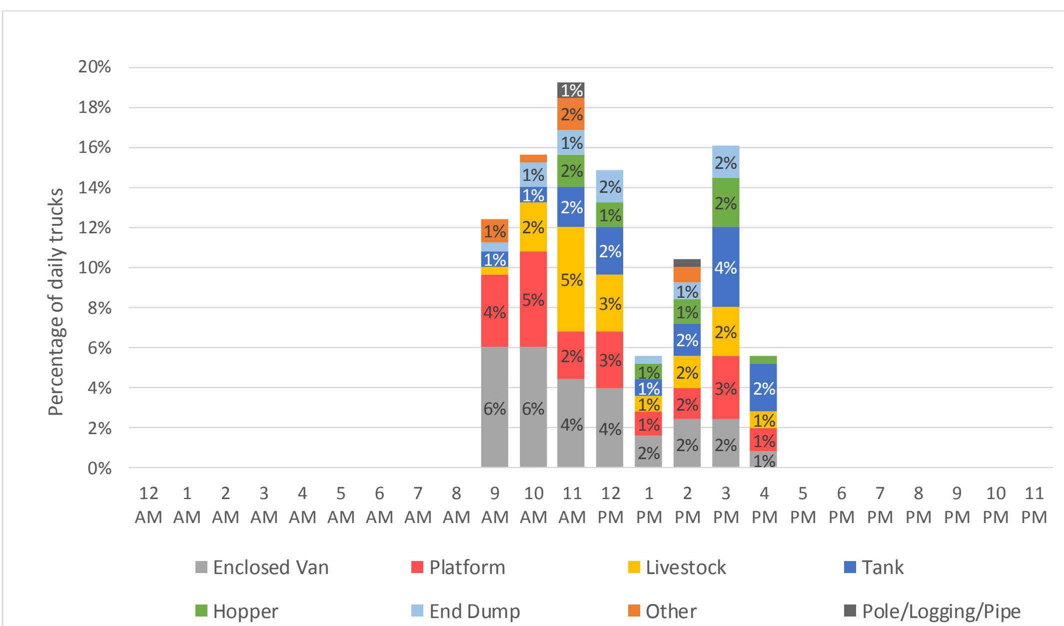


Figure 14 Distribution of Five-Axle Tractor Trailers by Time-of-day for the Van Buren IC per Industry Served

Figure 14 shows a breakdown of time-of-day usage of Van Buren IC per industry served by trucks. Because of the Lidar sensor position, the time-of-day distribution shown in Figure 14 is comparable with the red dashed line on Figure 12. Unlike Figure 13, which is based on truck GPS data collected during 60 non-consecutive days in 2016, Figure 14 is based exclusively on data collected during one day, with the single-beam Lidar sensor developed for this work. These differences may account for the differing overall distribution of time-of-day usage of the IC which emerges from each of the two Figures. As for the industry served by trucks traveling on the IC, we note a higher proportion of five-axle enclosed vans and platforms during the morning (9-10AM), followed by livestock trucks around midday (11AM-12PM), and tank trucks in the afternoon (3PM).

Next, we analyze the distribution of trucks found on different days of the week, for each quarter and annually, in each of the two intersections along the IC (Figure 15). Similar to the time-of-day analysis, the distribution of day-of-week usage is more evenly distributed for the location near the NHS than on the port access road, with a clear reduction of truck volume on the weekends. Moreover, Figure 15.a shows a higher average number of trucks along both the port access road and the near NHS road on Tuesday and Wednesday. This pattern on weekly port access usage is observed during the first and third quarters of the year. During the fourth quarter, however, most trucks access the port on Thursdays.

Lastly, Figure 16 presents a seasonal analysis of Van Buren IC usage. The analysis consists of comparing the number of truck trips found along the two IC intersections for each quarter of the year, relative to the annual average. The results of this analysis show that a higher volume of trucks access the Van Buren port during the first and last quarter of the year, while the least number of truck trips are made during the third quarter of the year (63% less than the annual average) (Figure 16.a). A different pattern of seasonal IC usage emerges when we consider trucks passing through the IC. In this case, during the first quarter of the year, 8% fewer trucks travel through the IC than average, while only 26% less than average trucks are found on the third quarter (Figure 16.b).

Based on the data analyzed, we may conclude that the best season to perform maintenance on Van Buren IC is during August-September (Q3). The volume of trucks during Q3 is lower than in other time of year, and thus freight disruptions due to maintenance or construction work would be diminished during this season (Figure 16). To perform short-duration works (i.e. less than one week), the best days to intervene port infrastructure would be Thursday and Friday (other than Saturday and Sunday, when freight is reduced to a bare minimum) (Figure 15.a). Future work will examine the commodity types being moved at different times of the year. This may be done by deploying the proposed Lidar sensor at different times of the year, or by examining land use patterns of stops associated with port trips by fusing different business location and other geospatial data.

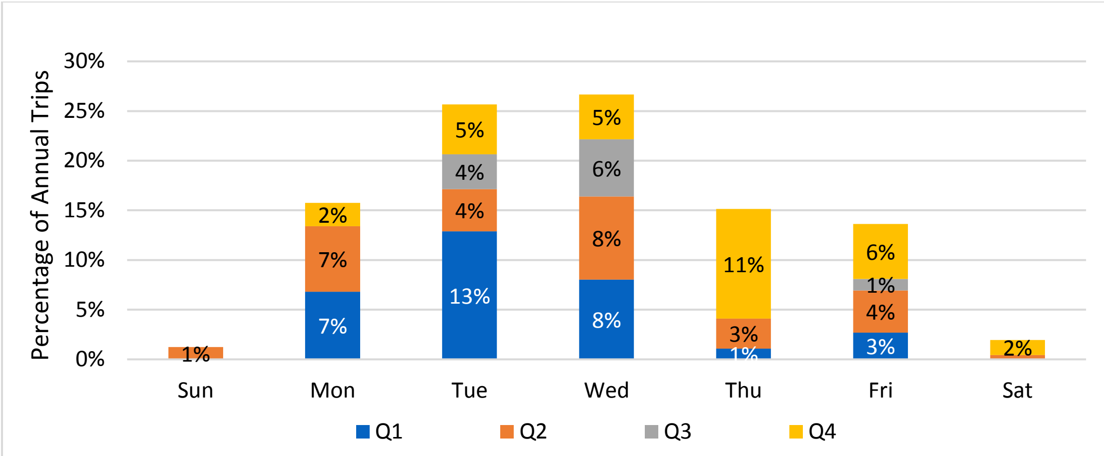


Figure 15.a Trips per day at Van Buren port access

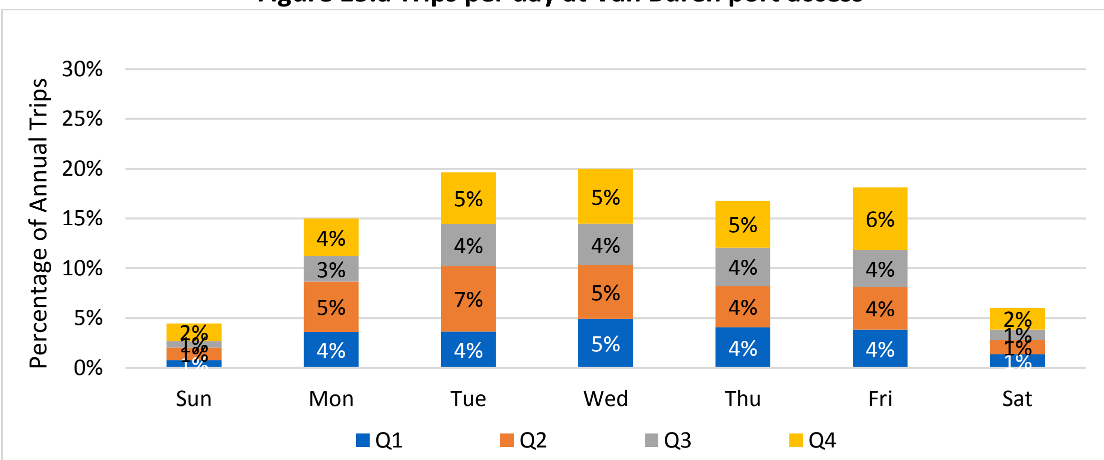


Figure 15.b Trips per day at Van Buren IC near NHS

Figure 15 Day-of-week usage at two locations on Van Buren IC

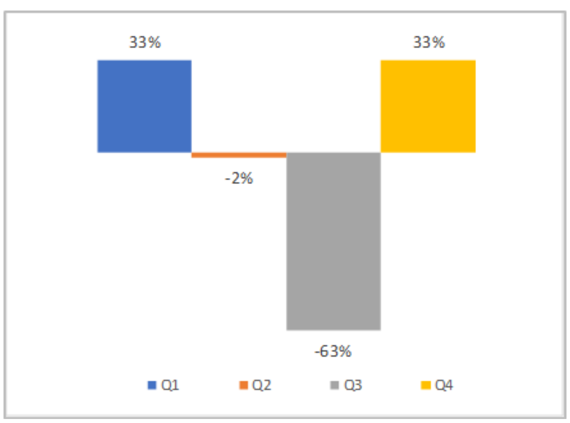


Figure 16.a. Van Buren port access

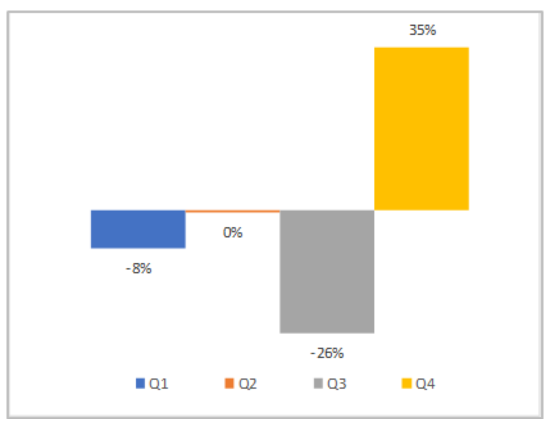


Figure 16.b. Van Buren IC near NHS

Figure 16 Seasonal usage at two locations on Van Buren IC: Percentage of change of truck traffic volume with respect to annual average

4.1.2 Little Rock IC

The analysis of Little Rock IC usage is based on truck GPS data and limited to the intersection where trucks access the Little Rock Port Complex (Figure 12.b). The distribution of truck trips per hour along an average day is presented in Figure 17. Although trucks can access the port at any time of the day, port operations seem to concentrate between 6AM and 6PM. The peak volume of trucks found at the port access road happens between 8AM and 9PM, potentially representing trucks entering the port to load/unload, while trucks exiting the port are distributed throughout the rest of the day.

As for the day-of-week analysis, considering the annual average, Wednesdays and Fridays seem to be the days with highest truck loading and unloading activity at the port of Little Rock (Figure 18). This pattern is somewhat followed, on average, during the third and fourth quarters of the year. During the first quarter there is a slightly higher number of truck trips on Fridays than the rest of the days, while during the second quarter most truck trips occur on Mondays and Fridays.

The seasonal usage of Port of Little Rock Complex shows that the volume of trucks is 25% higher than the annual average during the fourth quarter of the year (Figure 19). On the other hand, the first quarter of the year shows the least number of trucks, i.e. 31% less than the annual average.

Based on the data above, the first quarter of the year would be the most suitable time of year to perform maintenance or construction works in the access to Little Rock Port Complex, because traffic is much lower than annual averages and thus, disruptions to freight flows would be minimized (Figure 19). As for daily interventions, in general, Mondays seem to be a better day than other week-days, because of its relatively lower freight traffic (Figure 18). Commodity movements per season will be analyzed in future work, by examining business data and land use patterns at stops associated with port trips.

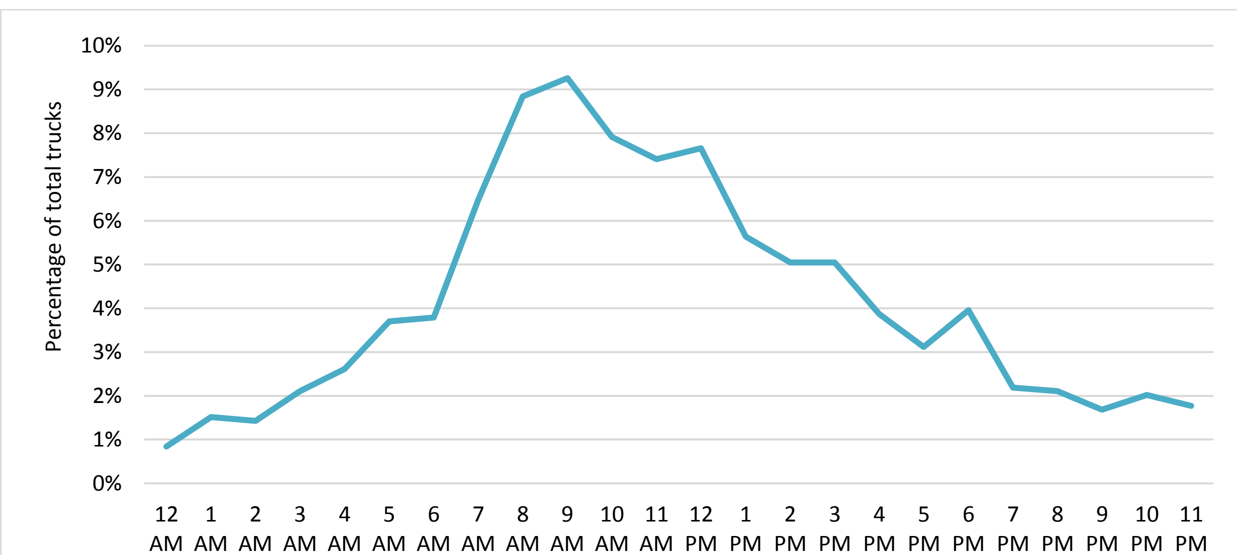


Figure 17 Time-of-day usage on the Little Rock IC

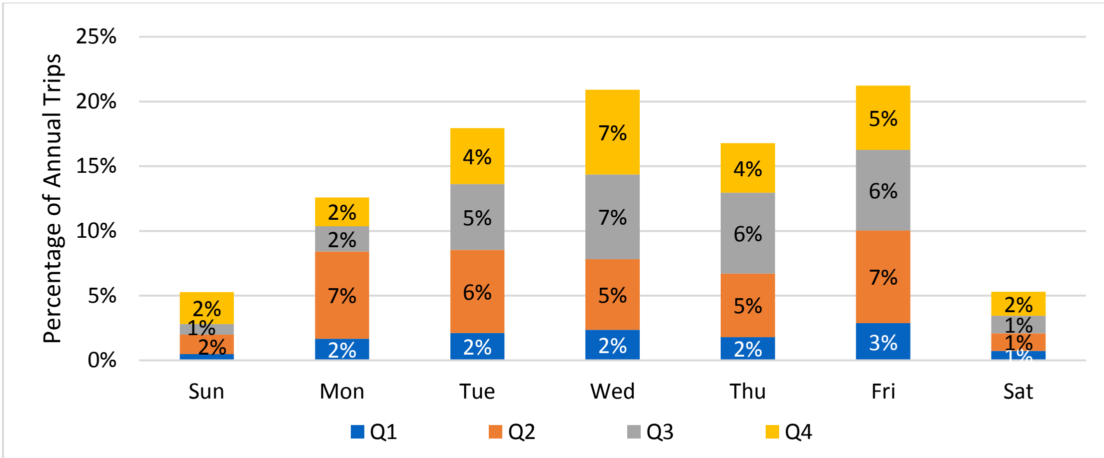


Figure 18 Day-of-week usage on the Little Rock IC

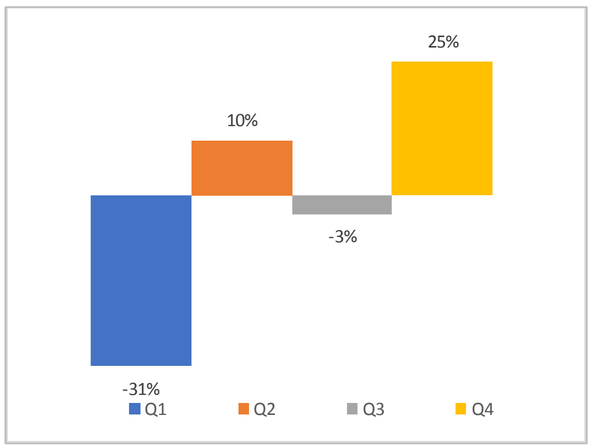


Figure 19 Seasonal usage on the Little Rock IC

4.1.3 Pine Bluff IC

The analysis of temporal patterns on the Pine Bluff IC is based on GPS data from trucks found at two locations along the IC corridor, one intersection near port access and another one near the NHS (Figure 12.a). The annual average time-of-day usage of Pine Bluff IC is show in Figure 20. In contrast with the patterns identified in Van Buren, both Pine Bluff intersections show a similar distribution of trips per hour, potentially indicating that the trucks found along the port access road are approximately the same trucks which are later found near the NHS link. In other words, there may be less pass-through traffic on Pine Bluff IC than in Van Buren. In addition, Figure 20 shows that the hours of highest port activity at Pine Bluff are between 6AM and 3PM.

The results of the analysis of day-of-week usage of Pine Bluff IC are shown in Figure 21. As observed in the time-of-day analysis, both IC locations (i.e. the port access and an intersection near the NHS) show a similar day-of-week usage pattern, based on annual averages. When observing the percentage of trucks traveling on the IC per day-of-week per quarter, we observe that both intersections show a somewhat similar usage pattern, further supporting the evidence of having less pass-through traffic in Pine Bluff IC (Figure 21).

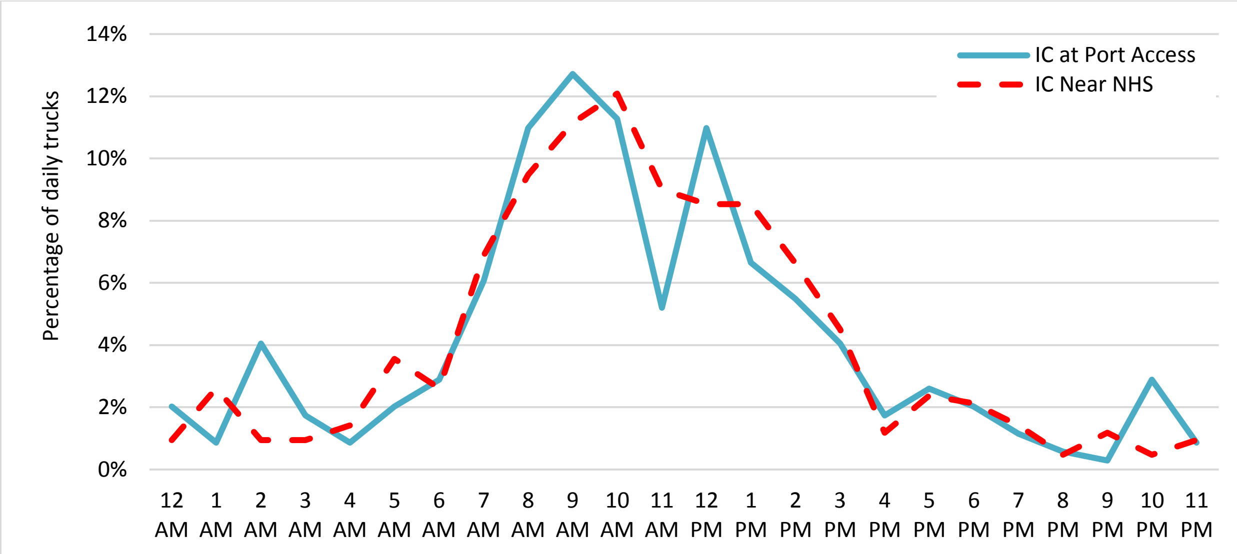


Figure 20 Time-of-day usage at two locations on the Pine Bluff IC

However, the seasonal usage of the Pine Bluff IC, analyzed by comparing the number of trucks per quarter with the annual average at the two intersections, may indicate that the trucks on the two locations follow different patterns (and thus, belong to different populations). At the Pine Bluff port access road, most trucks use the IC during Q4 (26% more than the annual average), and the least number of trucks is found in Q1 (29% less than average). In contrast, the quarters with most and least volume of trucks near the NHS are Q1 (21% more than average) and Q3 (31% less than average), respectively (Figure 22).

Based on the data above, in order to minimize disruption to freight flows, the best season of the year to perform maintenance or construction works on the IC at port access would be during the first quarter (Figure 22.a), while works on the IC corridor near the NHS would cause less disruption if performed during the third quarter (Figure 22.c). On a daily basis, work carried out in the afternoon would potentially disrupt less traffic than in the morning (Figure 20). Mondays and Fridays, on average, seem to be the days with least visits of trucks to the port (Figure 21.a), allowing for a 4-consecutive-day window (Friday to Monday) to perform maintenance work at Pine Bluff port access. On the other hand, Fridays would be the best days to intervene Pine Bluff infrastructure near the NHS and cause the least traffic disruption to freight flows as possible (other than the weekends) (Figure 21.b). As stated before, the commodities that are transported through the IC per season will be analyzed by fusing business location and other geospatial data and examining land use patterns at stops associated with port trips.

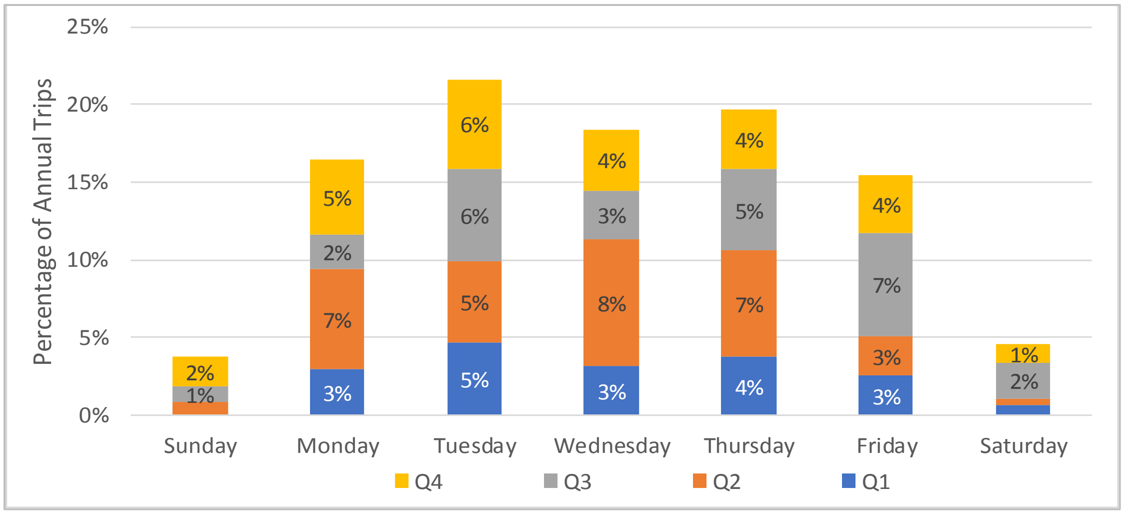


Figure 21.a. Trips per day at Pine Bluff port access

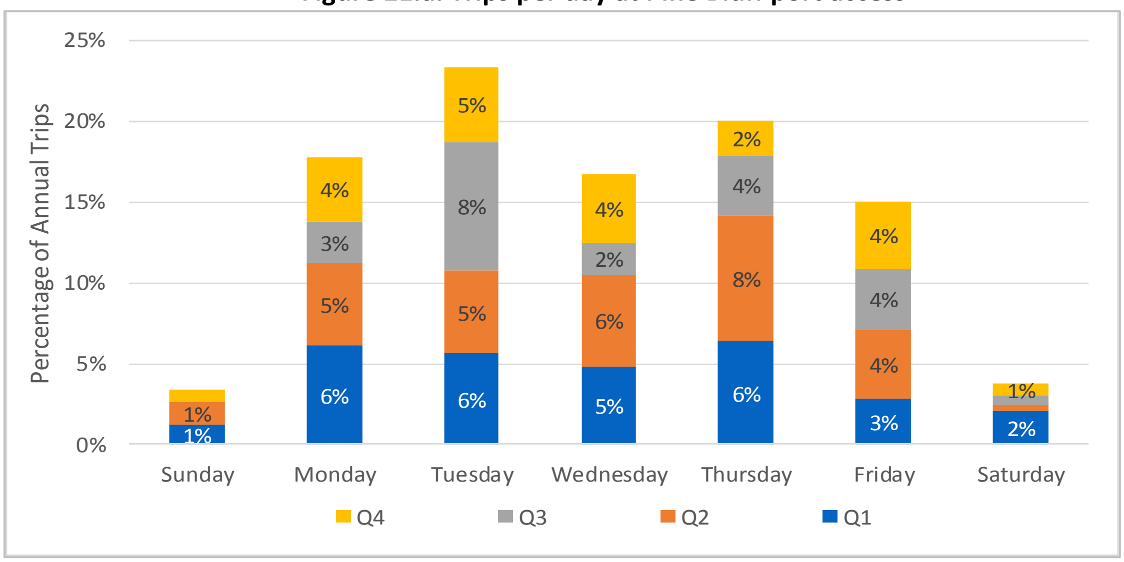
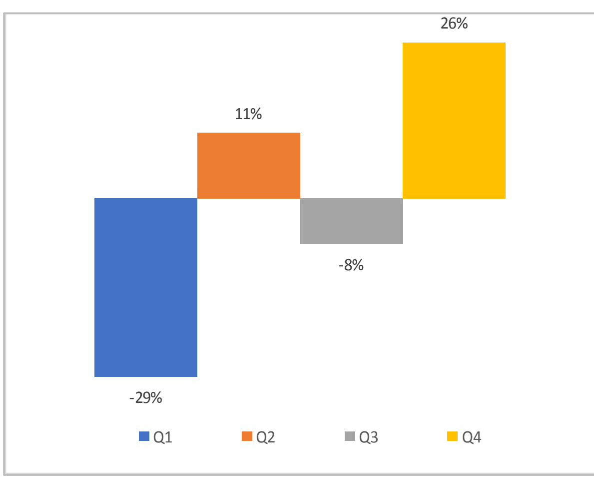


Figure 21.b. Trips per day at Pine Bluff IC near NHS

Figure 16 Day-of-week usage at two locations on Pine Bluff IC



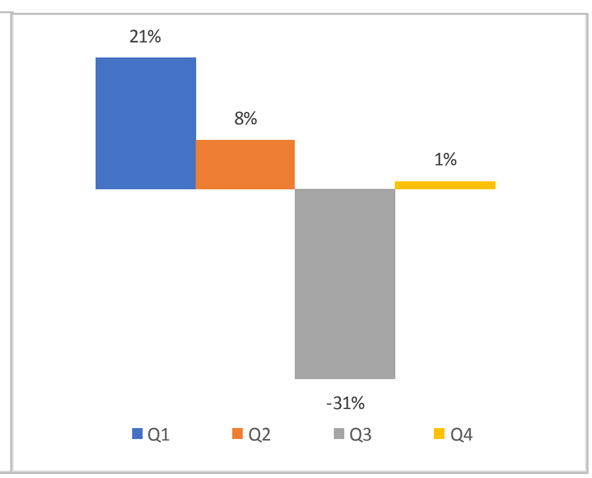


Figure 22.a. Pine Bluff port access **Figure 22.b. Pine Bluff IC near NHS**

Figure 22 Seasonal usage at two locations on Pine Bluff IC: Percentage of change of truck traffic volume with respect to annual average.

4.2 Spatial Patterns of IC usage

This section focuses on identifying the in-state portions of routes followed by trucks found on the three port ICs in Arkansas, and the location of the stops made along those routes. The methodology is implemented on different intersections along each IC corridor: one near port access and another one near the NHS (Figure 12). Each IC is analyzed per quarter, and annually. Summary statistics on spatial patterns of IC usage are shown in Table 8, indicating daily averages of: (i) volume of truck trips from each port, (ii) VMT in state of truck trips from each port, and (iii) total number of stops.

Table 8 Spatial Patterns of Trucks Accessing IC Ports. Daily Averages.

Van Buren					
	Q1	**Q2**	**Q3**	**Q4**	***Total***
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					
	Q1	**Q2**	**Q3**	**Q4**	***Total***
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					
	Q1	**Q2**	**Q3**	**Q4**	***Total***
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*

The spatial pattern for each IC is defined by the routes taken by trucks that used the IC to access the port. More specifically, the spatial usage pattern is defined by the "catchment area" of the port. The "catchment area" is the geographic extent covered by the set of truck trips which accessed the port via the port access road and thus had an origin or destination at the port. The "catchment area" represents the land side impacts of the port. Only once these catchment areas are spatially defined, a more comprehensive understanding of the economic and environmental impacts of the port and of projects or events that may affect the activity of such port can be realized. 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 impacted by port activities on the land side.

Building upon the application of the concept of "catchment area", if we consider GPS data to be a representative random sample of the total population of trucks moving freight within Arkansas, this analysis helps to identify the usage of roads that serve inland waterway ports by time of day, day of week, and season. This seasonality analysis supports several planning and infrastructure decisions. For example, we can analyze which seasons experience the lowest volumes of freight movements, to perform maintenance and construction work on existing highways or port infrastructure and dredging activities, in a way that minimizes disruptions to freight flows.

The remainder of this section is organized as follows: first, maps identifying the catchment areas for each IC and each analyzed intersection, corresponding to annual truck-trips, are shown. Next, a discussion on the routing maps (annual and seasonal) is provided. Later, Appendix III contains the maps corresponding to the analysis for each quarter.

4.2.1 Van Buren IC

Figure 23 shows all the trips and stops made by trucks found on Van Buren IC. Figure 23.a focuses on trucks found on the port access road. All the paths followed by those trucks are shown as red lines. A selection of such paths, including only the trips entering or exiting the Port of Van Buren, are shown as blue lines. When analyzing the trucks accessing the port (Figure 23.a), a comparison of the proportion of red and blue lines indicates how much the fleets of trucks accessing the Port of Van Buren depend on port activities. A higher proportion of blue lines indicate the trucks are highly dependent on port activities, making almost all of their trips exclusively to or from the port. In contrast, a higher proportion of red lines indicates a more diversified truck activity.

In addition, Figure 23.a and Appendix III map the locations of stops made by each truck that visited the port (as shaded areas of varying intensity). Most trucks going to or from the Port of Van Buren have the other end of the trip in Benton/Washington counties, Pulaski County (Little Rock), and the Russellville / Dardanelle / Centerville area, serving Northwest Arkansas region more than any other region in the state. Centerville is the origin / destination of most trips made during the third quarter of the year (Appendix III). Since this area is an active agriculture production region, and one of the berths at Van Buren Port is capable of handling agricultural products, these trucks may be carrying the harvest happening during the third quarter of the year.

Figure 23.b shows all the trips made by trucks which passed through the IC on at least one of their trips during the GPS data collection period. Figure 23.b differs from Figure 23.a in that the trips shown in Figure 23.a correspond to the routes taken on the particular trip where the truck visited the port; Figure 23.b includes all the trips of trucks that accessed the port at some point, but not on each trip. From all the trips made by those trucks, some trips passed through the IC (blue lines), while other trips did not pass through the IC (red lines). By comparing the truck volume on the two different intersections along Van Buren IC corridor (Figure 23), we observe that approximately 5% of the trucks travelling on Van Buren IC access the port.

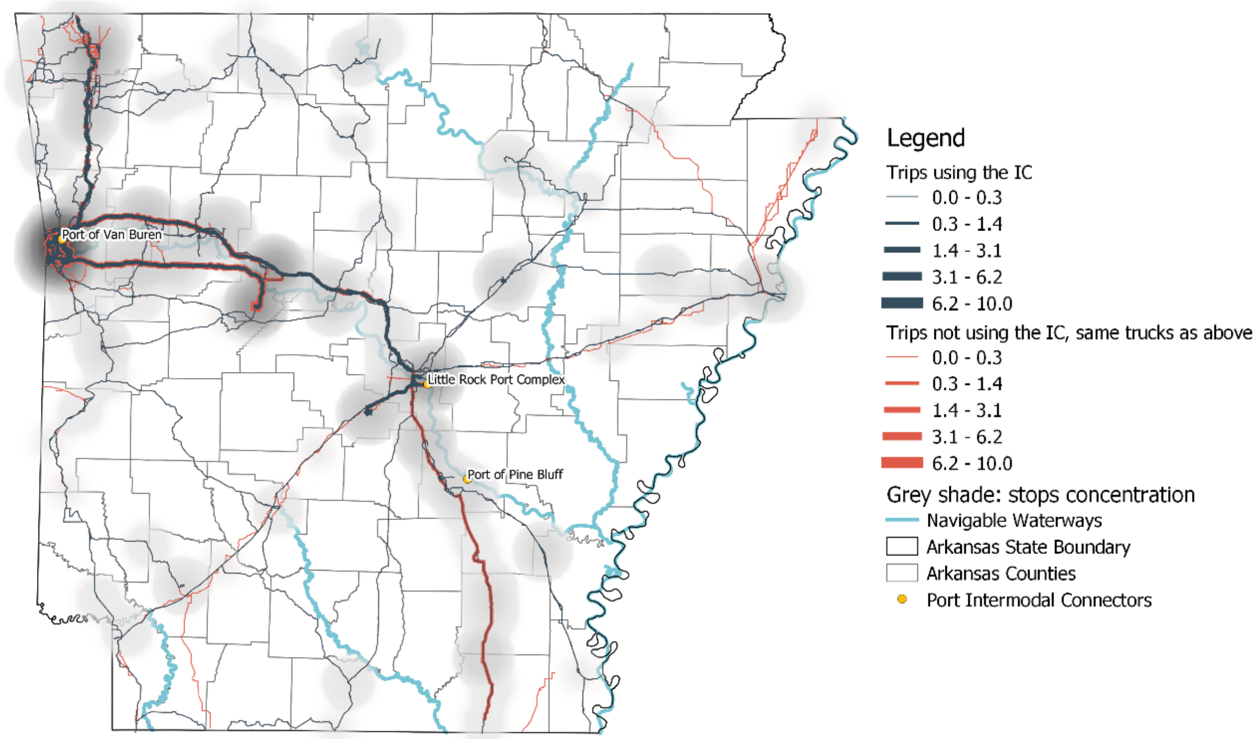


Figure 23.a. Van Buren IC. Average daily trips of trucks found on the IC, at port access. 2016, annual.

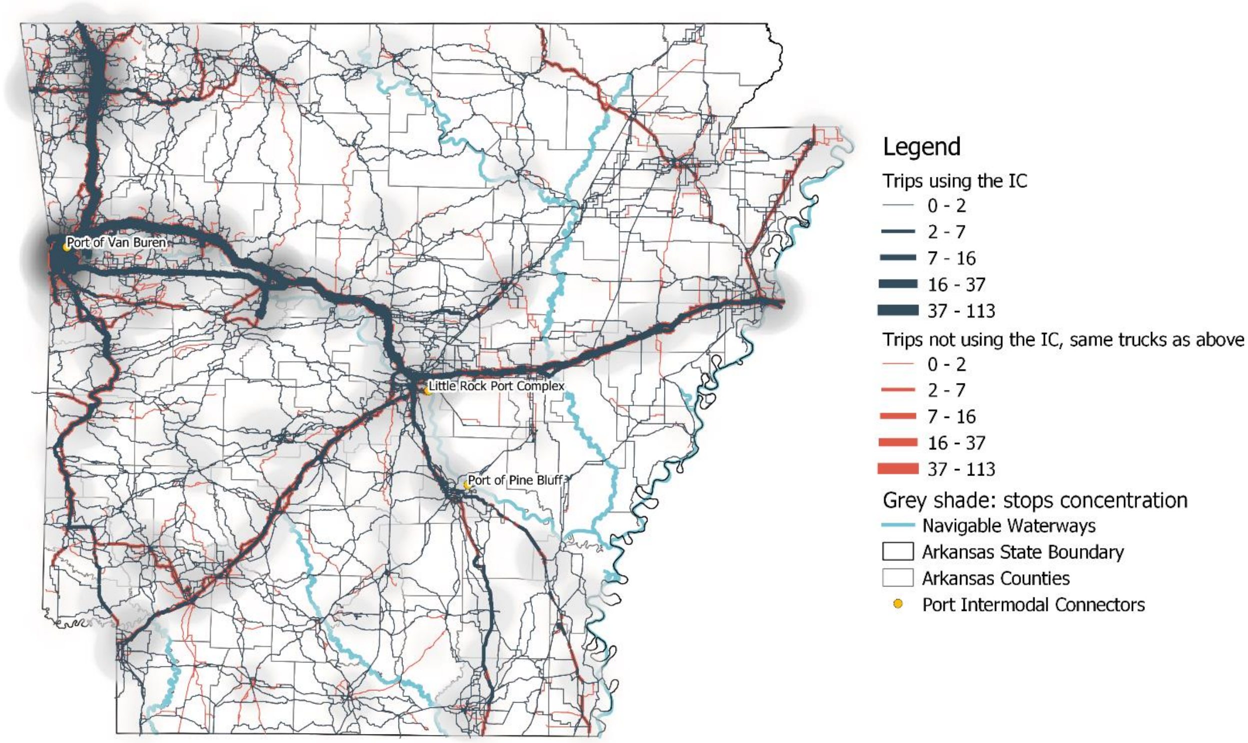


Figure 23.b. Van Buren IC. Average daily trips of trucks found on the IC, near NHS. 2016, annual.

Figure 23 Spatial analysis of Van Buren IC usage

4.2.2 Little Rock IC

Figure 24 shows the trips made by trucks found at Little Port Complex access road, following the same approach used to analyze the Ports of Van Buren and Pine Bluff. Notably, we observe that several trucks move freight between the Ports of Van Buren, Pine Bluff, and Little Rock along I-40 and other east-west roadways. Considering that I-40 runs parallel to the Arkansas River, a navigable waterway with access to Van Buren, Little Rock, and Pine Bluff, it is interesting to note that the landside movement could have been moved by river but was instead picked-up/delivered between ports via truck. This may indicate a potential opportunity to shift freight from truck to water, so it continues its path along Arkansas River instead of transloading to truck at Little Rock. Further research through industry interviews would likely reveal the rationale for this particular movement and lend insight into policy development to promote mode shift. The same transload behavior is observed in each of the seasonal maps for the Little Rock IC analysis.

From Figure 24 we observe that trucks accessing the Little Rock Port Complex are highly dependent of such port activities, since a vast majority of their trips are exclusively dedicated to port-related trips. In addition, the vast majority of truck trips with origin or destination in the Little Rock Port Complex have the other end of the trip in the eastern and southern portions of the state, in contrast to the region served by the trucks accessing the Port of Van Buren (Figure 23.a) and using the Van Buren IC (Figure 23.b). In particular, a higher concentration of stops made by the trucks visiting the Little Rock Port Complex is observed in Memphis and in cities located along interstate I-30, south of Little Rock.

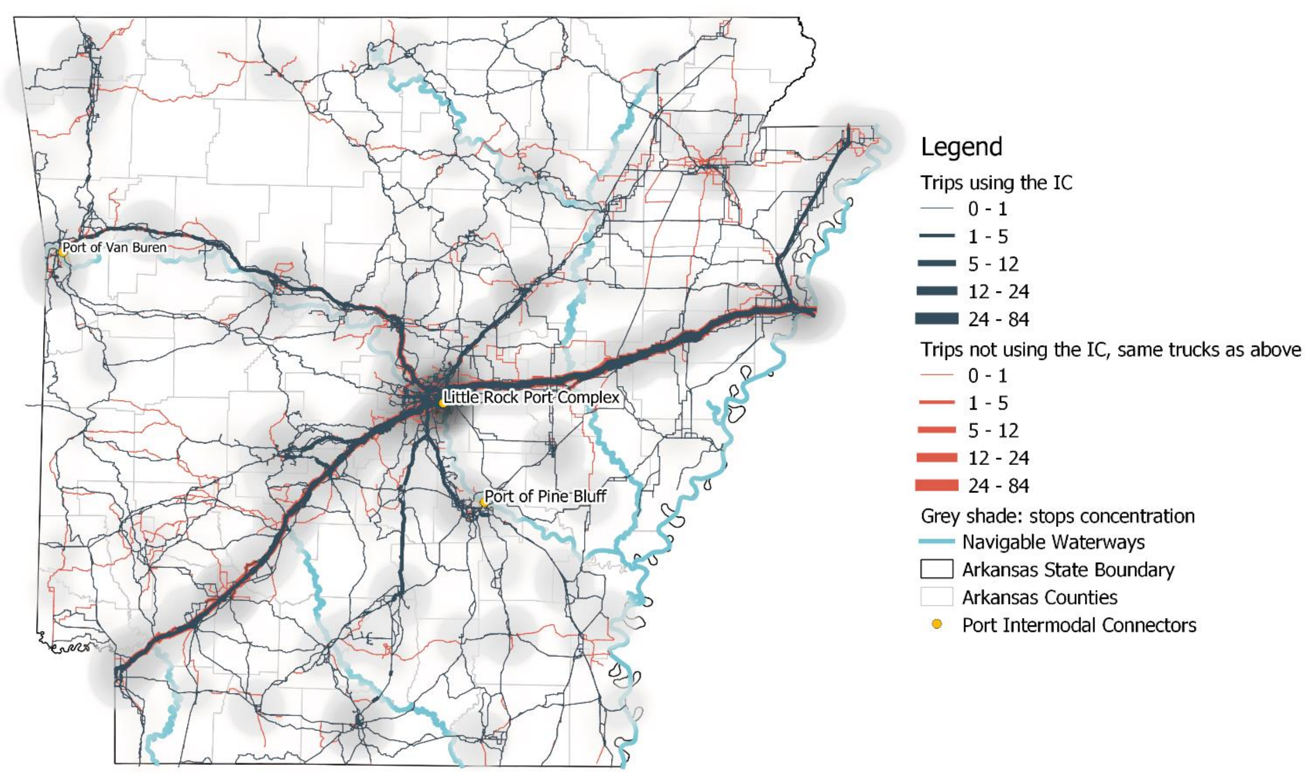


Figure 24 Spatial analysis of Little Rock IC usage, near NHS. 2016, annual.

4.2.3 Pine Bluff IC

By examining the port-related trips made by trucks accessing Pine Bluff IC (i.e. blue lines in Figure 24.a), versus all the trips made by the same trucks (i.e. red lines in Figure 24.a), we observe that most trips made by trucks found at Pine Bluff port access are port-related trips. Thus, we conclude that the truck fleets accessing Pine Bluff port are highly dependent on the port activity (Figure 25.a). Figure 25 shows an even higher concentration of truck trips covering the south-eastern region of the state than any other region, making most stops on I-530 between Pine Bluff and Little Rock, in Memphis, and in Searcy. Moreover, during the first quarter (Appendix III), the vast majority of trucks found on the Pine Bluff IC along the port access road follow the same route from Pine Bluff to Little Rock, which could also be continued by barge, as noted in the previous section.

Figure 25.a shows that trucks take different routes between two cities (e.g. in North-East Arkansas between Reyno and Mammoth Spring, indicated by the yellow box), even though no stops are detected on those paths. 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 observation is also valid for other “parallel” roadway corridors found in other maps made for this analysis.

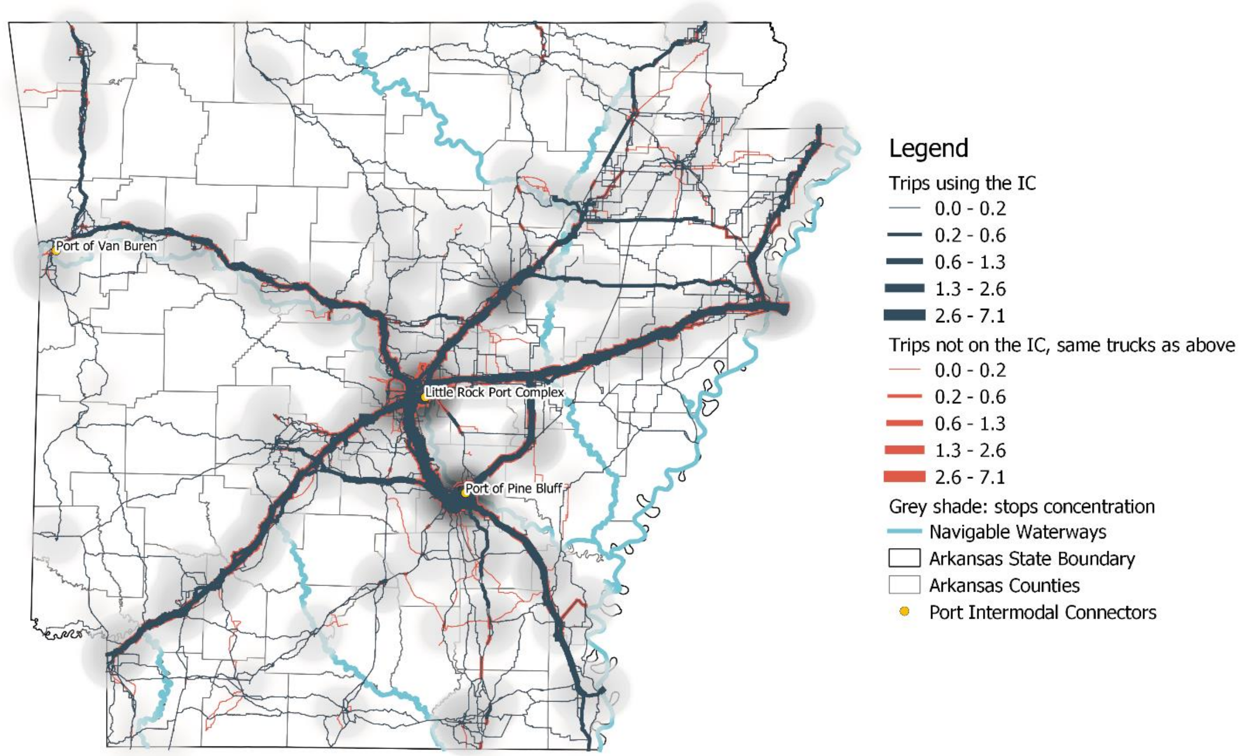


Figure 25.a. Pine Bluff IC. Average daily trips of trucks found on the IC, at port access. 2016, annual.

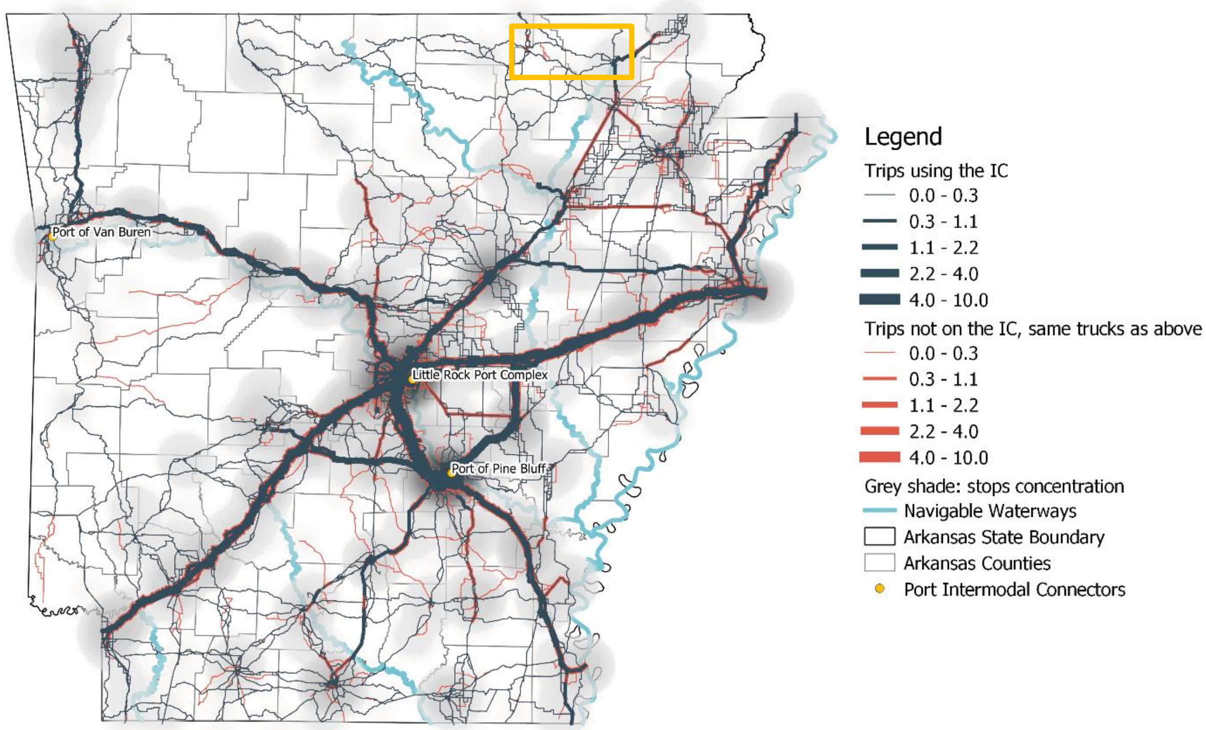


Figure 25.b. Pine Bluff IC. Average daily trips of trucks found on the IC, near NHS. 2016, annual.

Figure 25 Spatial analysis of Pine Bluff IC usage

4.3 Identification of Potential Non-designated IC Routes

The purpose of this section is to identify corridors of the roadway network which are not currently designated as freight ICs serving Arkansas' inland waterway ports, but meet the criteria to be designated as such. As discussed, the criteria related to freight to designate ICs are (RPC, 2010):

- provide access to container terminals that handle more than 50,000 Twenty-foot Equivalent Units (TEUs) per year or more than 100 large single unit or combination trucks per day per direction, or
- provide access to bulk commodity terminals that handle more than 500,000 tons per year or 100 trucks per day per direction.

The analysis is as follows. First, we identify the routes followed by trucks accessing each of the three ports served by currently designated ICs, and observe the volume of such trucks on local roads in the proximity of these ports, which may constitute potential Alternative Routes. Truck GPS data is used for this purpose. Then, the volume of trucks on such local roads is compared with the minimum required to meet the IC designation criteria.

Figure 26 shows the volume of daily trucks on roadway links within the Little Rock Port Complex and the Pine Bluff Port area, based on truck GPS data. Certain roads within the Van Buren port area are not modeled in the road network file used for truck GPS data analysis. Because of this limitation, a potential alternative route on Van Buren IC cannot be analyzed with GPS data. However, on the day of the field data collection exercise, it was observed that 98% of the trucks accessing Van Buren port used the IC instead of alternative routes. From Figure 26 we observe that the majority of trucks take the currently designated IC route at the Little Rock Port Complex and the Pine Bluff Port area, and not the potential alternative routes. In addition, we observe that the number of average daily trucks on the potential alternative routes does not meet the criteria to be formerly designated as intermodal connectors.

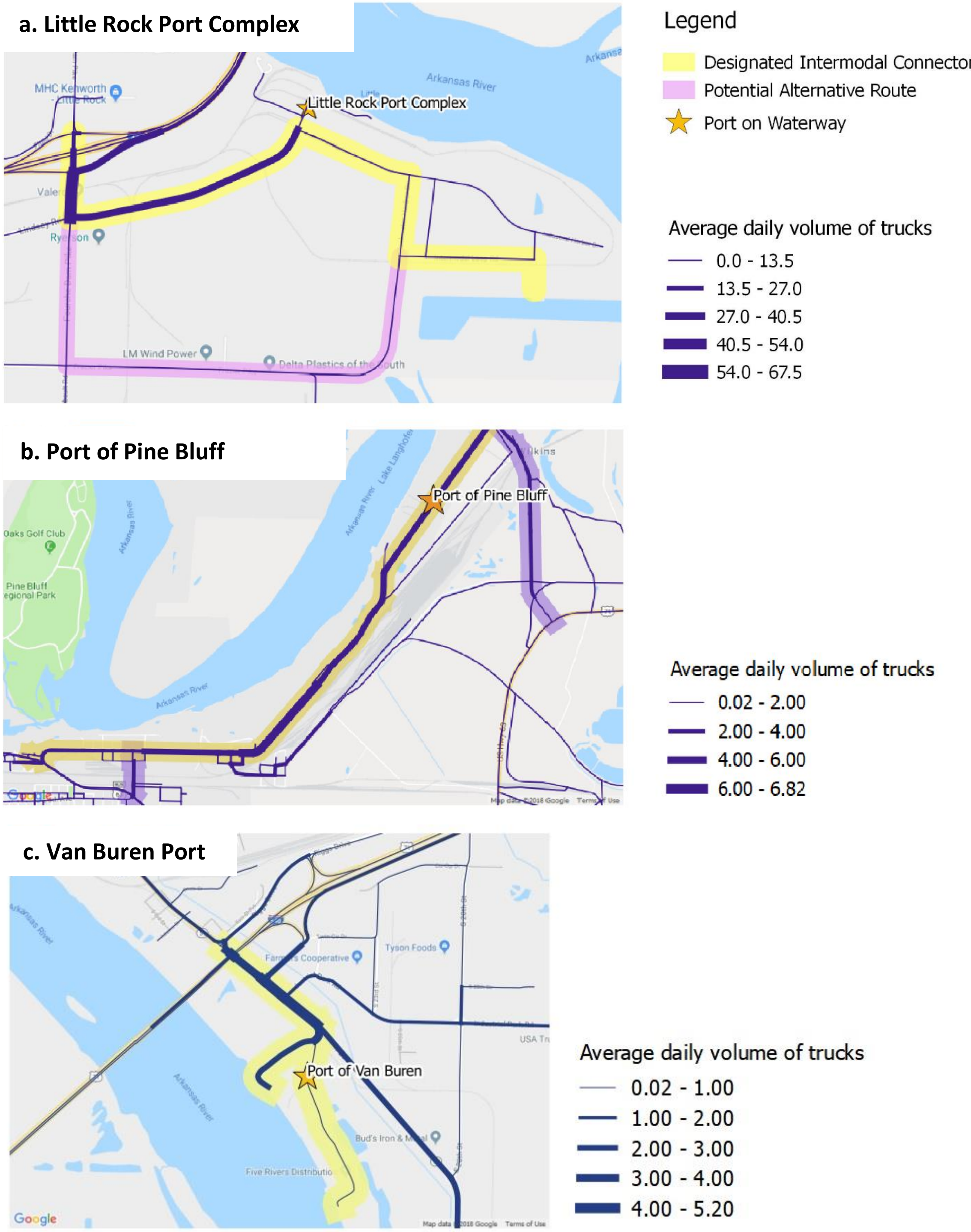


Figure 26 Paths followed by trucks accessing ports

5 Conclusions

This report identifies data gaps that hinder a comprehensive evaluation of the performance of port intermodal connectors (ICs) in Arkansas. The major data gap identified in this work is information on the temporal and spatial patterns of trucks accessing port areas stratified by commodity carried or industry served. Such information can help assess the impact of inland waterway ports and the need to maintain efficient connections to those ports via ICs. To close the data gap, this work developed a proof-of-concept Lidar sensor bundle, capable of identifying the industry served by trucks traveling on a network link. The non-intrusive, point-based sensor was coupled with truck GPS data to infer the geographic extent and temporal patterns of each port area serving an inland waterway port in Arkansas. By coupling a sensor capable of providing robust truck classification with truck movement data derived from truck GPS it is possible to fully characterize the usage and performance of ICs and, consequently, inland waterway ports. In this section, a summary of the Lidar sensor and related vehicle classification models is presented followed by a summary of insights provided by the truck GPS data analysis is provided.

This report presents a strong starting point to further develop low-cost, single-beam Lidar sensor capabilities to understand commodity flow through ICs and evaluate ICs performance. To the best knowledge of the authors, the proposed sensor is the first non-intrusive prototype providing data to classify trucks by body-type- a much needed data element for freight planning applications, in particular performance evaluation. This classification is key to understand commodity flow through a region, and support estimations of demand for transportation facilities, services, energy consumption, and safety risk and environmental concerns.

The low-cost, non-intrusive sensor consists of two single-beam Lidar units mounted on the road shoulder in a side-fire configuration, approximately 4ft above the ground. Each vehicle is detected as it passes in front of the sensor and a Lidar *signature* is generated for each vehicle. The *signature* consists of an array of distance measurements from the sensor to the moving vehicle. Derived features used for classification of trailer-body-type include: the time spent by the vehicle in front of the Lidar (*duration*), and a normalized set of longitudinal vehicle-body-points *(vehicle-body-points)*, characteristic of trucks body configuration. A machine learning classification model trained on data collected at an IC location identified five truck-body-types for five-axle tractor trailers: Enclosed vans, Basic platforms, Tanks, Livestock Vans, and End Dumps. The same model framework was applied to train a model on data collected at a high speed interstate and was able to distinguish five classes: Enclosed Vans, Basic Platforms, Low Boy Platforms, Tank, and Hoppers. Both models showed class-specific TPR up to 95%, and overall TRP up to 79%.

The main contributions of the sensor are: (i) novel, non-intrusive technology for freight-commodity-type identification; (ii) low-cost; and (iii) portable and transferable. The non-intrusive characteristics of this sensor makes it attractive for places where pavement conditions are poor (such as heavily trafficked freight corridors like intermodal connectors), or where high traffic volumes difficult maintenance operations for intrusive sensors. Moreover, the cost of a single beam Lidar sensor is magnitudes lower than the scanning sensors used in other work and in this way it can be more widely deployed. In addition, the proposed sensor is portable, and may be used to evaluate link performance and freight truck characteristics at remote locations. Such remote locations are hardly ever served by sensors with similar capabilities, such as loop detectors and/or WIM stations. However, the proposed sensor could be adapted to a permanent mount on a side-fire configuration for network links or for temporary data collection for site-specific studies.

While the Lidar sensor can distinguish detailed truck body types that correlate to industry served or commodity carried, the sensor cannot determine the paths or spatial extent of trucks accessing the port. Notably, truck GPS data is the only dataset that positively facilitates routing analysis for trucks travelling on ICs, allowing for an estimation of the impact that each IC has on a broader geographical area. The "catchment area" of each port, on the land side, is defined in this work as the region covered by trips of trucks with an origin or destination at the port. The analysis of truck trips shows differing catchment areas for each port in Arkansas:

- Trucks accessing the Port of Van Buren have subsequent stops concentrated in Benton/Washington counties, Pulaski County (Little Rock), and the Russellville/Dardanelle/Centerville area. The heaviest concentration of stops is in the Northwest Arkansas region.
- Trucks accessing the Little Rock Port Complex have subsequent stops concentrated in the eastern and southern regions of Arkansas. The heaviest concentration of stops is in Memphis and in cities located along I-30, south of Little Rock.
- Trucks accessing the Port of Pine Bluff have subsequent stops concentrated in the south-eastern region of Arkansas. The heaviest concentrations of stops is along I-530 between Pine Bluff and Little Rock.

Locations of stops help 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. By defining catchment areas and stop locations of trucks accessing the port areas, a more comprehensive understanding of the economic and environmental impact of the port and of projects or events that may affect the activity of such port can be achieved. Interestingly, from the routing analysis, we note that 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. Lastly, GPS data further supports the identification of temporal patterns on IC usage, allowing for the identification of the best windows to perform maintenance, construction, and dredging works on the IC and the port.

Using truck GPS data, this research also examined the possibility of identifying alternate routes using GPS or other data sources. An identification of potential alternative routes, currently not designated as ICs, but followed by trucks serving the ports can help decisions makers properly classify port access routes and help prioritize investments for these routes. The analysis showed that GPS data is viable for identifying alternate routes, given proper network representation of the local roads in the vicinity of the port areas. For example, in the Van Buren Port area, local roads were not included in the network file and thus could not be evaluated as potential alternate routes. The analysis for Pine Bluff and Little Rock port areas showed that while some trucks use alternate routes, the average daily and annual volumes along these routes do not meet the thresholds for designating an IC.

6 Future Work

The analysis carried out in this research assessed the usage and performance of intermodal connectors using a newly developed non-intrusive, point-based sensor and truck GPS data. In this section, recommendations for future work to improve the sensor design and to more fully evaluate ICs and inland waterway ports are suggested.

One limitation of the proposed sensor is the inability to deal with changes in speed, such as during congested conditions or the onset of congestion (i.e. stop-and-go traffic). However, the addition of a Lidar unit in a speed trap configuration is relatively straightforward and will be carried out in future work. Other future improvements include better occlusion detection, optimal sensor deployment height identification, and optimal vertical distance setting between the lower and top Lidar beams. For example, refrigerated vans may be separately identified from non-refrigerated enclosed vans by capturing the refrigeration unit with the top Lidar beam. As for the classification model, additional features will be investigated that capture the detailed shape of the signature can be developed to improve model performance. Most importantly, even though the size of the dataset is small when compared to other studies (Hernandez, Tok, & Ritchie, 2016), the results obtained demonstrate that it is possible to distinguish trailer-body-type classes from a single-beam Lidar sensor. In future studies, the research team will expand the data set for model training and validation and perform sensitivity analyses for spatial transferability.

In future work, a complete data fusion approach is recommended. By fusing sensor data to determine the industry classification of trucks with GPS data to understand the temporal and spatial patterns of such trucks, a comprehensive understanding of the usage of an inland port by industry is possible. Moreover, fusion of the truck trip and stop data with land use and business location information can further reveal commodity flow patterns tied to port activities. This data can be used to support policy development, operational assessments, and maintenance programming. For example, the GPS data clearly showed the opportunity for mode shift between port areas along the Arkansas River. To develop targeted policies to promote mode shift along this corridor, it is necessary to understand which industries are affected. In future work, the sensor can be deployed to the three ICs to determine the industry served by the trucks transporting goods between the three ports. Then, an assessment of each ports' ability to transload different commodities can be performed to see if there are limitations in equipment available at the ports that limit shipment along the waterway. Further, targeted interviews of port operators, fleet managers, and/or trucking companies connected to the identified industries could be carried out to understand the motivations for mode shift.

Port performance is an increasing area of interest at the federal and state level as a result of the MAP-21 and FAST Act's data-driven performance measurement initiatives. While the work described in this report focused on the performance of ICs, it is valuable to extend the work to port performance. To do this, it is necessary to combine our understanding of the land-side freight movements related to port activities to marine-side freight movements. Truck characteristic and movement data derived from sensors and GPS depicts the land-side efficiency of the multi-modal freight network while marine vessel characteristics and movement data from marine Automatic Identification Systems (AIS) can depict the marine-side efficient of the multi-modal network. It is necessary to investigate methods to fuse the land and marine side freight data sources to create multi-modal freight performance measures. In searching the literature, there is a lack of true multi-modal performance measurement data for port areas, and therefore future work should aim to address this larger data gap.

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A1. Preliminary Site Visit Report

Van Buren Intermodal Connector

<u>Site Visit Date:</u> November 7, 2017.

<u>Location</u>: From I-540 (Exit 3) SE 0.48 mile on SH 59, S 0.15 mile on Port Rd.

<u>Attendees</u>: Karla Corro Diaz and Magdalena Asborno.

<u>Objective</u>: To visit the site and familiarize with the intermodal connector serving Van Buren Port. The information collected is used to further select the location of the sensor to identify truck body types.

<u>Methodology:</u>

The site visit consisted on two stages:

Stage one: Driving through the IC. A video was recorded on site. It is stored in the project folder.

Stage two: Collecting information at three specific locations where to potentially locate the sensor. These specific locations were preselected in the lab using Google Maps and Google Earth tools. The locations are denoted as Zone A, B and C in Figure AI.1.

During stage two, we spent approximately 20 minutes at each location (A, B, C) and observed the number of trucks, the variety of truck body types, site topographic characteristics, and nearby industries / business.

Figure AI.1 - Van Buren IC Overview

<u>Observations:</u>

Zone A

- Location: On Twin Cir. Dr. between I-540 northbound exit ramp and SH59 (S 4th St.)
- Time of Visit: 12:35 to 12:55 pm

- Truck Movement Observed: Approximately 13 trucks were observed. Many trucks using this road did not turn into or come from the port direction. Refer to pictures and video in project folder. Industries served / body types of those trucks included concrete mixers, flat bed (empty), dairy products, aggregates.
- Business on link: Only one truck shop that looked closed at the time of the visit.
- Site Topographic characteristics: There are areas where terrain is relatively plain, and with low vegetation.

Zone B

- Location: On SH59 (S 4th St.) at the corner of Port Rd.
- Time of Visit: 12:05 to 12:30 pm
- Truck Movement Observed: Approximately 13 trucks were observed on the main road, with 7 of them coming in or out of the port, and the remaining passing through the IC. Refer to pictures and video in project folder. Industries served / body types of those trucks included steel rolls, landfill, aggregate/minerals, grain (potentially), machinery. Trucks passing through the IC (not coming from or to the port) carried wood, precast concrete, live chicken.
- Business on link:
  - consolidated terminals and logistics (minerals and grain).
  - five rivers distribution and warehouse (steel)
  - municipal landfill
- Site Topographic characteristics: The shoulder opposite to the port entrance has a relatively pronounced slope. The sensor should be located relatively near the road or in the shoulder for better stability. Refer to Figure A1.2 showing the legs of the sign at the side of the road.

Figure A1.2 -Zone B

Zone C

- Location: On Riggs Drive between I-540 southbound exit ramp and SH59 (S 4th St.)
- Time of Visit: 13:00 to 13:20 pm
- Truck Movement Observed: Approximately 13 trucks were observed. Many trucks using this road did not turn into or come from the port direction. Refer to pictures and video in project folder. Industries served / body types of those trucks included Machinery, food, aggregate, minerals, chemicals, scrap, copper cable.
- Business on link: Wilsons air conditioning, DTI (mainly closed van trucks).
- Site Topographic characteristics: There are areas where terrain is relatively plain, and with low vegetation.

<u>Conclusions:</u> The site visit provided important information that is not available at distance, such as the types of trucks serving the intermodal connector and the variety of truck body types that can be observed in it. In addition, the site visit allowed us to observe the current topographical situation of each site to identify which sites are suitable or not to locate the sensor.

A2. Field Data Collection Plan

Field Data Collection Plan

Objective:

The objective of the Filed Data Collection Plan is to set the basis to deploy the sensor equipment on site, and use its collected data to evaluate the truck flow in an intermodal connector in Arkansas. In particular, the sensor is to collect data about the truck body types observed in the intermodal connector.

Study Area:

The set of possible locations to collect data include the three intermodal connectors serving Arkansas ports. These locations are: Van Buren, Little Rock and Pine Bluff.

Based in its proximity with the University of Arkansas, Van Buren Intermodal Connector is selected. Van Buren intermodal connector is described by the U.S.DOT as: From I-540 (Exit 3): SE 0.48 mile on SH 59, S 0.15 mile on Port Rd. (1). Refer to Figure 1.

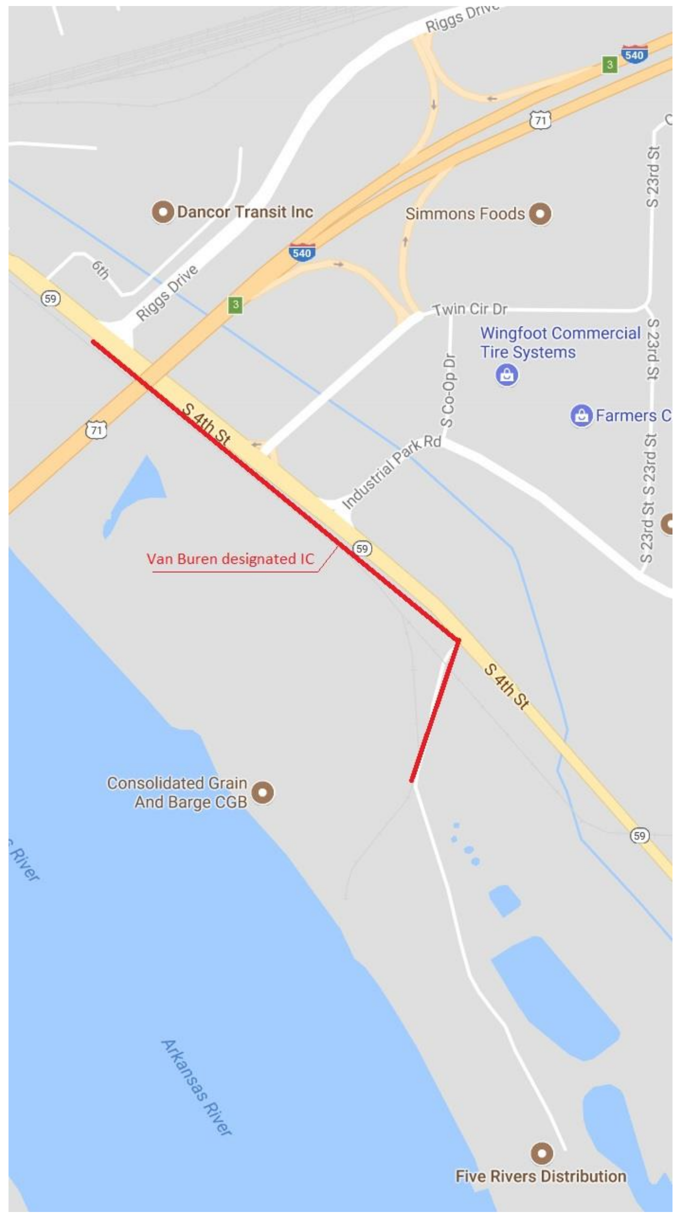

Figure AII.1 Van Buren Intermodal Connector Overview

Data Collection Plan:

Data collection should be made during operating hours of the Van Buren port. The two main transportation and warehousing industries located in the port are: Consolidated Terminals & Logistics, and Five Rivers Distribution. The latter works 24/7.

It is proposed to deploy the equipment on a clear weekday from Tuesday to Thursday, an any time between 8:00 am and 5:00 pm. Severe weather should be avoided. In case of severe weather on the proposed date, data collection should be postponed to the next weather-permitting day within the conditions specified above.

Data collection date and time (one full day):
Wednesday, February 21, 2018
Alternative date in case of severe weather:
Monday, February 25, 2018
Data collection should start at around 9:00 am and finish by 5:00 pm.

Resources:

Human Resources A team of at least four (4) people would be required. Each person is expected to stay next to the equipment while it is deployed on site, for security purposes. One person will be assigned at each of the proposed data collection points. If a fifth person is available, they will rotate so that the other people can take rests.

Sensor Equipment

- The Lidar traffic sensor developed for this project (SEN#1)
- Three (3) camcorders with dust protectors (Sony PXW-Z150) (CAM#1, CAM#2 & CAM#3)
- Two (2) Bluetooth devices (BLU#1 & BLU#2)
- One additional camcorder device (Casecam, or Raspberry Pi camera). This equipment may be replaced by a photo camera. (CAM#4)
- Field laptop and/or Raspberry Pi to connect BLU#2 device.

Other Equipment

- Four (4) tripods, one for each Sony camcorder and LiDar sensor. One stool or standing device for the fourth video-recording device
- Measuring tape to record equipment positioning on site (height, distance from road, etc.)
- Cell phones, at least one of them with photo camera and GPS. Their purpose is to serve as communication device to coordinate field efforts, to take pictures of equipment deployment on site, and to obtain the exact location (latitude and longitude coordinates) where the equipment is set-up.
- Health, Safety & Security (HSS) resources: one safety vest per person, four sets of safety cones (with at least two cones per set).
- Chairs (one per person). Umbrellas may be required to cover personnel and equipment, weather-depending (in case of very light rain or summer sun exposure).
- Two vehicles are preferable to move around the IC.

Deployment:

Notes and pictures should be taken to record details of the equipment deployment on site, such as height, distance from road, and position (GPS coordinates). All equipment should be placed in a unique, steady position during the full data collection process.

The LiDar sensor (SEN#1), one of the camcorders (CAM#1), and one of the Bluetooth devices (BLU#1) should be located as near the port entrance as possible (Zone B in Figure AII.2). SEN#1 should capture traffic in a side-fire position (avoid capturing vehicles while turning). In addition, SEN#1 should be placed in a spot where vehicles travel at constant speed (avoid acceleration and de-acceleration), and are not turning. CAM#1 should be located next to SEN#1, to record all trucks captured by SEN#1.

CAM#4 should be angled so that truck traffic accessing and leaving Van Buren Port is recorded (whether or not using the intermodal connector), for potential use of that data to evaluate port turn-times. In the event this video-camera is replaced by a photo camera, the person in charge at this spot should take a picture of every truck entering or leaving the IC, in such a way that the truck could be identified when comparing two different pictures. Landfill trucks do not need to be photographed. Make sure every picture has a date and time stamp on it.

The other camcorders (CAM#2 and CAM#3) should be located at the other end of the intermodal connector, right before the access/exit ramps of I-540 Exit 3. CAM#2 and BLU#2 are to be located to capture traffic traveling in I-540 northbound direction, on Twin Cir Dr (Zone A in Figure AII.2). CAM#3 is to be located in Riggs Drive, between SH 59 (S 4th St) and I-540 southbound access/exit ramps (Zone C in Figure AII.2). These camcorders should be placed side-fire to the road. The distance between the camcorders and the road should be so that that the complete height of a truck is captured within a single frame of video.

The equipment is proposed to be situated as shown in Figure AII.2. Figure AII.2 shows the current situation of the proposed locations for (a) CAM#1 and SEN#1, (b) CAM#2, and (c) CAM#3, respectively. These pictures were taken during a site visit made on November 8, 2017.

Figure AII.1 - Proposed equipment positions

<u>Field Safety:</u>

Safety precautions must be adopted on site to avoid injuries to personnel and damages to equipment. As a minimum, these precautions include:

- Personnel should wear reflective safety vests, closed shoes and long pants while on the side of the road. Bring clothes suitable for forecasted weather conditions.
- The equipment should be placed on the side of the road, away from the carriageway. Preferably, equipment and personnel should not be standing on the hard shoulder but away from it.
- A set of safety cones or warning triangles should be placed on the shoulder of the road, where the equipment is to be deployed. Proper distance starting at back of equipment on a two lane or undivided highway is: 1st triangle 10' off back on the shoulder, near the white line. 2nd triangle

centers 100' back. 3rd triangle centers 100' ahead of the equipment. The white line-center positioning is to give the oncoming traffic the indication that they need to move left*. (2)*

- In order to avoid vandalism, such as equipment to be stolen, a person should stay together with the equipment during the time it is deployed on site.
- Avoid leaving vehicle(s) parked on the shoulder. Park the vehicle safely on a parking spot and walk to the final equipment position.
- Personnel should bring with them water bottles and light lunch.

Site Conditions:

Figure AII.3 – Current situation of proposed location of CAM#4,, in Zone B

Figure AII.4 – Current situation of proposed location of CAM#2, in Zone A

Figure AII.5– Current situation of proposed location of CAM#3, in Zone C

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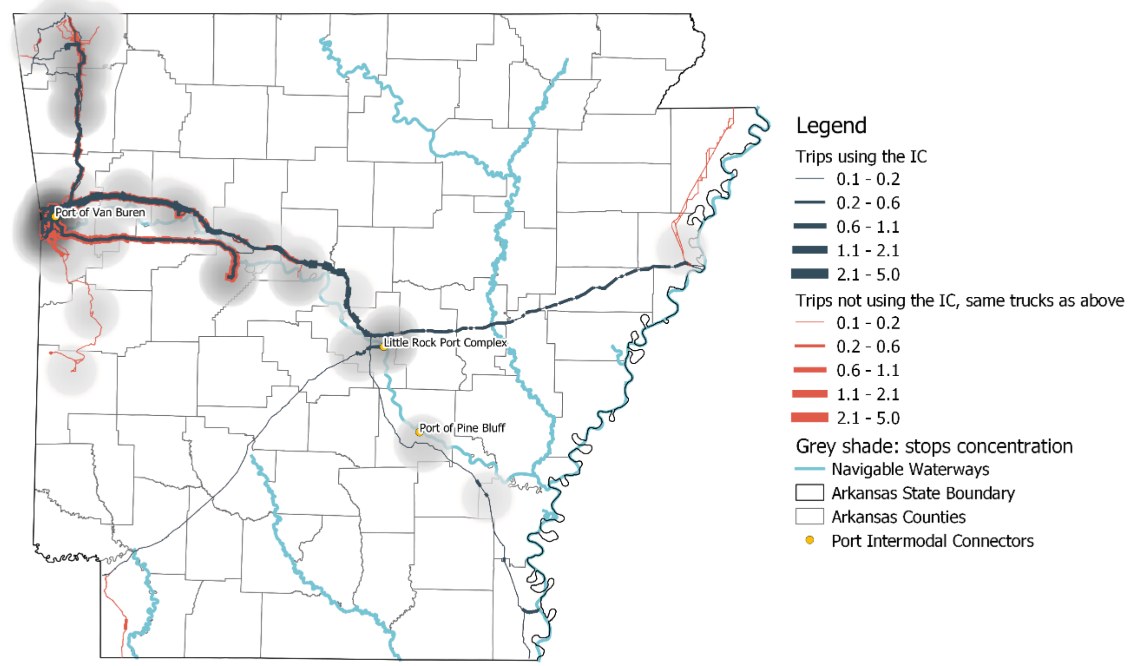
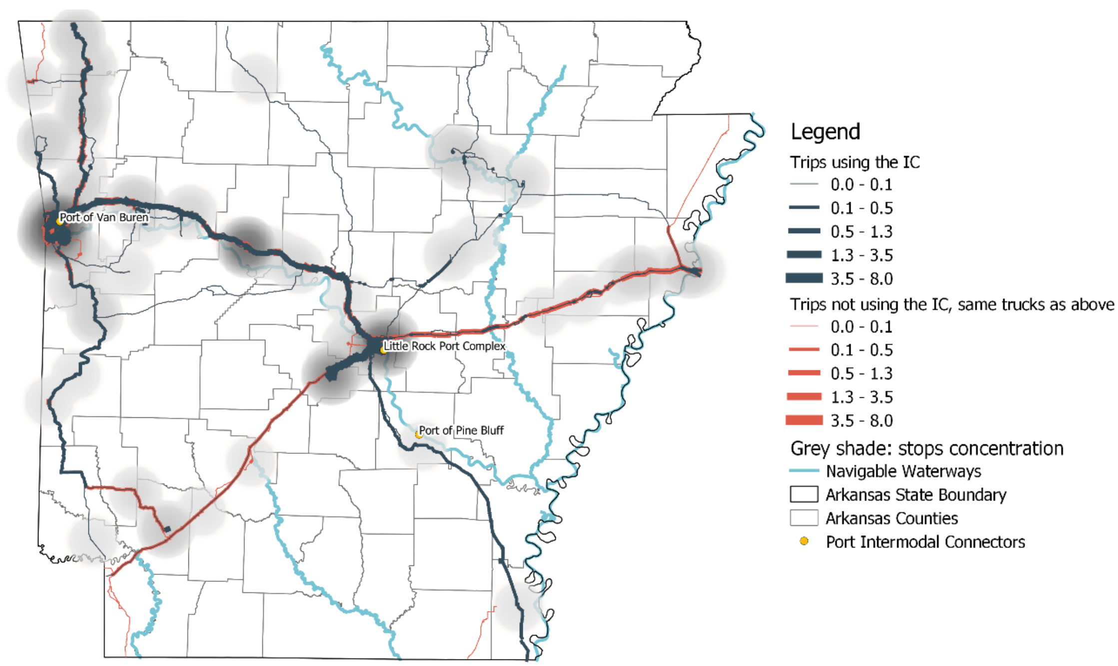
A3. Spatial Analysis of IC Usage per Quarter

Van Buren IC

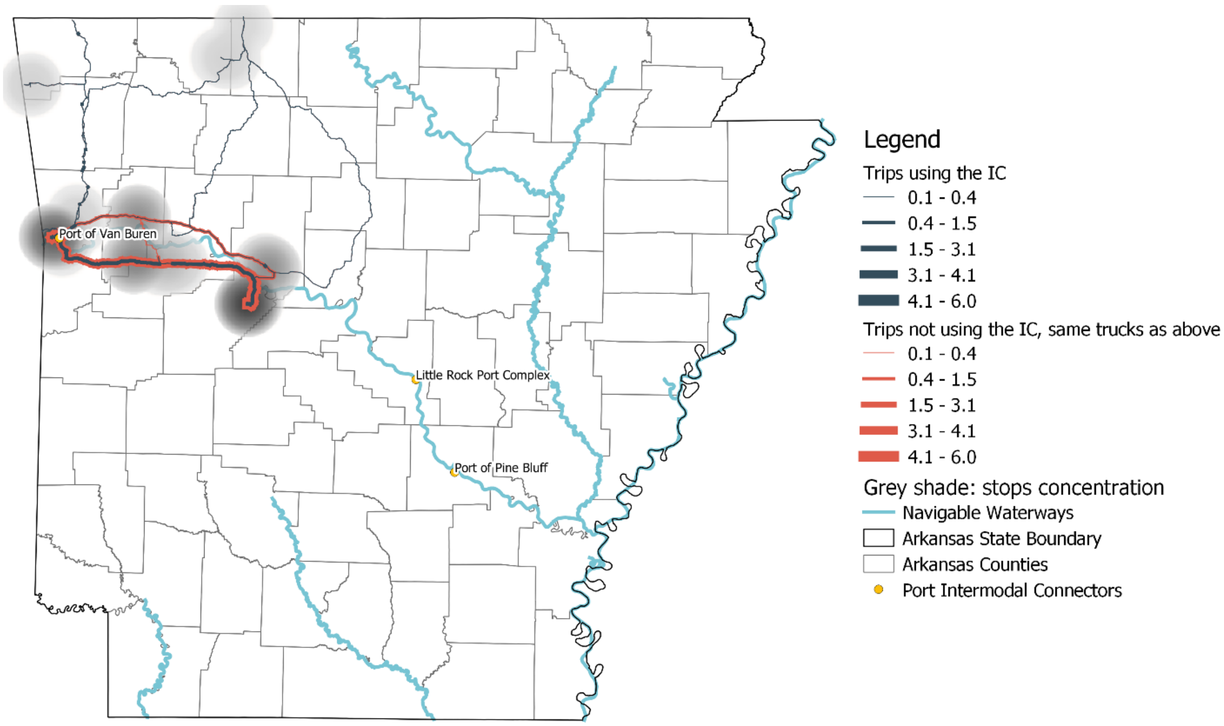
Van Buren IC at port access



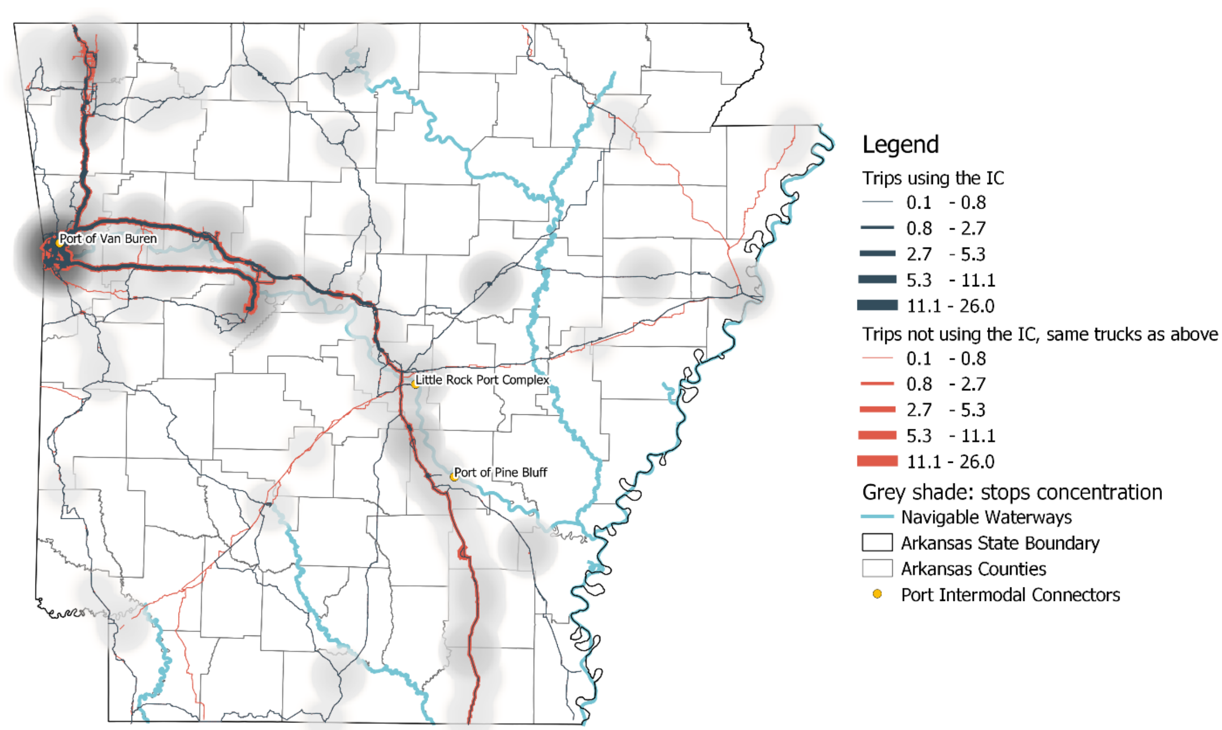
Van Buren Intermodal Connector (IC).
Average daily trips of trucks found on the IC, at port access
1st Quarter 2016.



Van Buren Intermodal Connector (IC).
Average daily trips of trucks found on the IC, at port access
2nd Quarter 2016.

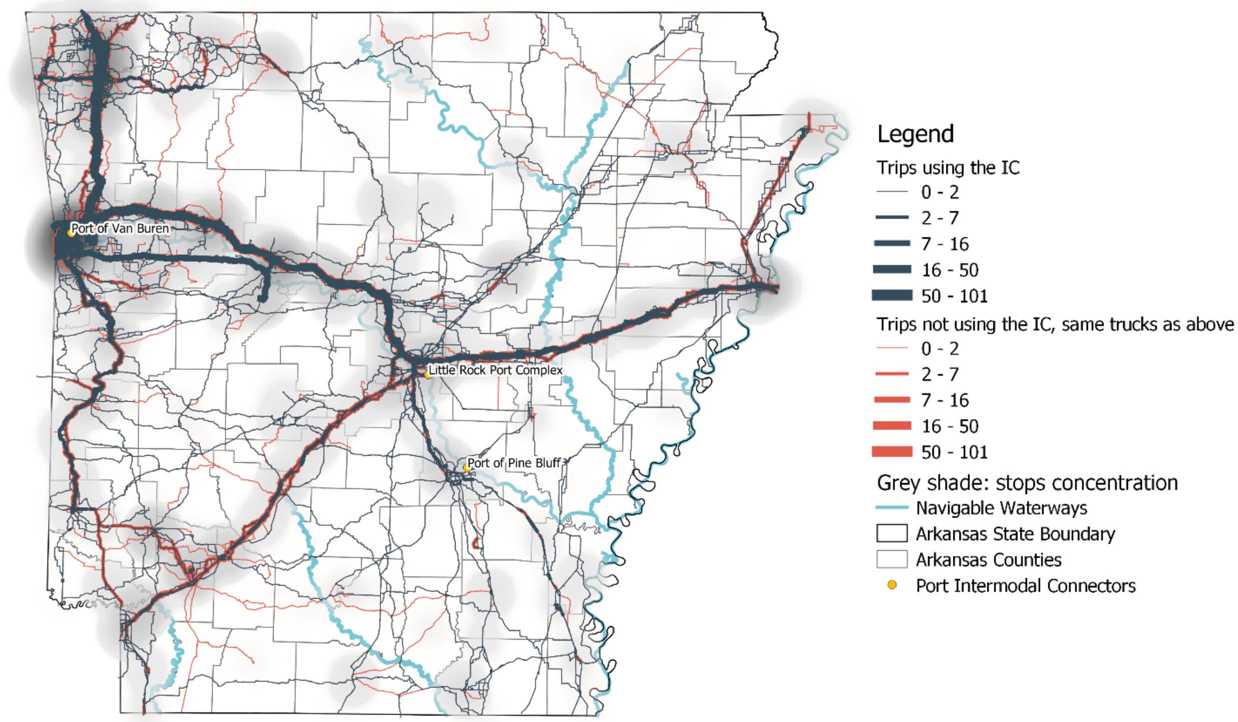


Van Buren Intermodal Connector (IC).
Average daily trips of trucks found on the IC, at port access
3rd Quarter 2016.

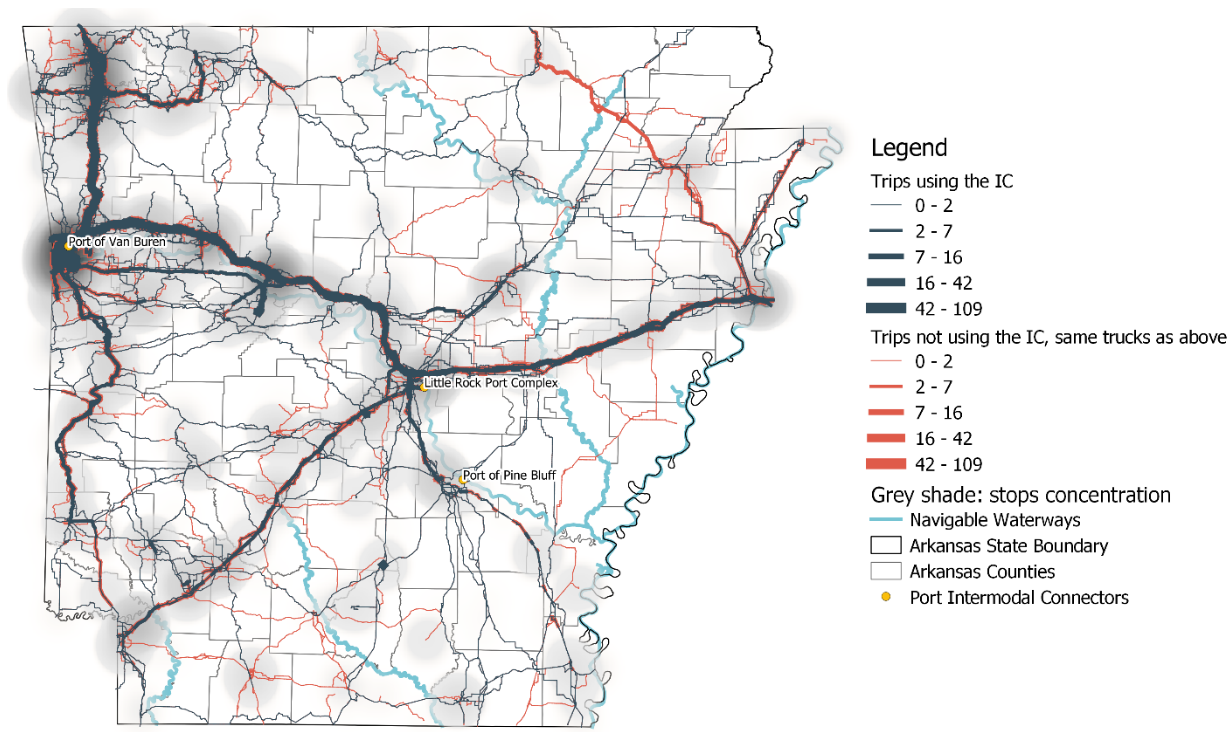


Van Buren Intermodal Connector (IC).
Average daily trips of trucks found on the IC, at port access
4th Quarter 2016.

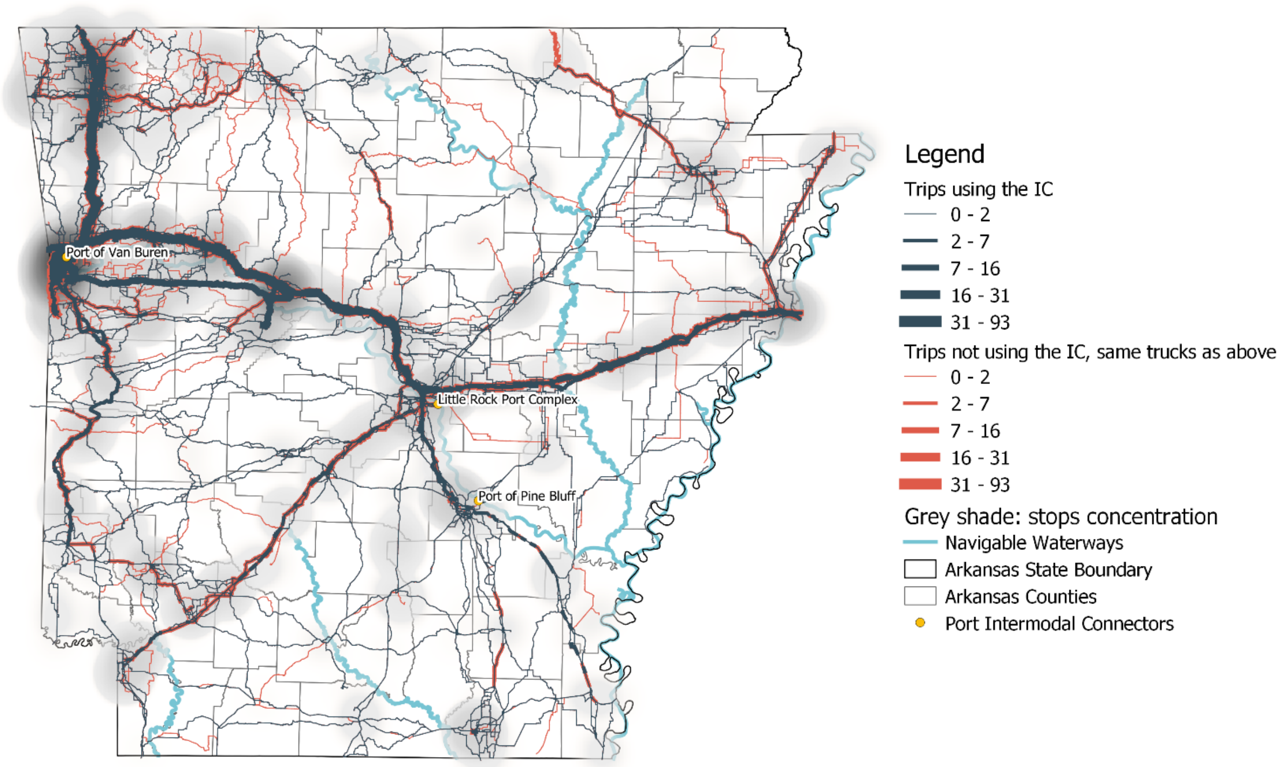
Van Buren IC at intersection near NHS



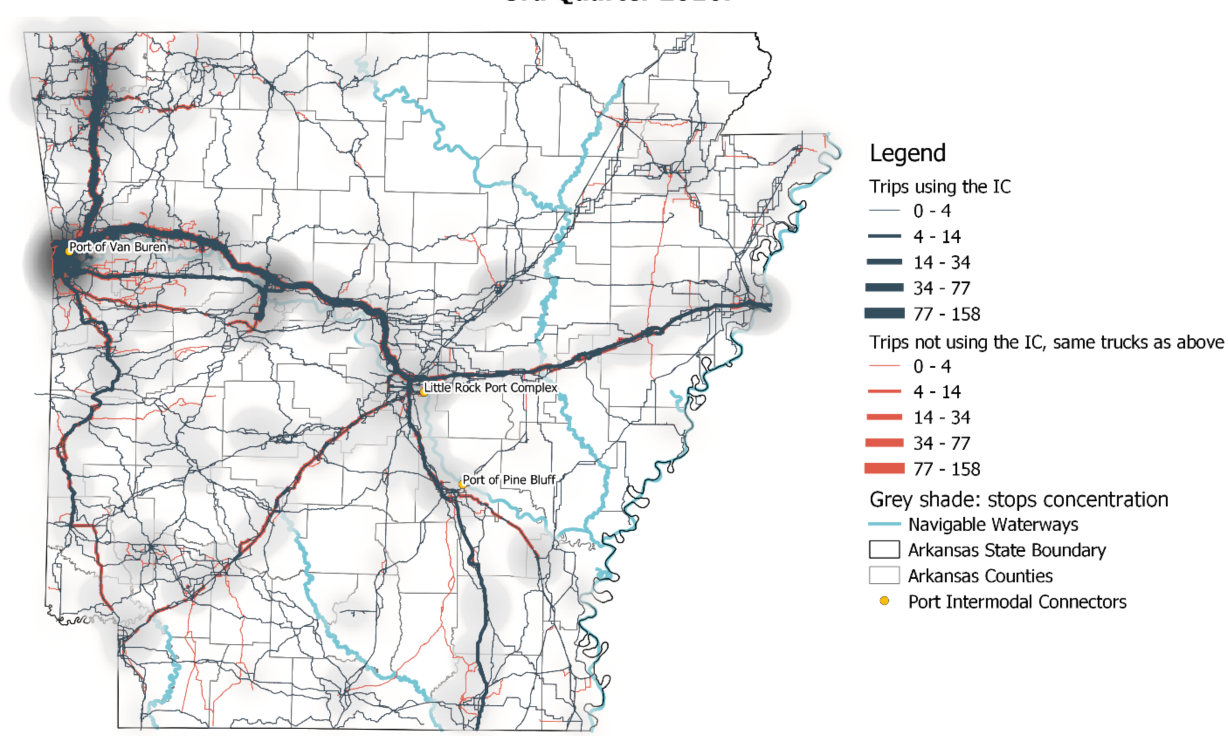
Van Buren Intermodal Connector (IC).
Average daily trips of trucks found on the IC, near NHS
1st Quarter 2016.



Van Buren Intermodal Connector (IC).
Average daily trips of trucks found on the IC, near NHS
2nd Quarter 2016.

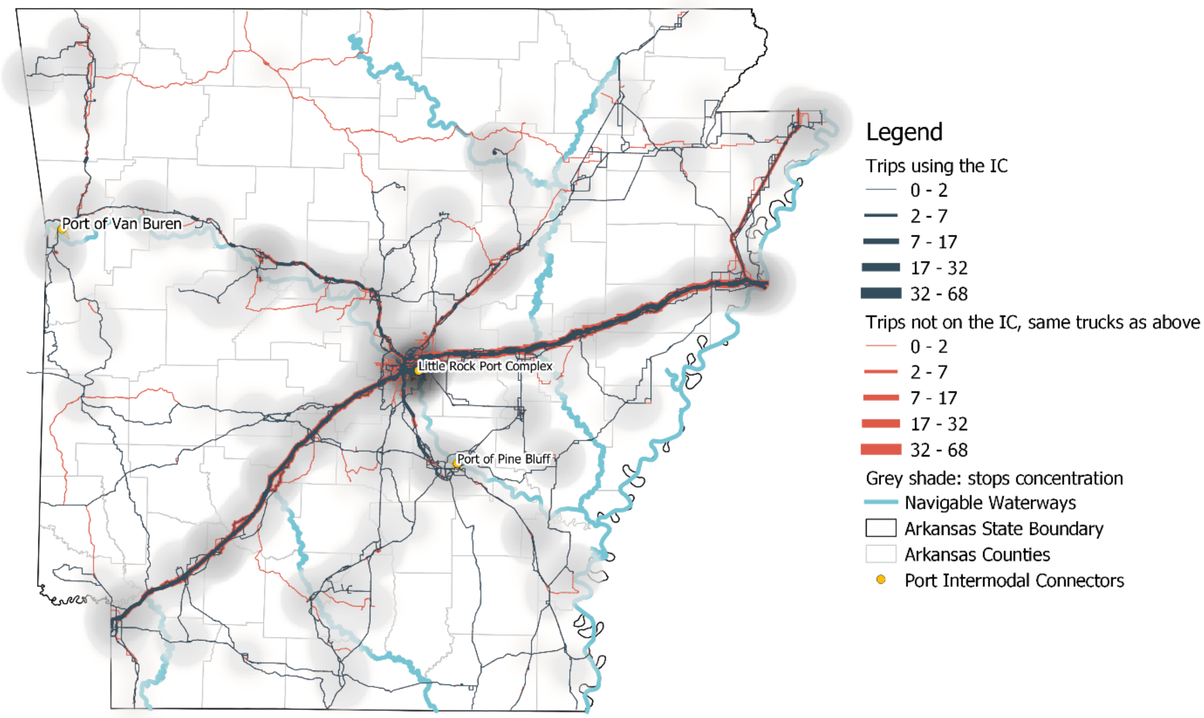


Van Buren Intermodal Connector (IC).
Average daily trips of trucks found on the IC, near NHS
3rd Quarter 2016.

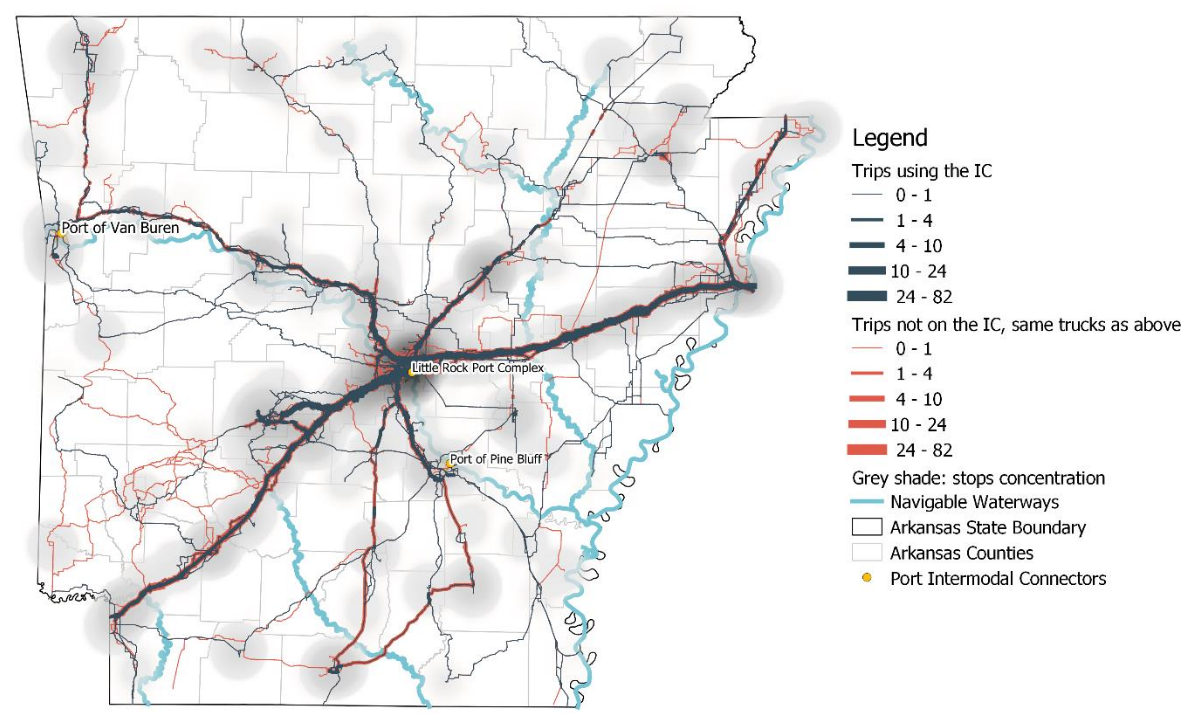


Van Buren Intermodal Connector (IC).
Average daily trips of trucks found on the IC, near NHS
4th Quarter 2016.

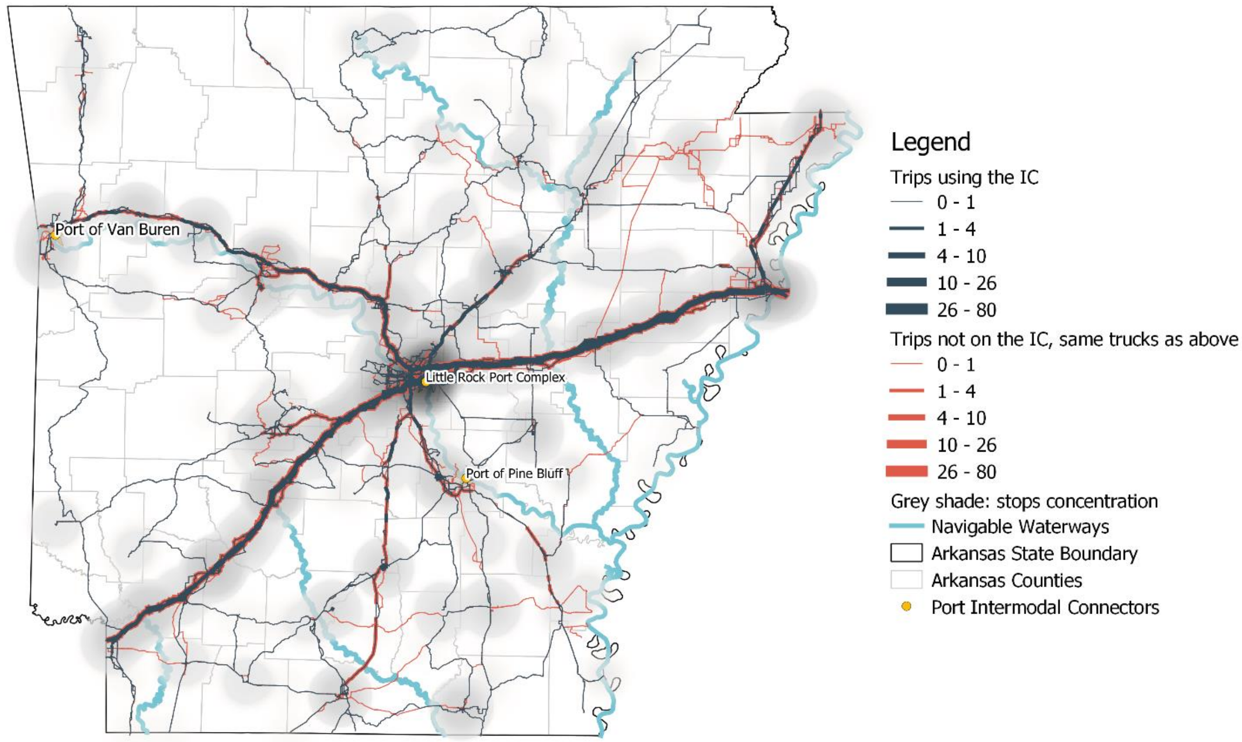
Little Rock IC



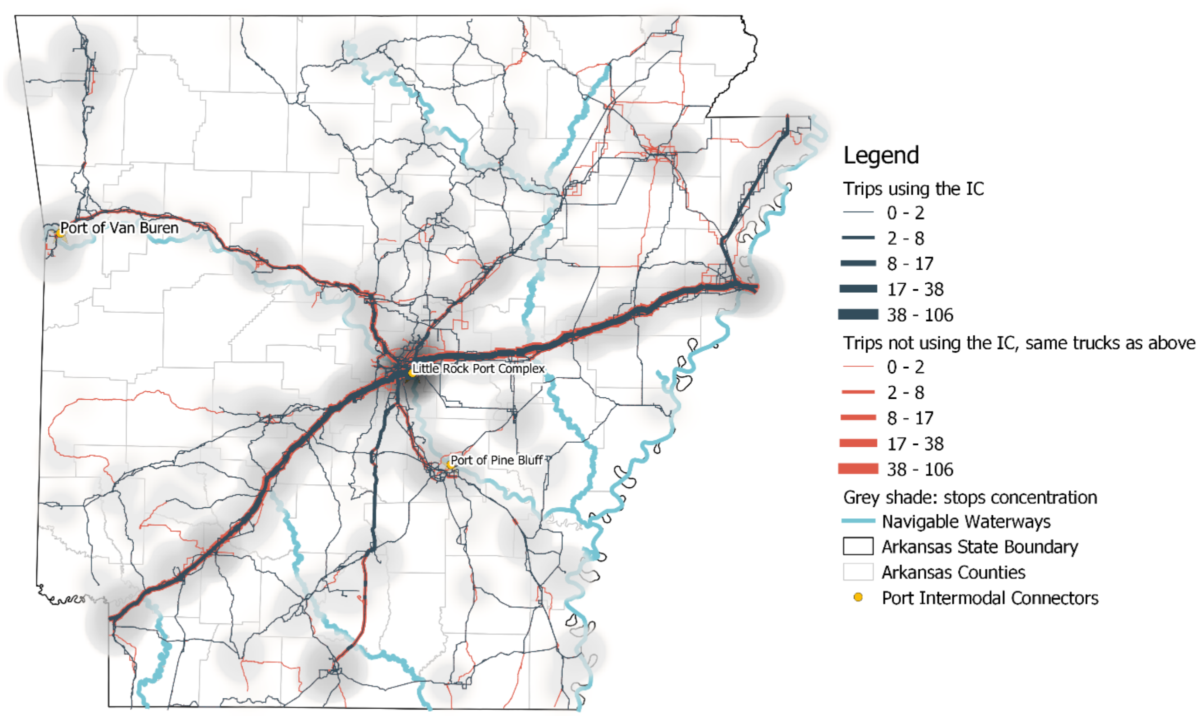
Little Rock Intermodal Connector (IC).
Average daily trips of trucks found on the IC, at port access
1st Quarter 2016.



Little Rock Intermodal Connector (IC).
Average daily trips of trucks found on the IC, at port access
2nd Quarter 2016.



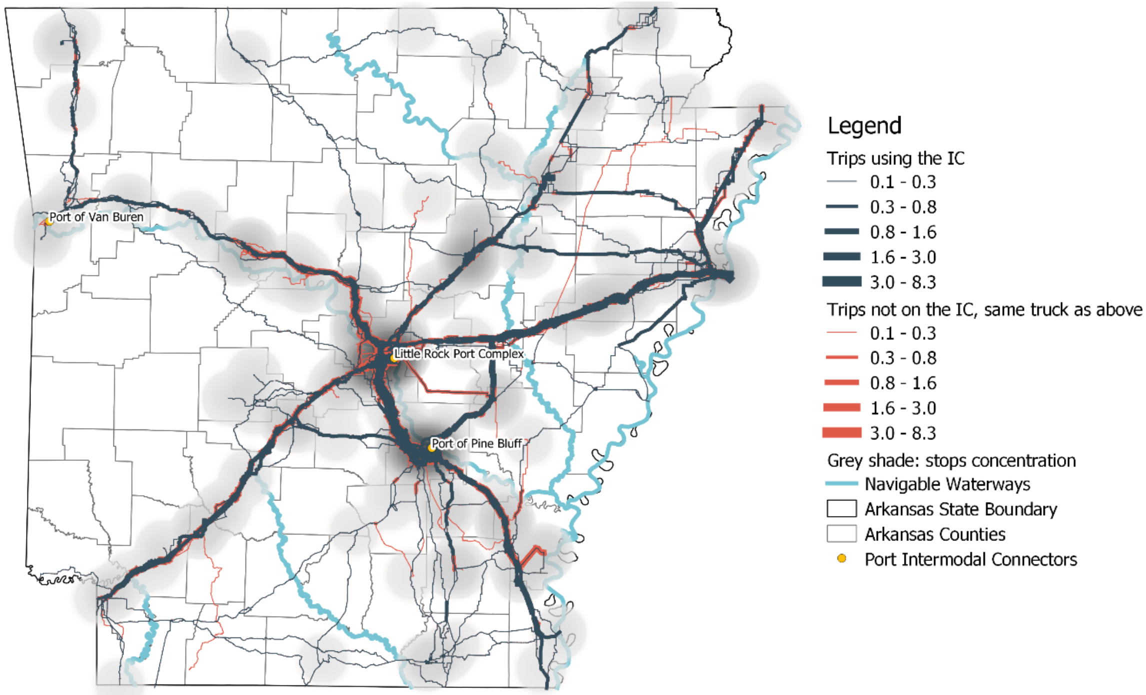
Little Rock Intermodal Connector (IC).
Average daily trips of trucks found on the IC, at port access
3rd Quarter 2016.



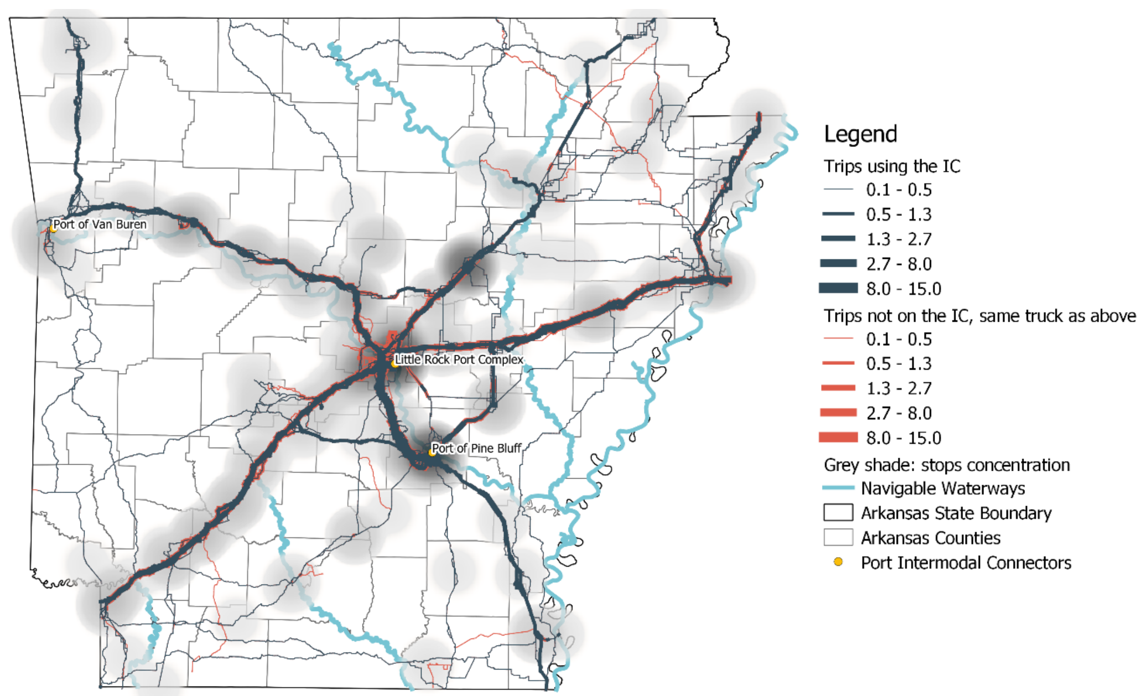
Little Rock Intermodal Connector (IC).
Average daily trips of trucks found on the IC, at port access
4th Quarter 2016.

Pine Bluff

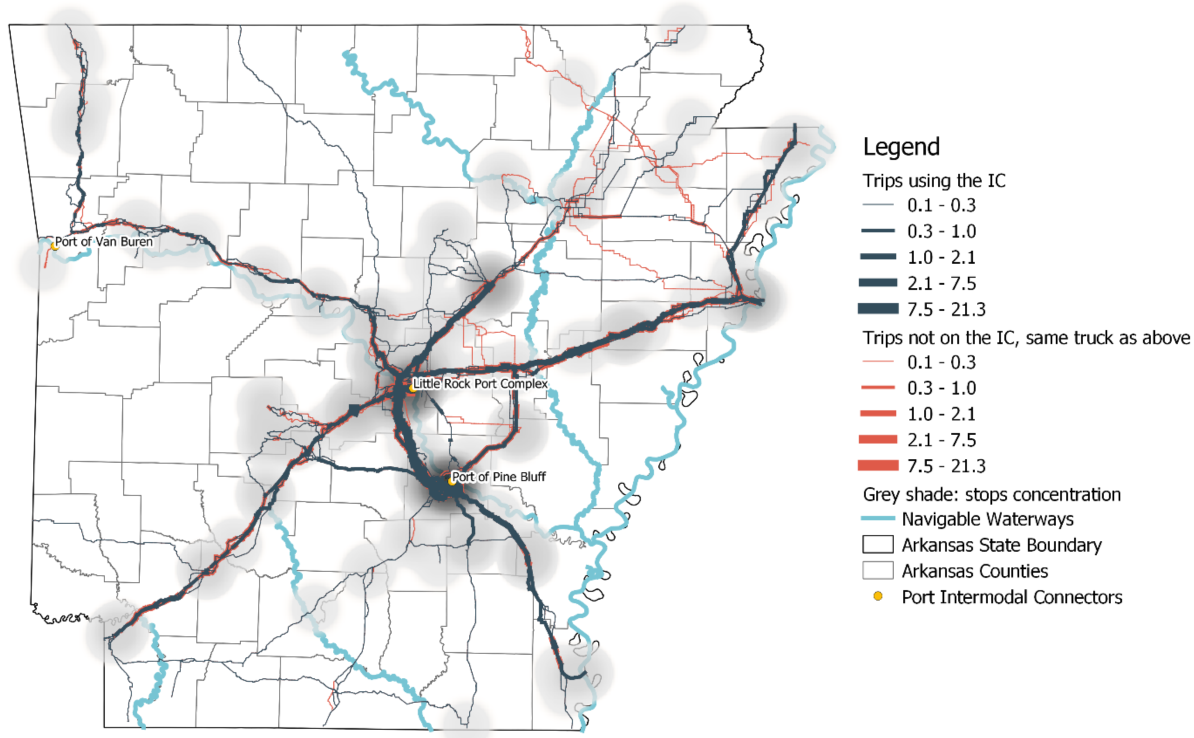
Pine Bluff IC at port access



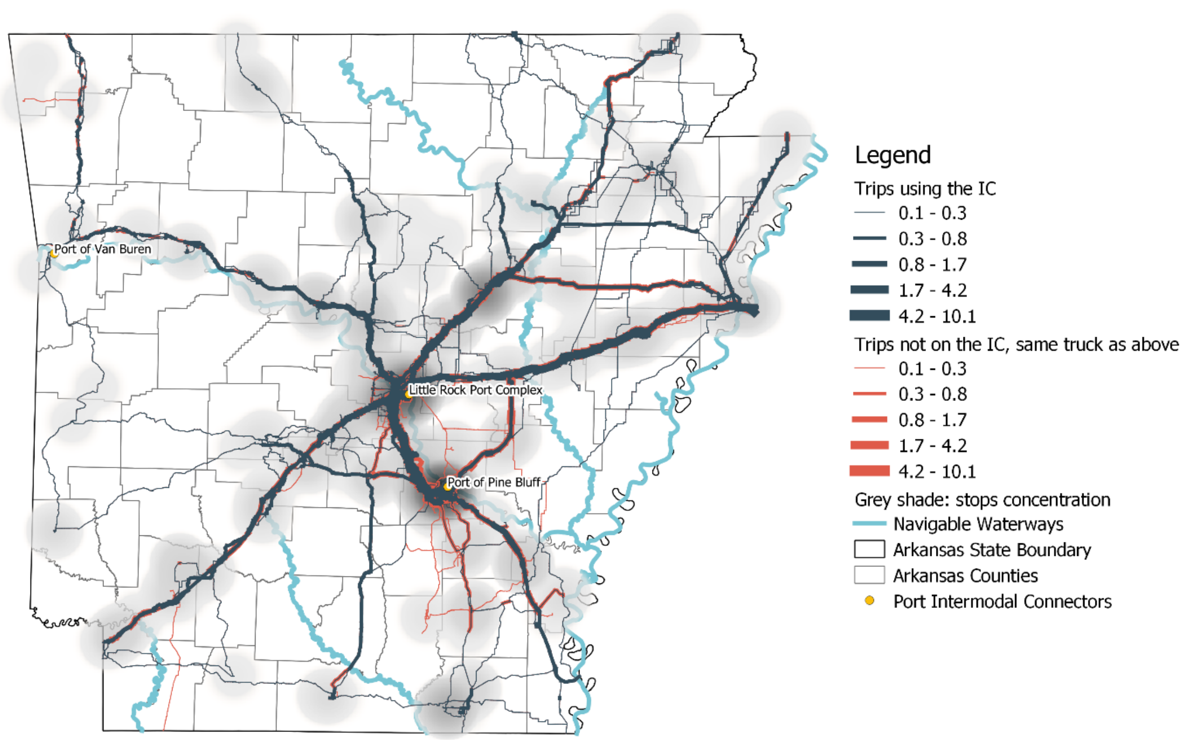
Pine Bluff Intermodal Connector (IC).
Average daily trips of trucks found on the IC, at port access
1st Quarter 2016.



Pine Bluff Intermodal Connector (IC).
Average daily trips of trucks found on the IC, at port access
2nd Quarter 2016.

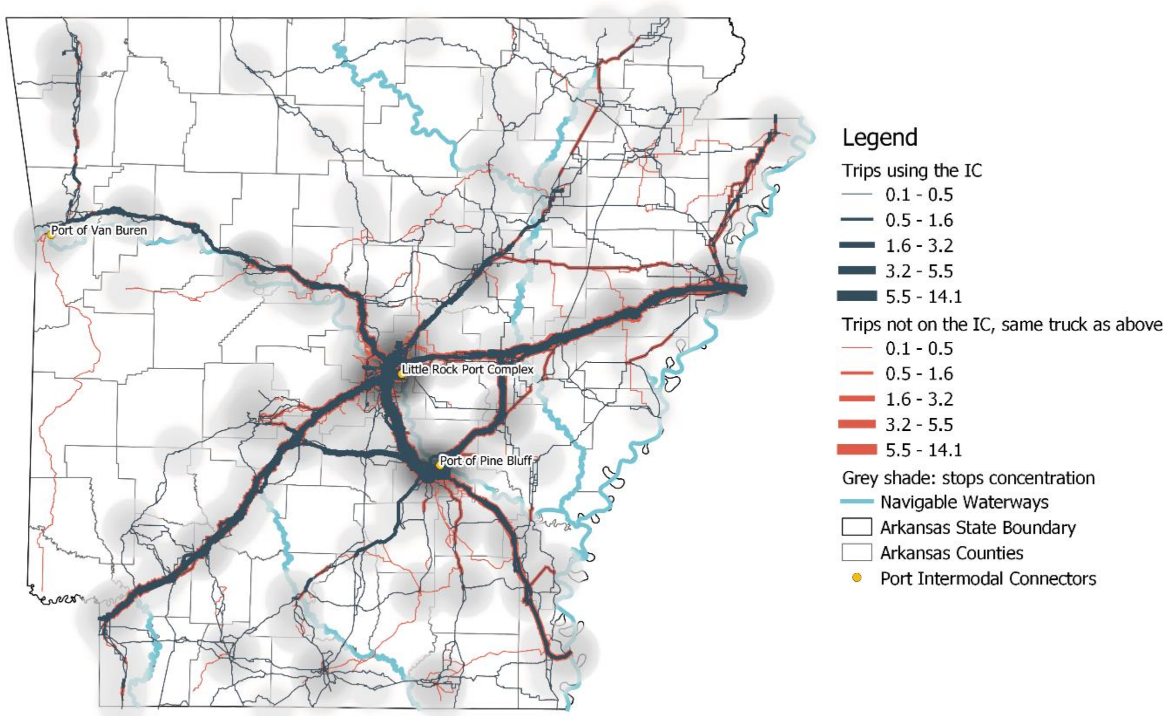


Pine Bluff Intermodal Connector (IC).
Average daily trips of trucks found on the IC, at port access
3rd Quarter 2016.

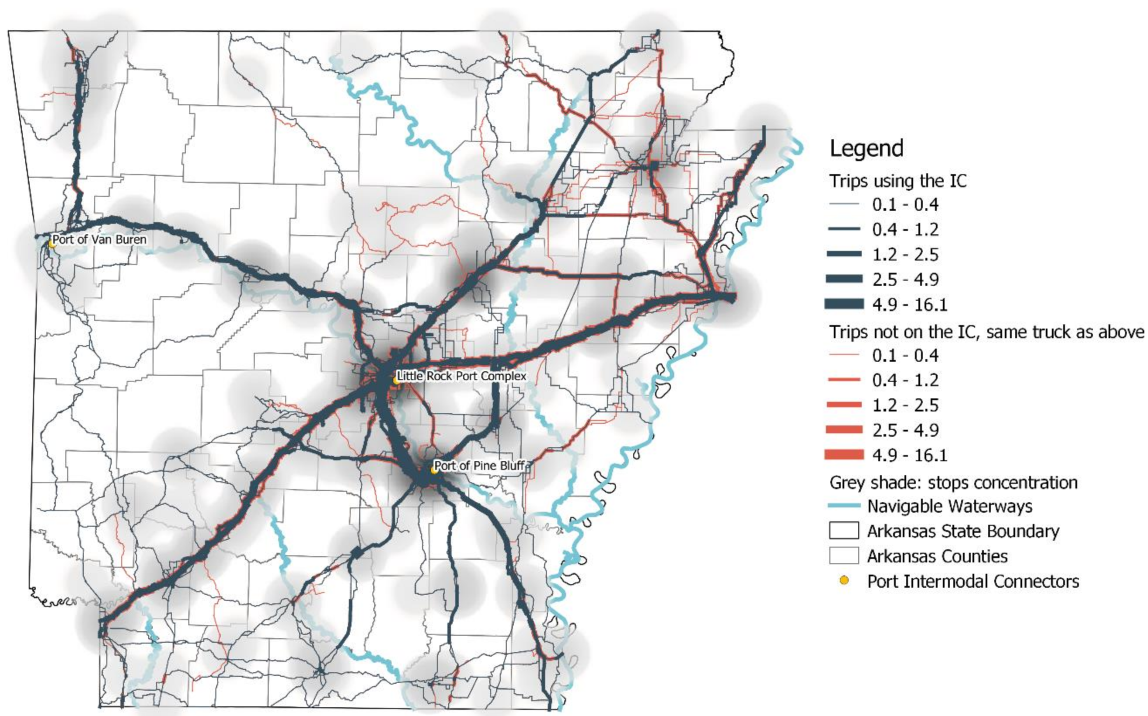


Pine Bluff Intermodal Connector (IC).
Average daily trips of trucks found on the IC, at port access
4th Quarter 2016.

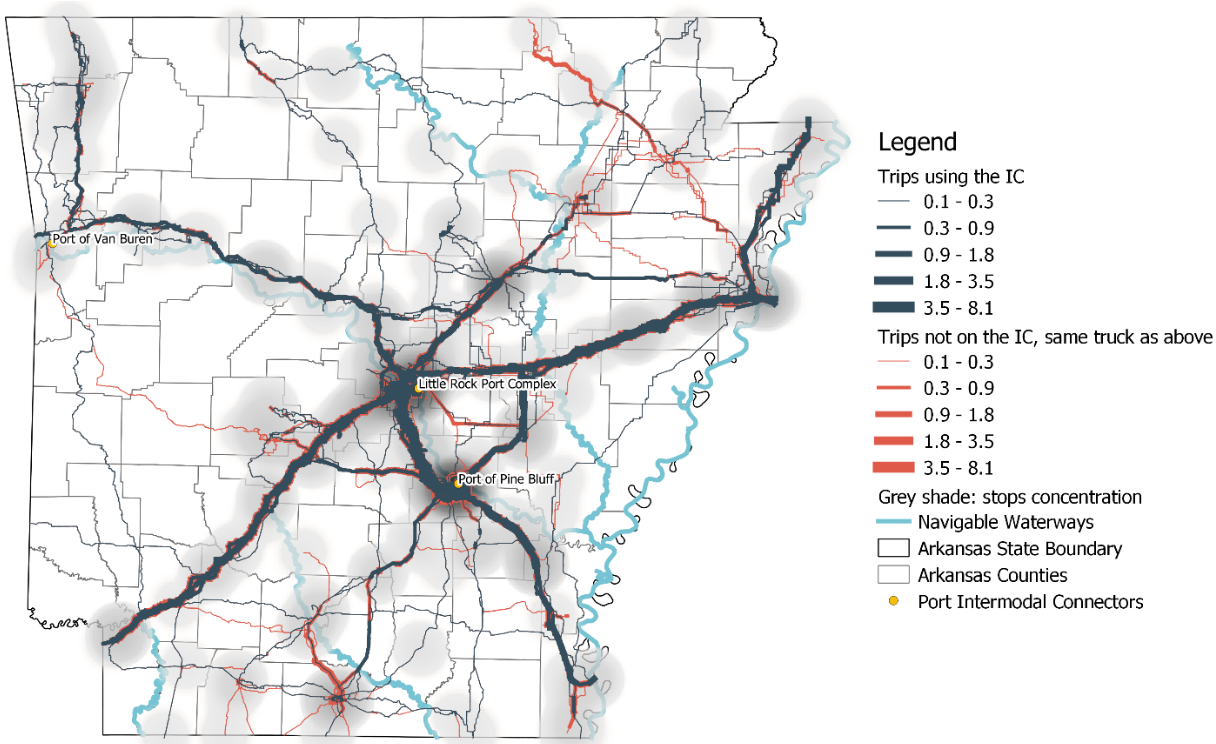
Pine Bluff IC at intersection near NHS



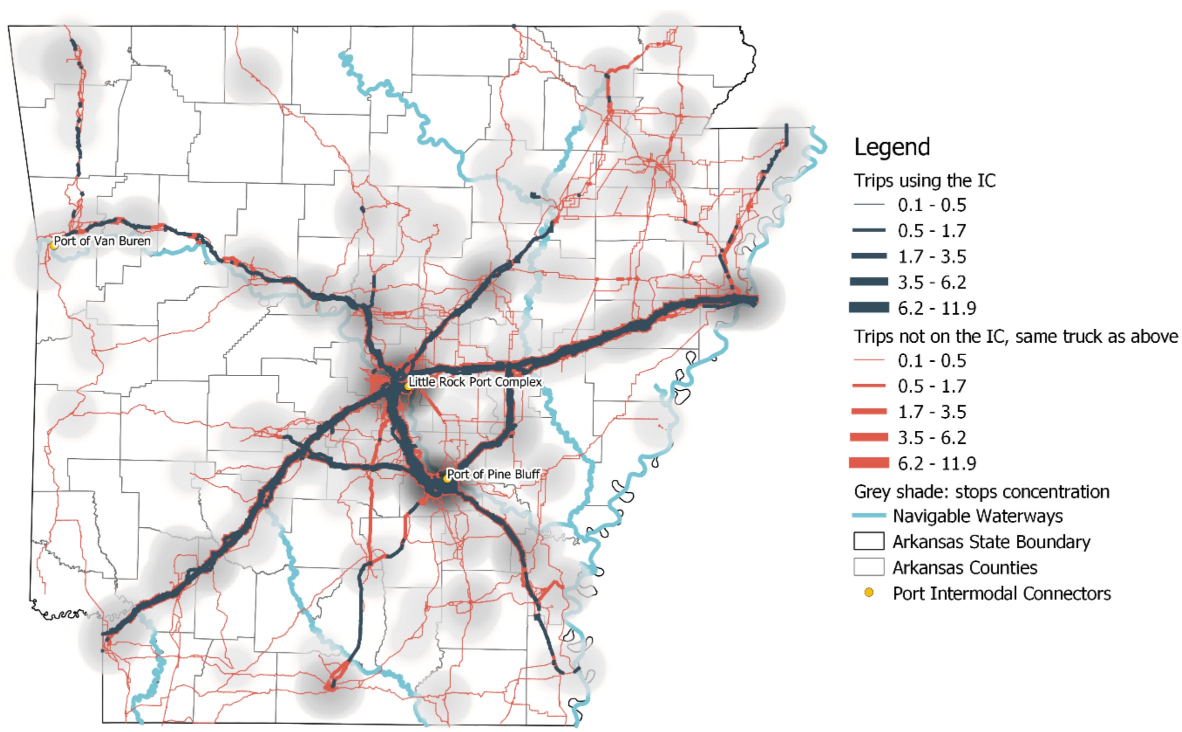
Pine Bluff Intermodal Connector (IC).
Average daily trips of trucks found on the IC, near NHS
1st Quarter 2016.



Pine Bluff Intermodal Connector (IC).
Average daily trips of trucks found on the IC, near NHS
2nd Quarter 2016.



Pine Bluff Intermodal Connector (IC).
Average daily trips of trucks found on the IC, near NHS
3rd Quarter 2016.



Pine Bluff Intermodal Connector (IC).
Average daily trips of trucks found on the IC, near NHS
4th Quarter 2016.