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Combining Truck and Vessel Tracking Data to Estimate Performance and Impacts of Inland Ports

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1 Project Description

1.1 Project Overview and Objectives

The purpose of this project is to estimate the performance of multi-modal supply chains that use inland waterway ports. This is accomplished by developing a method to fuse publicly available datasets including truck and marine vessel tracking data and lock performance data. The study builds on a growing body of research related to multi-modal freight performance measurement, specifically freight fluidity measures. Freight fluidity measurement attempts to capture freight system performance from a multi-modal supply chain perspective. To date, most freight fluidity measures are not truly multi-modal, and rather capture only one end of the supply chain, i.e. the long-haul portion of the trip that uses either truck, rail, or barge. In addition, freight fluidity measures are yet to be implemented on inland waterways. In this study, we effectively combine marine Automatic Identification System (AIS) data with truck Global Positioning System (GPS) data. Both data sources track vessel and vehicle movements and can be used to determine measures such as travel times, dwell times, and other freight activity characteristics. By spatially, temporally, and contextually conflating vehicle tracking data and aggregated commodity data sources (i.e. maritime Lock Performance Monitoring System (LPMS)), it is possible to measure port throughput, vessel to truck ratios, multimodal geographic extents (or freight "catchment areas") of ports, and characterize vessel trips and trip chains by commodity. Each of these derived performance measures can assist freight planners in identifying critical freight corridors and bottlenecks both on the marine and land side. This can ultimately help guide and prioritize investment decisions and be used to develop effective transportation policy.

The specific objectives of this project are to:

I. **spatially, temporally, and contextually conflate AIS data and truck GPS data,**
II. **develop measures of freight fluidity for inland waterway port terminals based on the conflated data, and**
III. **apply the developed performance metrics to inland port terminals in Arkansas to demonstrate value for highway and marine planning activities.**

1.2 Motivation and Contribution

In relation to the objectives of the MarTREC research program, this project contributes to the areas of maritime and multimodal logistics management and infrastructure preservation by providing necessary data for effective (1) freight planning and travel demand modeling efforts, and (2) mode shift analyses. Valuable performance metrics, which constitute parameters commonly used in freight planning and modeling, can be derived from the multi-modal data conflation proposed in this work. These include:

- annual port throughput by commodity, mode, and direction,
- spatial distributions of vessel and truck movements to and from port terminals, allowing for identification of corridors with competition between modes and thus, potential mode shift,
- multimodal vehicle hours and miles travelled to and from port terminals,
- number and identification of unique Traffic Analysis Zones (TAZ) that constitute the origin, destination, or intermediate stop of multimodal shipments to and from a port terminal,
- population and businesses within multimodal port terminal catchment areas,

- vessel dwell time by port terminal,
- travel time share within the multimodal transportation system

Each performance measure has significant implications for long-range freight planning and travel demand modeling practices carried out by the Federal Highway Administration (FHWA) and state Departments of Transportation (DOTs). Commodity based freight forecasting models (**Figure 1**) produce forecasts of vehicle volumes and are used primarily for surface highway project prioritization, project selection, policy development, and policy analysis. In these models, commodity specific payload factors (e.g. tons to vessel/truck ratios) for barge and truck play a critical role in converting from commodity forecasts to network volumes. These payload factors could be greatly enhanced with the multi-modal data conflation proposed in this project. For example, truck GPS data alone does not contain commodity information, but such information may be derived from marine data and used to determine port throughput by commodity.

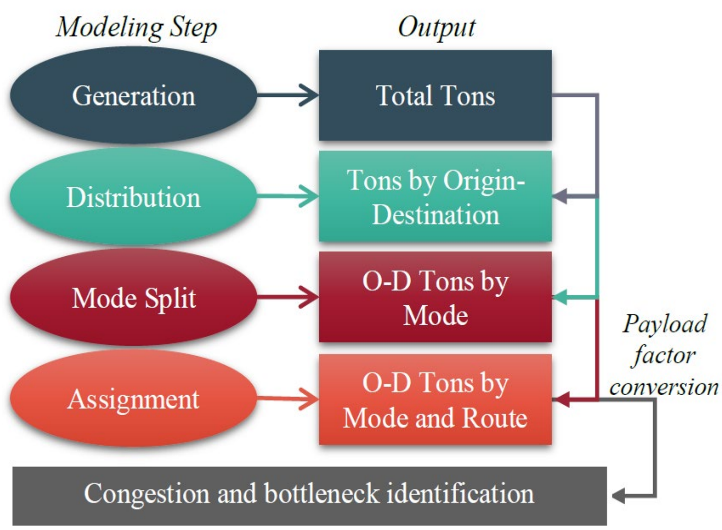


Figure 1. Overview of a standard commodity-based freight travel demand model.

Commodity tonnages are predicted for a forecast year ('Generation') based on industrial sector employment and other predictors and distributed across zones ('Distribution'). Then Origin-Destination (OD) tonnage flows are split among modes ('Mode Split') according to predefined mode percentages or models estimated from costs and travel times. Finally, payload factors are applied to convert OD tonnage flows to vehicles and assigned to the respective network ('Assignment').

Fused multi-modal data can also support mode shift scenario development and policy analysis. For example, mode shift to the U.S. Marine Highway Routes is purported to maximize freight efficiency and preserve existing transportation infrastructure. Insight into port performance indicated by vessel trips characterized by commodity and dwell time, and landside constraints indicated by traffic congestion may explain why port-to-port shipments were made by truck and along the waterways. Overall, by including marine vessel inflow and outflow in the analysis of truck GPS data we have more insight into the volume of commodities shifting between truck and barge, how dwell time and frequency impact landside traffic flows temporally and spatially, and the ways in which land side traffic constraints might affect inland port operations. Through a multi-modal perspective on what affects inland port throughput, we can more effectively allocate resources and direct operations and maintenance programs towards ports and areas that would be likely to experience efficiency gains resulting from mode shifts.

The research objectives highlighted above are in line with the marine transportation system priorities recommended by the U.S. Committee on the Marine Transportation System (CMTS). In particular, some of the recommendations highlighted by CMTS are: i) coordinate and apply big data analytics to reveal research gaps and overlap, foster potential collaboration, manage knowledge, and inform decision-making; ii) couple the newly-available vehicle probe data sets with more traditional freight data resources to quantify and contextualize travel times, dwell times, trip counts and other metrics; iii) create specific MTS system-scale performance indicators that relate to the freight flow network so they may be periodically updated and used for network calibration and validation; iv) develop and use decision support tools to identify nationally significant priority areas and project locations where agencies can leverage a variety of funding opportunities (U.S. Committee on the Marine Transportation System (CMTS), 2018).

1.3 Scope

In the context of inland waterway transportation, more than 25,000 miles of U.S. inland waterways carry about 14% of all domestic freight, representing more than 600 million tons of cargo annually (American Society of Civil Engineers, 2017). In particular, the methodologies developed for this project are applied to the Arkansas portion of the McClellan Kerr-Arkansas River Navigation System (MARNS), which consists of 308 miles of river, and contributes to the national economy with $4,535M in sales, $168M in business taxes, and 33,695 jobs (Nachtmann et al., 2015). Within the next 50 years, the net present value of sales, Gross Domestic Product (GDP), and generated taxes of the MKARNS are expected to be $232.5B, $111.3B, and $7.8B respectively (Oztanriseven et al., 2019). In 2017, the MKARNS transported 11.5M tons of goods, equivalent to 7.7 thousand barges, 443.9 thousand trucks or 115.4 thousand railcars, respectively. There are 43 freight port terminals are located along the Arkansas River (**Figure 2**), and 14 locks divide the river into 13 sections. Each lock chamber on the MKARNS is 110 feet wide by 600 feet long and can handle up to eight barges and a towboat. The U.S. Army Corps of Engineers (USACE) maintains a channel depth of nine feet on the MKARNS, allowing for barges to be loaded up to 1500 short tons (ODOT 2018).

Commodities transported on the MKARNS include iron & steel, fertilizers, petroleum products, minerals & building materials, grain (soybeans, wheat, and others), equipment and machinery, etc. (ODOT 2018). For this project, products transported on the MKARNS are grouped into nine categories, following the Lock Performance Monitoring System (LPMS) scheme (**Table 1**). Crosswalk tables between LPMS and other commodity classification schemes can be found in (US Army Corps of Engineers 2018). The temporal scope is one year. Data from 2016 was gathered from the sources listed in **Table 2**.

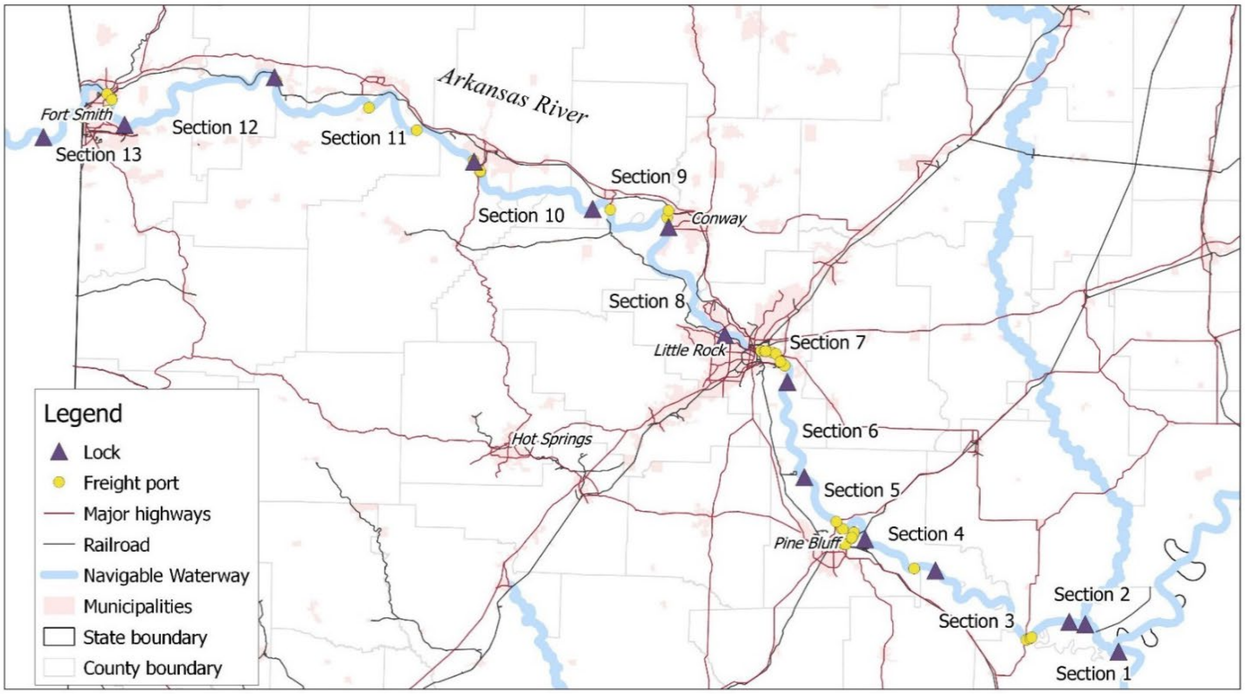


Figure 2. Arkansas portion of the MKARNS

Table 1. LPMS Commodity Classification

Code – Commodity group
10 – Coal, lignite, and coal coke
20 – Petroleum and petroleum products
30 – Chemicals and related products
40 – Crude materials, inedible, except fuels
50 – Primary manufactured goods
60 – Food and farm products
70 – Manufactured equipment and machinery
80 – Waste material
90 – Unknown or not elsewhere classified

Table 2. Datasets Used in This Work

Data type	Brief Description	Entity	Reference
Commodity flow data	LPMS Waterborne monthly commodity data, 2016.	USACE	(U.S. Army Corps of Engineers)
Freight vehicle tracking data	Statewide Truck GPS data, 2016.	ATRI	(American Transportation Research Institute, 2019)
Freight vehicle tracking data	Waterborne AIS data (timestamped geospatial vessel locations), 2016	U.S. Guard & USACE	(Office for Coastal Management, 2018)
Freight vehicle count by location	LPMS: number of commercial vessels per lock, 2016	USACE	(U.S. Army Corps of Engineers, 2018)
Business	County business patterns, 2016	U.S. Census Bureau	(U.S. Census Bureau, 2018)
Demographics	Arkansas TIGER/Line® Shapefiles: Census Tracts	U.S. Census Bureau	(U.S. Census Bureau, 2019b)
Geopolitical boundaries	Traffic Analysis Zones polygon layer	Arkansas Department of Transportation	AR-STDM zone layer (Alliance Transportation Group, 2015)

1.4 Background

1.4.1 Freight Fluidity

Given the complexity of the multimodal freight transportation system, there has been increased interest in developing multimodal "freight fluidity" indicators that capture end-to-end supply chain performance (Transportation Research Board 2014). Freight fluidity is a measure of the ease at which freight (in quantities of tonnage or volume) can move through the multi-modal supply chain. Fluidity indicators were first introduced by Transport Canada with the purpose of evaluating the efficiency and competitiveness of the multimodal transportation system, by examining how gateways and key multimodal freight corridors interact operationally (Transport Canada 2012).

Focused on the time component, end-to-end supply chain performance is examined, and capacity and demand of the multimodal system is evaluated by determining issues and bottlenecks that affect the efficiency of international freight flows. In particular, Transport Canada measures freight fluidity as the total transit time of inbound containers from overseas markets to strategic North American inland destinations via various Canadian gateways (Transport Canada 2017). Since there is no single data source (or provider) that can capture transit time data for the entire container trip, total transit times are calculated by summing all mode segments of end-to-end movement (Transport Canada 2012).

Transport Canada collects and publishes monthly port performance indicators for key gateways. Five ports are considered in the set of gateways and the following metrics are reported for each: average truck turnaround time (minutes), berth utilization (TEU/meter of workable berth), average vessel turnaround time (measured both in hours and seconds/TEU), average container dwell time (days), dwell target (percentage under 72 hours), port productivity (TEU/gross Ha), vessel on-time performance, crane productivity (lifts per hour), number of vessel calls per month, average number of TEU per vessel call per month, and container throughput (number per month) (Bureau of Transportation Statistics 2017).

In the U.S., an application of multi-modal freight flows encompassing the end-to-end trip of goods (e.g., port-rail-highway-customer) such as the one Canada has implemented has not yet been developed (FHWA 2017). The FHWA is leading national efforts to implement freight fluidity system performance measures and analysis. In particular, the I-95 Corridor Coalition and the U.S. Department of Commerce are applying the concept of fluidity to major supply chains and corridors. However, those efforts are currently limited to the use of truck probe data.

In Maryland, the I-95 Corridor Coalition gathers the following freight fluidity metrics: approach travel time index, buffer time index, planning time index, truck volume, truck miles of travel, and vehicle miles of travel (Cambridge Systematics, Inc. 2011). Such measures are obtained for critical supply chains, and updated on a quarterly basis on a database, GIS mapping, and dashboard visualization tools that help to better communicate this information to decision makers (I-95 Corridor Coalition 2019). Such mapping and visualization tools are the basis to understand origin-destination patterns, resiliency, and reliability for public officers to identify and monitor the performance of critical freight corridors (Eisele, et al. 2016) (Transportation Research Board 2018). Similarly, the North American Transportation Statistics Interchange apply the fluidity concept using probe data to the North American Free Trade Agreement (NAFTA) corridor from Windsor, Ontario to Nueva Laredo, Mexico. These efforts focus on the use of truck probe data and will supplement multi-modal data as their projects progress, to illustrate the performance of multi-modal connections (FHWA 2017).

Contributing to the measurement of multimodal transportation system performance and freight fluidity, the USACE developed several applications of fluidity using Automatic Identification System (AIS) data, namely: i) Lock operations management (interactions between individual vessel operators and the system), ii) Inland Marine Transportation System Travel Time Atlas (under development, will include travel time, travel time reliability, and port terminal dwell time); and iii) Port Fluidity Performance Measurement Methodology (port system time from anchorage to exit, cycle time from entrance to channel exit, travel time, travel time indices) (Transportation Research Board 2018). For the development of the Inland Marine Transportation System Travel Time Atlas, USACE produces travel time estimates for key waterway segments, updated quarterly. Travel time is estimated from AIS historical data, allowing reports generated on a variety of spatial scales (DiJoseph and Mitchell 2015). The output is presented in vessel travel time tables that summarize the 25th, 50th, and 75th percentile travel times between inland waterway ports that constitute origin-destination pairs per river segment (Kress, et al. 2016).

1.4.2 Port Performance Metrics

Data on port throughput by commodity can be used by public agencies and private investors to identify opportunities for port capability and capacity expansion at existing or new facilities. While data about the commodity flows through each port may be collected by port operators, this data is proprietary and is not regularly shared with public agencies. Publicly available maritime port statistics, namely the Port Performance Freight Statistics Program introduced by the U.S. Bureau of Transportation Statistics, informs port throughput and capacity metrics, as well as dwell times (**Table 3**). However, the Port Performance Freight Statistics is limited to the top-25 ports in the US (U.S. Department of Transportation, 2019), which excludes most inland waterway ports. Notably, the USACE collects comprehensive port throughput and vessel cargo by commodity through the Waterborne Commerce Statistics Center (WSCS) (U.S. Army Corps of Engineers, 2018), but such datasets have limitations. First, the data is collected from manually-completed surveys and are thus prone to human error. Second, the data is confidential and its use is restricted to collecting agencies, thus it is not available in the public domain (U.S. Army Corps of Engineers, 2018).

The purpose of this project is to create methods for fusing multi-modal freight data to quantify and describe port and vessel trip level commodity flows along inland waterways from publicly available datasets. Port-level commodity throughput linking waterborne and roadway freight flows supports the development of commodity-specific, multimodal freight fluidity performance measures.

Table 3. Port Performance Freight Statistics Measures
(U.S. Department of Transportation, Bureau of Transportation Statitics 2020)

Port Throughput Metrics	Annual total tonnage (domestic, foreign, import, export, and total short tons)
	Annual container throughput (inbound loaded, outbound loaded, empty, and total TEU)
	Annual dry bulk tonnage (domestic, foreign, import, export, and total short tons)
	Annual Roll-on/Roll-off units (total units)
	Annual vessel calls by vessel type (current and percent change from previous year)
	Top food and farm products (total short tons and percentage share of total)
	Top commodities (total short tons and percentage share of total)
Vessel Dwell Times	Average container vessel dwell time
	Average liquid bulk vessel (tanker) dwell time
	Average Roll-on/Roll-off vessel dwell time
Port Capacity Metrics	Channel depth (feet)
	Air draft restrictions (vertical clearance in feet)
	Berth length for container ships (feet)
	Container terminal size (acreage)
	Number and type of container cranes
	Presence of rail transfer facilities

1.4.3 Public Datasets for Performance Evaluation and Fusion Needs

This report explores the use of vehicle tracking data, namely AIS and truck GPS, and aggregated commodity data from the USACE LPMS to derive freight port and waterway system performance. Data used in this project is summarized in **Table 4**.

Table 4. Datasets Characteristics

Datasets Characteristics	Automatic Identification System (AIS) data	Lock Performance Monitoring System (LPMS) data	Truck Global Positioning System (GPS) data
Mode	Maritime	Maritime	Truck
Relevant data values provided	Vessel location (latitude & longitude), timestamp, vessel characteristics	Monthly tonnage of commodities observed in each lock	Anonymous heavy truck location (latitude & longitude), timestamp
Geographical coverage	All waterways	All U.S. inland waterways where lock & dams are located	All U.S. territory
Temporal coverage & update frequency	Temporal disaggregation to the minute of each day. Public file updated annually	Monthly aggregates, updated annually	Temporal disaggregation to the minute of each day
Commodity	No commodity available	36 commodities in 9 groups	No commodity available
Cost & availability	Free download from MARAD website	Free download for current and last year from USACE website	For purchase from private vendors

1.4.3.1 Lock Performance Monitoring System

The Lock Performance Monitoring System (LPMS) is operated and maintained by the U.S. Army Corps of Engineers (USACE). The USACE collects data of a complete sample of U.S. flag vessels and foreign vessels operating in U.S. waterways that transit a USACE-owned or operated lock structure; which is managed and shared by the Navigation Data Center (NDC) (U.S. Army Corps of Engineers). Publicly available records summarize annual and monthly tonnage of 36 commodities carried by vessels at each lock chamber and direction. Commodities are aggregated into nine commodity groups (**Table 1**). In addition, LPMS records all vessels that traverse each of approximately 200 locks and dams along the U.S. inland waterways, constituting a valuable source of data to evaluate coverage of AIS. Historical lockage data (1993-2017) is openly available in (U.A. Army Corps of Engineers, 2018c). Details on specific companies or commodities are confidential and not included in the public dataset. In addition, the database provides information about the total number of loaded and empty barges, and number of vessels observed at each lock chamber by type. Examples of vessel types are: tows, recreation, commercial, and other. The information is organized in a series of reports, available in .pdf and .xlsx format. For example, annual summaries of lock use, performance, and characteristics are available in a Commodity report, a Lock usage report, and an Unavailability report (U.S. Army Corps of Engineers, 2018c). Monthly tonnage summaries per commodity and lock chamber are available for download in excel format for the current and previous year exclusively (U.S. Army Corps of Engineers, 2016).

1.4.3.2 Automatic Identification System (AIS)

The AIS consists of vessel's traffic data, collected for navigational safety purposes (collision avoidance). It is required for all passenger vessels and all commercial vessels over 300 gross tonnage that travel internationally, by the International Maritime Organization (IMO), since December 2004. An onboard navigation device transmits location and characteristics of large vessels in real time. The receivers are base stations on shore, buoys, satellites, and other vessels (U.S. Department of Homeland Security). In the U.S., AIS data is collected by the U.S. Coast Guard in U.S. waterways. For inland waterways, AIS is mandatory in the Ohio River, between Mileposts 593 and 606, when the McAlpine upper pool gauge is at approximately 13.0 ft or above, and in the Lower Mississippi River, up to 20 mi above Baton Rouge, Louisiana, at Milepost 254.5 (Dobbins et al., 2013). Even though AIS is not currently required in most U.S. inland waterways, most vessels are using the AIS transponder (DiJoseph and Mitchell 2015). Historical AIS data (2009-2017) is organized in file geodatabases, including vessel, voyage, and broadcasting information, and it is available for free download at (NOAA Office for Coastal Management, 2018). Examples of vessel data elements are: Vessel name, length, width, and MMSI. Voyage data elements include destination, cargo, draught, ETA, etc. Notably, several of these features are entered to the database manually, and contain substantial errors and omissions. For example, cargo details are too broad to provide any meaningful information pertaining the commodity carried by each vessel. Examples of broadcasting features are: location, speed over ground, course over ground, heading, status, etc. Each file contains point location data at 1-minute interval, per month and UMT zone (NOAA Office for Coastal Management, 2018). In addition to vessel positioning, AIS captures information that may be used for freight planning purposes. In particular, AIS data includes the type of vessel, size, and the potential ability to track a vessel path with time stamps. This information is suitable to identify freight flows though U.S. inland navigable waterways, and in combination with highway and USACE Locks data, constitute a valuable source for freight planning purposes. The main limitation of AIS data is its lack of information about the commodity carried by vessels, which is complemented by combining AIS and LPMS data. The USACE has used AIS data to evaluate travel time and reliability on waterways (Transportation Research Board, 2014), but it is yet to be integrated with truck GPS data and with commodity databases to evaluate multimodal freight fluidity.

AIS data coverage differs by region and/or port. In the Gulf Coast region, Perez at al. (2009) compared tug counts by port derived from AIS data with WCUS data concluding that AIS data accurately represented activity in the biggest port area, but overestimated or underestimated activity in smaller port areas, potentially due to the presence of fewer AIS reception points (Perez, et al. 2009). Dobbins and Langsdon (2013) generated inland waterway one-day tow-trips from AIS data collected by a single AIS antenna and compared them to lockages reported by the USACE's Lock Performance Monitoring System (LPMS). They found that LPMS lockages were three times higher than AIS-detected lockages. A coefficient of coverage was calculated to estimate the total number of vessels and trips traveling on the waterway (Eq. 1).

$$Coefficient\ of\ Coverage = \frac{Unprocessed\ AIS\ data\ lockages}{LPMS\ data\ lockages} \qquad 1$$

Where,

"Unprocessed AIS data lockages" is the annual number of tugs observed from the reduced AIS data in transit through each of the locks located in the study area, and

"LPMS data lockages" is the annual number of commercial vessels reported by LPMS for the same locks during the same time period (U.S. Army Corps of Engineers USACE Digital Library - Public lock reports).

To estimate the number of tugs observed in the AIS data in transit through the locks ("Unprocessed AIS data lockages"), each AIS data point (latitude-longitude) was connected with a straight line, e.g., referred to as 'point-to-path' in most GIS packages. Then, a screenline approach was used such that point-to-path geometries of tugs/tows that intersected locks (represented by line segments) were counted as vessels in transit through the lock. Overall, the reduced AIS data sample used in this case study represents 91% of commercial vessels operating on the MKARNS during 2016. Coverage varies per lock, possibly indicating that the AIS sample excluded more vessels observed in the proximity of the locks where a lower coefficient of coverage was found, i.e. in the proximity of the Oklahoma portion of the MKARNS (**Table 5**).

Table 5 Coefficient of Coverage of AIS Data

State	Lock & Dam Name	MKARNS Mileage	Commercial Vessels		Coefficient of Coverage
			AIS	LPMS	
Arkansas	NORRELL	10	1,071	1,100	84.0%
	WILBUR D MILLS	13	1,062	1,126	82.2%
	JOE HARDIN	50	1,039	1,096	91.1%
	EMMETT SANDERS	66	1,077	1,148	91.0%
	COL CHARLES D MAYNARD	86	978	1,082	88.2%
	DAVID D. TERRY	108	966	1,057	90.0%
	MURRAY	125	801	858	90.1%
	TOAD SUCK FERRY	156	948	1,195	71.2%
	ARTHUR V. ORMOND	177	784	831	78.0%
	DARDANELLE	206	788	819	72.3%
	OZARK	257	712	771	59.1%
	JAMES W. TRIMBLE	293	726	784	53.6%
Oklahoma	W.D. MAYO	320	875	1,051	43.2%
	Grand Total		**10,756**	**11,818**	**91.0%**

1.4.3.3 Truck GPS

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 (Transportation Research Board, 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. (Transportation Research Board, 2014). Truck GPS data can be acquired from private vendors.

Truck GPS data is a valuable source of truck routing, time-of-day corridor usage, volume and speed data. For reference, GPS data in Arkansas for 2016 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 (Diaz-Corro et al., 2019). The spatial and temporal analysis based on truck GPS data has several advantages over other truck data, such as Weigh-in-Motion (WIM)[1] or Annual Average Daily Truck Traffic (AADTT data) gathered by the Federal Highway Administration (FHWA). 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 (**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 it needs to be complemented with other commodity databases, such as USDA (for agriculture) or from business sources (for other commodities).

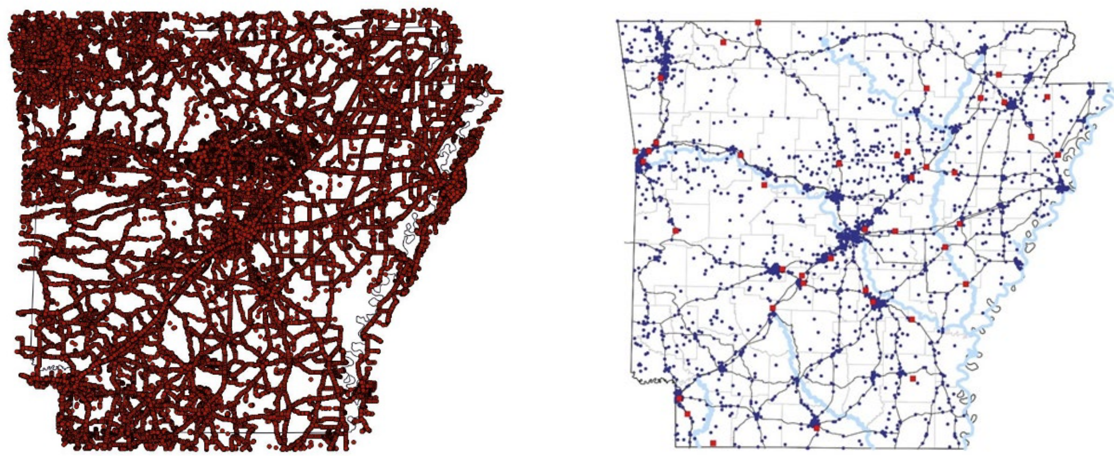


Figure 3. Truck GPS (left), AADT (blue dots, right), and WIM (red dots, right) data coverage

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 et al., 2018). Coefficients of coverage of sample locations considered in this work are shown in **Table 6**.

Table 6. Sample GPS Data Coverage Coefficients in Arkansas

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*

1.4.4 Data Fusion for Freight Fluidity: A Multimodal Challenge

Freight fluidity measures should reflect performance of all modes within the supply chain to evaluate mobility, reliability, resilience, cost, and quantity of freight in a multimodal transportation network

[1] WIM are embedded roadway sensors that continuously measure truck volume and weight by axle configuration (FHWA, 2016).

(Eisele, et al. 2016). This requires different types of data (e.g., movements, transactions, cost, commodity type) from a variety of sources (e.g., government databases, private industry). Given the historical mode-specific approach to freight data collection and analysis, challenges remain to collect and analyze multimodal data for freight fluidity purposes (Transportation Research Board 2018).

National Cooperative Freight Research Program (NCFRP) Report 10 analyzes existing data sources and freight performance measures corresponding to different sectors, modes and geographical applications. State of the practice on freight performance measures applied at national, state, and metropolitan level is synthetized. The authors conclude that considerable mode-specific performance information exists today and propose to create a Freight System Report Card framework to gather such information. However, while trucking, rail and maritime performance measures are discussed, the authors identify a lack of systematic data about multimodal freight performance. Given that freight movement is often multimodal, recommended future research includes the need to capture multimodal freight efficiency for private and public decision makers interested in optimizing performance of freight efficiency across all modes (Gordon Proctor & Associates, Cambridge Systematics, Inc., American Transportation Research Institute, StarIsis Corporation, and Council of Supply Chain Management Professionals 2016).

Multimodal freight fluidity indicators require not only mode-specific data, but an understanding of the interaction between individual modes (Transportation Research Board 2016). To date, most modal interactions are captured by fusing mode-specific datasets via demand models, visualization tools, etc. (IHS Global Insight 2011, Parker 2019, Hwang, et al. 2016). For example, the FHWA National Freight Fluidity Monitoring Program combines waterborne data from USACE, railway data from TransCore and the Carload Waybill Sample, highway data from the National Performance Management Research Data Set (NPMRDS), and supply-chain data from U.S. private companies to generate a mapping tool to track the reliability, cost, and travel time (but not quantities) for multimodal freight movements across selected supply chains on a quarterly basis (Parker 2019).

Another example of models to combine different modes is the implementation of freight fluidity in Texas. The Texas Department of Transportation (2019) assessed the performance of critical highway segments accessing the seaport of Brownsville. The relationship between sea and ground freight flows was determined by performing statistical analyses and a legged regression model. The model was built upon data for ship calls, inbound and outbound commodity flow tonnage and value, and highway truck volume probe data from the NPMRDS (Texas Department of Transportation 2019). The results of the analysis are coefficients that represent the increment of road traffic (per direction) corresponding to a unit of change in import or export freight volume (measured in weight), and the time when those increments on road traffic could be expected. For example, a vessel call with 1,000 TEU would increase traffic on Tx-36 inland by 499 to 585 trucks in the same week, and decrease by 444 trucks two weeks later. The authors explain that counter-intuitive results may be caused by container inventory at the port yard, and further explore simulation scenarios of yard utilization and capacity (Monsreal, et al. 2019). Xu et al. (2017) developed a Generic Target Monitoring System (GTMS) to monitor multimodal vehicles, and tested it with AIS and truck GPS data collected at a seaport terminal. To overcome multimodal data heterogeneity, vehicle tracking data from different sources (i.e. truck, vessel) was converted to a uniform data format. A GIS web-based interface allowed users to visualize and analyze real-time and historical multimodal vehicle tracking data within a designated geographical area (Xu et al., 2017).

The combination of datasets is a necessary approach to solve existing data gaps in the public domain for freight fluidity, while avoiding costs associated with the development and implementation of expensive data collection techniques. This is a challenge because each data provider follows different procedures to define, collect, process and share the data (Tok et al., 2011). Resolving data heterogeneity is necessary to link data across levels of geography, topics, and modes. In particular, the challenge in fusing truck and vessel tracking data is overcoming data heterogeneity in units of time, space, and context. The purpose of this project is to create methods for fusing multi-modal freight data in an effort to quantify and describe port terminal level commodity flows along inland waterways.

2 Methodological Approach

The methodology presented in this section consists of three main steps: i) Data preparation; ii) Data fusion model development and application, and iii) Model evaluation (**Figure 4**).

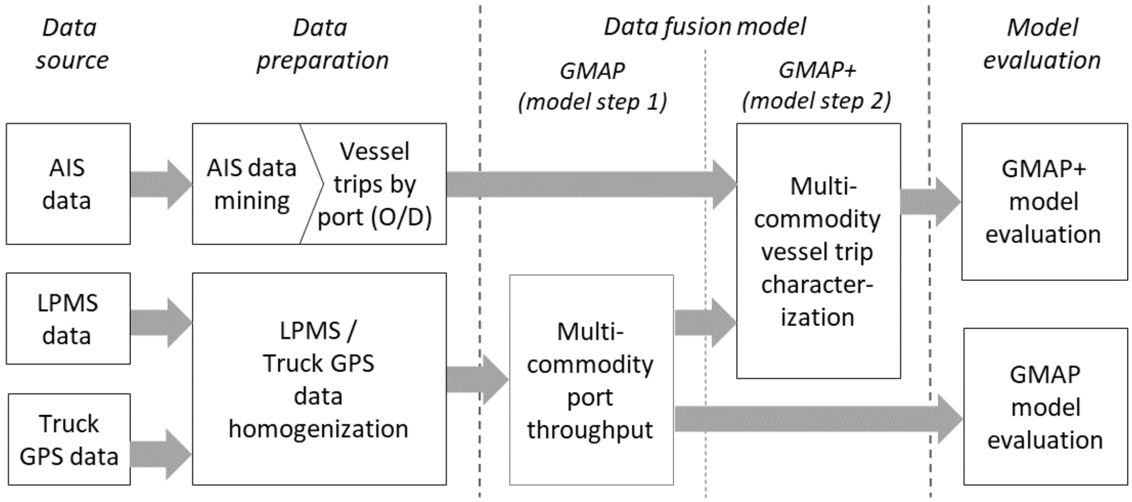


Figure 4. Methodology Overview

2.1 Data Preparation

This section describes the sources of freight port terminal location data, methods to locate anchoring grounds from AIS data on inland waterways, and methods to homogenize otherwise heterogeneous public datasets for conflation purposes, namely AIS, truck GPS, and LPMS.

2.1.1 Port terminals and navigation infrastructure

2.1.1.1 Port terminals: location and characteristics

Method The location and commodities handled by freight port terminals within the study area are gathered from the “Master Docks Plus” geometric (.shp) file, generated by USACE Waterborne Commerce Statistics Center. This database contains more than 40,000 facilities, identified as docks, fleeting areas (i.e., where individual barges are moored or assembled to make a tow), locks and/or dams, and milepoints. The publicly available version of this database indicates the waterway where each facility is located, as well as its location (latitude and longitude), name and identifier code, and commodities handled (but not its volume), among others. The data is collected by survey; it is accompanied by a database schema and data dictionary, and can be downloaded form (U.S. Army Corps of Engineers, 2019).

Results 43 freight port terminals are located within the study area (**Figure 2**).

2.1.1.2 Detailed Inland navigable waterway network

Method The methodology implemented in this report necessitates a detailed inland navigable waterway network representing all freight-related points within the study area, such as port terminals and barge anchoring areas. For the purpose of this work, a detailed inland waterway network was built following the procedure in (Asborno, Hernandez and Yves 2020), based on a national, non-detailed waterway network downloaded from (Bureau of Transportation Statistics 2015).

2.1.2 Vehicle tracking data processing: Marine AIS

Preparation of AIS data consists of three steps: i) data reduction, ii) data quality control, and iii) stop and vessel trip (and trip-chain) identification and characterization from AIS data mining. The methodology explained below follows closely the procedure in (Asborno, Hernandez and Yves 2020), which includes an analysis of vessel stops and trips on Arkansas waterways, including the MKARNS and the portion of the Mississippi River that constitutes Arkansas' eastern boundary.

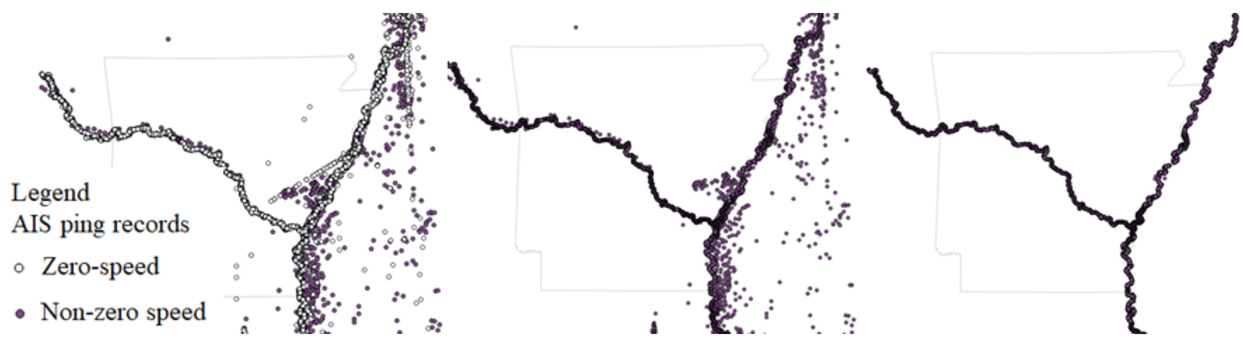
2.1.2.1 AIS Data Reduction

Method Data reduction is necessary to accelerate "big data" processing. In AIS datasets, records with zero speed outnumber the non-zero speed records (Osekowska, Johnson and Carlsson 2017) and, depending on the application, removal of zero speed records provides a mechanism for data reduction. For example, Fujino et al. reconstructed vessel trajectories from a reduced AIS dataset and applied unsupervised machine learning to identify vessel course and issue real-time off-course warnings. The original dataset of 5,756,438 records was reduced by 40% by removing records with zero speed (Fujino, Claramunt and Boudraa 2018).

Results Following this example, in this work, zero speed records are removed with no loss of representation of trip characteristics needed for map matching and stop identification heuristics. In total, 7,803,151 AIS records emitted with a 5-minute frequency by 776 vessels observed from Arkansas waterways were extracted from (**Figure 5.a**). 116 of the 776 vessels were observed within the MKARNS, while the remaining 650 vessels were observed within the Mississippi River (and did not use the MKARNS). Of these records, 53% corresponded to zero speed records, which were removed. By removing zero-speed records from the AIS dataset, computational time is reduced while still benefiting from highly disaggregated, ubiquitous AIS characteristics.

2.1.2.2 AIS Data Quality Control

Method AIS data contains erroneous or irrelevant records that result from transmission interference and device mishandling. Erroneous records (**Figure 5.a** and **b**) are defined as those with unusual high speed, or records located far from inland waterways. Irrelevant records come from vehicles that emitted less than 20 records within the reporting period, and/or from vessels whose records are outside reasonable waterway boundaries. After identifying erroneous and irrelevant records as described below, they are removed from further analysis.



a. AIS source data b. Reduced data c. Quality-controlled data

Figure 5. Example of AIS data preparation

To identify erroneous records, first, a spatial buffer is created for an inexact U.S. navigable waterway network from the National Transportation Atlas Database ("NTAD") (Bureau of Transportation Statistics 2015), clipped to the study area. The buffer width is derived from the Global River Bankfull Width &

Depth Database ("NARVIS") (Andreadis, Schumann and Pavelsky 2013). NARVIS and NTAD are provided as geodatabases. Because the NTAD waterway geometry is abstract, it may not follow observed and valid AIS records. Therefore, a spatial buffer should be established to exclude records grossly outside of the navigable waterways (**Figure 5.c**). Adopted buffer size of two standard deviations from the NARVIS mean width was found appropriate in this work. Records outside the buffer are removed.

Second, a forward sequential search iterates over consecutive AIS records to calculate the space mean speed (Eq. 2), which is checked against a reasonableness threshold of 27.7km/h (15 knots) (El-Reedy 2012). By applying the proposed speed threshold, records corresponding to non-freight vessels are discarded.

$$speed_i = \frac{travelled\ distance_{[\ i-1,i]}}{traveled\ time_{[i-1,i]}} \qquad 2$$

Where,

speed = space-mean-speed associated with pings *i-1* and *i*, in km/h

travelled distance = great-circle distance based on position (latitude, longitude) between pings *i-1* and *i,* in kilometers

travelled time = time to travel between pings *i-1* and *i*, in hours

Next, if less than 20 records are associated with one vessel, all the records for such vessel are removed. Last, spatial coverage of each remaining vessel records is calculated as the diagonal of a bounding box around all of its pings. Vessels with coverage less than 2km are removed. The coverage threshold is defined as the minimum distance between different port authorities in the study area.

Results The quality control process excluded 518,697 position records from the dataset. As a result, 3,398,279 AIS records (44% of the original sample) were subject to the stop and trip identification procedures.

2.1.2.3 Identification of Vessel Stops and Trips from AIS Data

Methods Vessel stops, trips, and trip-chains are identified and characterized by origin, destination, length, duration, and path (as mapped to the detailed inland waterway network) by mining AIS data following the heuristic in (Asborno, Hernandez and Yves 2020). The heuristic, adapted from (Camargo, Shuyao and Vladimir 2017), first identifies vessel stops by clustering successive AIS records based on their location, timestamp, and calculated speed. Then, each stop is associated with a network node based on proximity. Timewise-consecutive stops constitute the origin and destination of a path segment. Later, a map-matching algorithm reconstructs complete vessel paths by finding the shortest path between origin-destination pairs. Path segments are joined to define freight trips with origin and destination in ports. Lastly, freight trips are characterized by origin, destination, length, duration, time-of-year (week, season, etc.), and path (but not by commodity). Trip origin and destination are represented by network nodes, location type (port, anchoring ground, lock, or other), and a unique location identification number.

Results The stop identification algorithm identified 120,185 stops for the 3.4 million AIS position records, of which approximately 25% were on the MKARNS and the remaining 75% on the Mississippi River. The subsequent map-matching algorithm identified 47,555 trips, and 31,359 trip chains. The average number of annual trips per vessel was 63, with a mean trip length of 56.7 miles within a range of 0.2 to 1,085 miles, and a mean duration of 10 hours with a range of 1 to 214 hours. Vessel trips of shortest length and duration likely correspond to movements of tugs between docks within a given port, and to support construction projects concurrent with AIS data (2016), e.g., Broadway Bridge in Little Rock (Asborno, Hernandez and Yves 2020).

Vessel trips and trip chains to and from specific ports are selected to derive port performance measures. In particular, the group of vessel trips with origin or destination in a given port constitute the maritime port "catchment" area, defined as the region where the port draws and delivers freight from. Since most vessels carry a transponder (DiJoseph and Mitchell 2015), given that the AIS dataset used for this work represents 91% of the vessel population, it was not deemed necessary to apply a coefficient of coverage.

2.1.3 Vehicle tracking data processing: Truck GPS

2.1.3.1 Truck GPS Data Quality Control and Stop Identification

The anonymized truck GPS data used in this work consisted of timestamped locations (latitude and longitude) for a sample of the truck population covering a statewide region. Each truck's GPS transponder, identified by a unique but anonymous number, emits intermittent signals ("pings") over time, indicating its location.

First, the anonymous GPS pings were grouped by truck into "trips" and then subjected to quality control protocols to remove inconsistent records. Inconsistencies were defined as trips of less than 20 pings, trips with geographic coverage less than 1.2 miles (e.g. length of the diagonal of the bounding box including all pings), and calculated speeds higher than 81 mph. Then, a stop identification algorithm developed by Camargo et al. (2017) and adapted by Akter et al. (2018) was applied to identify stop locations and durations for each trip. A truck was considered to be stopped when its speed was lower than 3 mph for more than 5 minutes, and the stop coverage area was less than 0.2 miles. All pings corresponding to a single stop were clustered within a rectangular bounding box, and the location of the first ping in the cluster was assigned as the stop location. After the stops made by individual trucks were found, trucks with stops within port areas were identified. A port area was defined as a bounding box around the port facility (including the truck loading area) corresponding to a dock, identified by aerial imagery (**Figure 6**).

Figure 6. Example of port area geographic bounding boxes

2.1.3.2 Truck GPS Data Expansion

The GPS data used in this study contained four two-week samples, roughly capturing the start of each quarter of the year (**Figure 7**). Studies show the coverage of the GPS sampled data to be 10-15% of the total truck population (Diaz Corro et al., 2019). To later fuse annual commodity flows from LPMS with the truck GPS data sample, it was necessary to estimate annual, total (e.g. population level) truck volume for each of the ports. Thus, once the sample number of trucks *S* found at each port *i* during each sample period *w*, S_i^w, was found, two expansion factors were applied to estimate the annual truck volume at each port. First, the sample was expanded to represent population-level truck volumes. Expansion factors for each sample period, V_v^w, were derived as the ratio of the GPS sample volume to truck counts from nearby Weigh-In-Motion (WIM) stations for the same time period. The GPS-derived truck volume at each port, S_i^w, was multiplied by V_v^w to estimate the total population of trucks at each port, e.g. "volume-expanded". Next, temporal representation of the GPS sample was addressed by extrapolating each volume-expanded two-week period to an annual volume. Each volume-expanded, two-week period was multiplied by a temporal expansion factor, V_t^Q (e.g. number of two-week periods in a three-month quarter) (Eq. 3). Lastly, quarterly volumes S'^Q_i were summed to obtain the annual number of trucks accessing each port (Eq. 4).

$$S'^{Q}_{i} = S_i^w \times V_v^w \times V_t^Q \qquad 3$$

$$T_i^{annual} = \sum_Q S'^{Q}_{i} \qquad 4$$

Where T_i^{annual} is the estimated (expanded) annual volume of trucks at port i

S'^{Q}_{i} is the expanded sample of trucks at port i, during quarter Q

S_i^w is the sample of trucks at port I, during period w

V_v^w is the volume expansion factor for sample period w

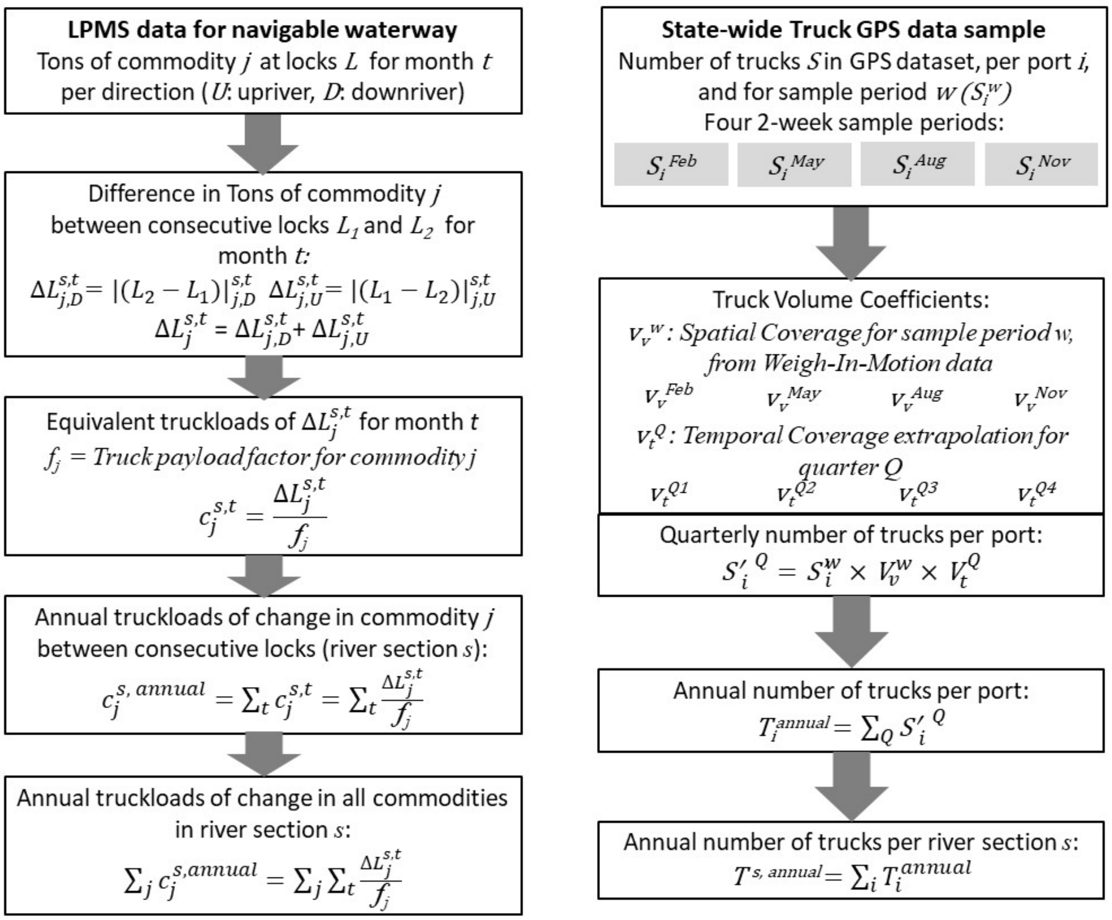
V_t^Q is the time expansion factor for sample period t in quarter Q

2.1.3.3 Truck Trip Identification from GPS Data

In parallel to the stop identification algorithm applied to truck GPS data, the heuristic by (Akter, et al. 2018) adapted from (Camargo, Shuyao and Vladimir 2017) identifies all links of the network that are likely used by the vehicle as it travels between stops. Using geospatial analysis, each ping is associated with a network link if its location falls within a pre-defined buffer distance from the link. Links with pings within their buffers are likely used by the vehicle as it traveled between stops. In some cases, a truck may traverse many links between ping recordings, thus the map-matching algorithm reconstructs the complete path of consecutive links using shortest path algorithms. For each and all trucks, the map-matching algorithm outputs a sequenced list of network nodes visited by each vehicle, the time when the vehicle arrived and left each node, and its associated network link. By joining the outputs of the stop identification and complete path for each vehicle based on timestamps, truck trips and trip chains are identified. Lastly, truck trips with origin or destination in network nodes representing inland waterway port terminals are selected. Similarly as with vessel trips mined from AIS data, truck trips with origin or destination in a given port terminal are selected, and their paths constitute the roadway freight "catchment area" of such port.

2.1.4 Commodity data processing: Lock Performance Measurement System

LPMS data consists of monthly quantities (by weight) of 36 commodities transported along U.S. inland navigable waterways by direction (e.g. upriver and downriver). The USACE collects data on the quantity of commodity at each of their approximately 200 locks and dams. LPMS data processing (**Figure 7**) consisted of calculating the difference in the quantity (by weight) of each commodity between each pair of consecutive locks, per direction, per month, ($\Delta L^{s,t}_{j,U;}$ $\Delta L^{s,t}_{j,D}$), referred to as 'commodity flux'. Upriver and downriver commodity flux were aggregated to quantify commodity flux per month, $\Delta L^{s,t}_{j}$, and then converted to equivalent truckloads by dividing commodity flux by commodity-specific truck payload factors $f_{j.}$ Truck payload factors for each of the nine commodity categories were derived from the 40 LPMS commodity sub-groups, using the Standard Transportation Commodity Codes (STCC2) payload factors included in the Arkansas State Travel Demand Model to assist with the commodity cross-walks (Alliance Transportation Group, 2012). Equivalent monthly truckloads $c_j^{s,t}$ were then summed over the year to obtain the annual equivalent truckloads of each commodity flux between each pair of consecutive locks, $c_j^{s,annual}$.



a. LPMS data preparation for GMAP b. Truck GPS data preparation for GMAP

Figure 7. LPMS and truck GPS data preparation for GMAP

2.2 Data Fusion Methodologies for Performance Measurement

This section presents the methodology developed to calculate performance measures for inland waterway system components from the analysis and fusion of publicly available freight tracking data with aggregated commodity datasets (LPMS). The metrics introduced are listed in **Table 7**.

Table 7. Inland waterway transportation system performance measures derived in this work

Metric	Description	Units	Data source
Port terminal throughput by commodity	Annual volume of freight transloaded at each port terminal on the Arkansas River by commodity, mode (truck/rail), and direction (upriver/downriver).	Tons	LPMS and truck GPS data fusion
Commodity-based vessel trip characterization	Quantity and type of commodities carried by vessel trips observed on the Arkansas River for one year.	Tons	LPMS, AIS, and truck GPS data fusion
Freight catchment area size	Area where a facility draws and delivers freight from/to (connected origin-destination pairs).	Acres	AIS and truck GPS data fusion
Vehicle Miles Travelled (VMT)	Aggregated distance of all trips to/from a port terminal, by mode (truck/vessel), and multimodal.	Miles; Percentage of VMT per mode	AIS and truck GPS data fusion
Vehicle Hours Travelled (VHT)	Aggregated duration of all trips to/from a port terminal, by mode (truck/vessel), and multimodal. $VHT_{multimodal}=VHT_{truck}+VHT_{vessel}$	Hours; Percentage of VHT per mode	AIS and truck GPS data fusion
Population within the catchment area [a]		Number of individuals	AIS, truck GPS, and census data fusion
Number of business registered within the catchment area [b]		Number of businesses	AIS, truck GPS, and business data fusion
Number and location of unique Traffic Analysis Zones (TAZ) as origin or destination of trips to/from each port terminal facility		Number of TAZs	AIS, truck GPS, and State Travel Demand Model (STDM) zones data fusion
Dwell time	Average duration of vessel stops at each port terminal	Hours	AIS

Notes: (a) Might be stratified per population characteristic
(b) Might be stratified per commodity (NAICS code)

Following the data preparation methods presented above, the model has sub-models both formulated as Generalized Multi-Commodity Assignment Problems (GMAP). The first model (GMAP) consists of fusing truck GPS and LPMS data to obtain throughput by port terminal, commodity, mode (barge-truck and barge-rail transloads), and direction (upriver or downriver flows). The second model (GMAP+) uses the output of the first model as input, together with vessel trips characterized by port of origin, destination, length, and duration (but not commodity) derived from AIS data, to obtain the volume and type of commodities transported in each vessel trip.

2.2.1 Model 1 (GMAP): Port throughput by commodity from Truck GPS and LPMS data fusion

This section presents a model to quantify annualized commodities transloaded at inland waterway port terminals by fusing two mode-specific datasets, truck GPS and marine AIS. The model is formulated as a Multi-Commodity Assignment Problem (GMAP) (Asborno, Hernandez and Akter 2020).

A GMAP seeks to optimally assign tasks to agents, subject to capacity restrictions on the agents; an agent may be assigned many tasks, and tasks may be duplicated and assigned to more than one agent (Kundakcioglu et al., 2008). In applying a Generalized Assignment Problem (GAP) to the quantification of port throughput, commodities were considered “tasks” to be assigned to ports, i.e. “agents”, and the total commodity flux on a river section may be transloaded at several ports. The objective function targets minimal deviation between freight flow observed on the land side (from truck GPS), and on the water side (from LPMS) at each river section (Eq. 5). Such minimization is subject to the following constraints: i) freight flow conservation, i.e. assurance that all commodities were assigned to at least one port (Eq. 6), ii) port “capacity”, defined as the proportional number of trucks accessing each port terminal (Eq. 7), and iii) non-negativity (Eq. 8-10). The model is applied to annual commodity flows to reduce the effects of long-term commodity storage or inventory holding at each port terminal.

The model was solved by adopting goal programming techniques, consisting of the relaxation of conflictive conditions in an optimization formulation to find a feasible solution (although not necessarily optimal) (Colapinto et al., 2017; Gardi et al., 2014). The relaxation techniques implemented in the MCAP formulation were: i) inequalities adopted in eq. 6-7 instead of equalities, and ii) discrete (integer) values were replaced with continuous values, e.g. trucks allowed to be partially loaded.

The decision variables obtained with the GMAP, e.g., the annual number of truckloads of each commodity transloaded at each port terminal, by mode, are post-processed to describe the upriver and downriver directionality, and to convert from the number of trucks (e.g., truckloads) back to commodity volumes by weight (tonnages). The post-processed results are the annual tonnage of freight transloaded to rail and the annual tonnage of freight by commodity transloaded to truck at each port, by direction (upriver, downriver). Rail transloads are quantified but not described per commodity due to rail data unavailability, such as number of railcars observed per port. From the truck GPS data, it was not possible to determine whether a truck was at a port to pick-up or drop-off an upriver or downriver cargo.

Objective function:

$$\boldsymbol{Minimize\ f(x,R)} = \sum_i \sum_j \boldsymbol{\alpha_{i,j}^{s} x_{i,j}^{s,t}} + \sum_i \boldsymbol{\beta_i^s R_i^{s,t}} - \sum_j \boldsymbol{c_j^{s,t}} \quad \forall\, \boldsymbol{j} \in \boldsymbol{a}, \forall\, \boldsymbol{i} \in \boldsymbol{s} \qquad 5$$

Subject to:

Freight conservation: $$\sum_i \alpha_{i,j}^{s}\, x_{i,j}^{s,t} \le c_j^{s,t} \quad \forall\, j \in a \qquad 6$$

Port capacity: $$\frac{\sum_j \alpha_{i,j}^{s}\, x_{i,j}^{s,t}}{\sum_j c_j^{s,t} - \sum_i \beta_i^s R_i^{s,t}} \le \frac{T_i^{s,t}}{\sum_i T_i^{s,t}} \quad \forall\, i \in s \qquad 7$$

Non-negativity: $$x_{i,j} \ge 0 \quad \forall j \in a, \forall i \in s \qquad 8$$

$$R_i \ge 0 \quad \forall i \in s \qquad 9$$

$$\sum_i \sum_j \alpha_{i,j}^{s} x_{i,j}^{s,t} + \sum_i \beta_i^s R_i^{s,t} - \sum_j c_j^{s,t} \ge 0 \quad \forall j \in a, \forall i \in s \qquad 10$$

Where,

$j \in a$ Set of commodities

$i \in s$ Set of ports within each river section

$s \in r$ Set of sections within a river

Decision variables:

$x^{s,t}_{i,j}$ Number of truckloads of commodity *j* transloaded from barge to truck (and vice-versa) at port *i* during time period *t,* on river section *s*

$R^{s,t}_{i}$ Equivalent truckloads transloaded from barge to rail (and vice-versa) at port *i* during time period *t,* on river section *s*

Input variables and model parameters:

$c^{s,t}_{j}$ Flux of commodity *j* on river section *s* during time period *t* (from LPMS)

$T^{s,t}_{i}$ Number of trucks *T* accessing port *i* on river section *s* during time period *t* (from truck GPS, eq. 11)

$$T_i^{s,t} = \sum_j \alpha_{i,j}^{s}\, x_{i,j}^{s,t} \qquad 11$$

$\alpha^{s}_{i,j}$ Coefficient to indicate whether port *i* on river section *s* handled commodity *j,* subject to loading equipment (from master dock plus database and aerial imagery)

$$\alpha_{i,j}^{s} = \begin{cases} 1 & if\ port\ i\ handles\ commodity\ j \\ 0 & otherwise \end{cases}$$

β^{s}_{i} Coefficient to indicate whether port *i* on river section *s* had rail access (from master dock plus database and aerial imagery).

$$\beta_i^{s} = \begin{cases} 1 & if\ port\ i\ has\ rail\ access \\ 0 & otherwise \end{cases}$$

2.2.2 Model 2 (GMAP+): Commodity-based vessel trip characterization on inland waterways from Truck GPS, AIS, and LPMS data

The type and volume of commodities transloaded at each port terminal, and vessel trips port of origin and destination mined from AIS data serve as input to the second model: a two-stage multi-commodity assignment problem (called GMAP+) (Asborno and Hernandez, 2020). Since the inputs are derived from diverse sources (AIS, GPS, and LPMS), the assignment model is a tool to minimize data heterogeneity by assuming a non-integer, linear, and stochastic model formulation.

The first modeling stage consists of a deterministic, linear objective function that seeks to minimize differences in the volume of commodity transloaded at ports and assigned to trips visiting such ports, for all ports, all commodities, and all trips in the study area during the study period (Eq. 12). Decision variables in this model constitute the volume (in tons) of each commodity carried per vessel trip, and are treated as non-integer variables to resemble a continuous volume of commodity loaded in any given trip (Eq. 13-16).

Objective function:

$$\boldsymbol{minimize}\ \boldsymbol{f}(\boldsymbol{x}) = \left(\sum_{\boldsymbol{i}}\sum_{\boldsymbol{j}}(\boldsymbol{a_{i,j}}\ /\boldsymbol{2}) - \sum_{\boldsymbol{i}}\sum_{\boldsymbol{j}}\sum_{\boldsymbol{t}}\left(\boldsymbol{v_{i,t}} \times \boldsymbol{x^{s}_{t,j}}\right)\right)\ \forall i \in P, \forall j \in C, \forall t \in T \qquad 12$$

Subject to:

Trip capacity: $$\sum_j x^s_{t,j} \leq b^s \ \ \forall t \in T \qquad 13$$

Port capacity: $$\sum_t \sum_j \left(v_{i,t} \times x^s_{t,j}\right) = \sum_j a_{i,j}/2 \ \ \forall i \in P \qquad 14$$

Commodity flow conservation: $$\sum_t x^s_{t,j} = \sum_i a_{i,j}/2 \ \ \forall j \in C \qquad 15$$

Non-negativity: $$x^s_{t,j} \geq 0 \quad \forall j \in C, \forall t \in T \qquad 16$$

Where,

$i \in P$ Set of ports

$t \in T$ Set of vessel trips

$j \in C$ Set of commodities

$s \in S$ Set of scenarios

Decision variables:

$x^s_{t,j}$ Volume (in tons) of commodity j transported in trip t in scenario s

Input variables and model parameters:

$a_{i,j}$ Volume (in tons) of commodity j loaded/unloaded in port i (from model stage 1)

b^s Maximum volume of cargo (in tons) transported per vessel trip, assumed for scenario s

$v_{i,t}$ Coefficient to indicate whether port i is the origin or destination of trip t (from trip characterization by AIS data mining – Data preparation)

$$v_{i,t} = \begin{cases} 1\ if\ trip\ t\ visited\ port\ i \\ 0 \qquad\qquad otherwise \end{cases}$$

A notable limitation of AIS data is that it is linked to tugs and tows pushing barges on inland waterways, but not to the barges that carry the load (Kruse, et al., 2018). In the absence of information pertaining the volume of total freight carried per vessel trip, the second modeling stage introduces stochastic elements to uncertainty in the volume of freight transported per trip. Thus, the deterministic model presented above (Eq. 12-16) is applied to different scenarios of trip capacity (Eq. 13). Then, the results of all scenarios are combined into a single model output considering the probability of occurrence of each scenario (Eq. 17). Model output represents the volume (in tons) of commodity j carried by trip t.

$$\boldsymbol{x_{t,j}} = \sum\nolimits_{\boldsymbol{p}} \sum\nolimits_{\boldsymbol{s}} \boldsymbol{p^s} \times \boldsymbol{x^s_{t,j}} \qquad 17$$

Where,
$x^s_{t,j}$ is the volume (in tons) of commodity j carried by trip t in scenario s,
p^s is the probability of occurrence of scenario s, and
$x_{t,j}$ is the volume (in tons) of commodity j carried by trip t (model results).

The parameter, b, sets an upper bound to the volume of freight carried per trip and is derived from LPMS. In particular, the lock usage report provides the number of loaded barges and the number of commercial vessels observed at each lock operated by USACE (2018). An average of 4.72 loaded barges per vessel were observed at the locks within the study area during 2016, with a standard deviation of 0.84. To account for the uncertainty in the maximum volume of freight carried per trip, five scenarios are modeled, where b takes the form of a discrete variable and is varied two standard deviations below and above the average, with a step of one standard deviation. Considering the capacity of most barges is 1,500 tons, the average volume of freight per trip, b is 7,085 tons, and the set of scenarios is S = {4,564; 5,825; 7,085; 8,345; 9,606}. In the absence of further statistical data pertaining the distribution of number of barges per vessel in the study area, the five scenarios are considered to have an equal probability of occurrence (Ahadi, Sullivan, and Mitchell, 2018), thus p = 0.20.

Each modeled scenario has 39,366 decision variables (4,374 trips and 9 commodities). Due to input data heterogeneity (AIS, truck GPS, and LPMS), relaxation of conflictive constraints, namely port capacity (Eq. 14) and commodity flow conservation (Eq. 15), is necessary for a feasible solution to be found. Under some scenarios, relaxing constraints in conflict may lead to an assignment of freight per trip that violates the commodity flow conservation principle, e.g., the volume of commodity assigned to trips (output) should be equal to the volume of commodity transloaded at ports (input) (Eq. 15). In particular, scenarios with an upper bound of the volume of freight carried per trip being equal or less than the average plus one standard deviation, i.e. $b \leq$ 8,345 tons, result in this violation. Thus, under such relaxed constraints, the stochastic model (all five scenarios combined) results in 80% of the total freight transloaded at ports being assigned to trips. The flow conservation principle stands when the analysis is done by commodity type for all commodities except chemicals and food and farm products. To account for the un-assigned freight flow of chemicals and food and farm products, model results are post processed. First, it is assumed that the distribution of volume of commodity per trip, for all the trips that carry the given commodity, is fixed. Then, the volume of commodity assigned per trip is increased proportionally, to match the total volume of such commodity transloaded at ports.

2.2.3 Model Evaluation

Since the two model steps described above produce distinct outputs, each model step is subject to an independent evaluation.

2.2.3.1 GMAP Model Evaluation

Method Commodity flows through inland ports were not publicly available for direct model validation. Instead, two indirect evaluation metrics were used: i) the difference in the percentage of trucks accessing each port terminal as observed from truck GPS data and model estimates ('EM', Eq. 18), and ii) the rail-to-truck freight ratio of transloaded freight at each river section ('RT', Eq. 19).

$$EM_i = \left| \frac{T_i^{s,t}}{\sum_i T_i^{s,t}}_{\ predicted} - \frac{T_i^{s,t}}{\sum_i T_i^{s,t}}_{\ observed} \right| \times 100\% \qquad 18$$

$$RT^s = \frac{\sum_i R_i^{s,t}}{\sum_i T_i^{s,t}} \times 100\% \qquad 19$$

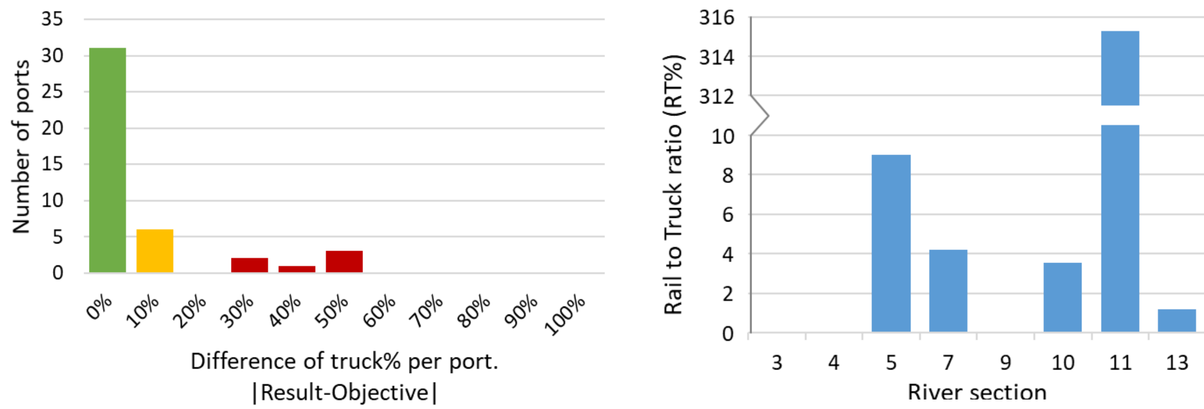
Where,
EM_i is the truck proportion GMAP model evaluation metric for port i
RT^s is the rail-to-truck ratio for river section *s*
$T_i^{s,t}$ is the number of trucks accessing port i located at river section s during time period t
$R_i^{s,t}$ is the volume of freight (measured in equivalent truckloads) transloaded between barge and rail at port i located at river section s during time period t

Results Generally, lower EM corresponds to better model results. Overall, 84% of the port terminals (36 out of 43) show EM less than 20% (**Table 8**, **Figure 8.a**). By averaging the EM of all ports within each river section, 75% of the river sections with ports (6 out of 8) show an average EM less than 20%.

RT captured the model ability to mimic rail-to-truck ratios observed in independent national datasets. With the exception of Section 11, all river sections showed RT between 0% to 9% (**Figure 8.b**). Since the decision variable *R* captured both barge/rail transload operations and freight consumed at facilities located at the ports (e.g., refineries, power plants), the high RT observed in Section 11 may be explained by commodities arriving by water and being consumed at a power plant with port access located along that river section. The overall RT considering all river sections was 13%, in line with 15% national freight mode share (U.S. Department of Transportation, 2019).

Table 8. Model Evaluation Metric (EM) per River Section

River sections	Number of ports	Average EM per section
3; 4; 5; 7; 10	30	< 10%
13	6	< 20%
9; 11	7	< 40%
1; 2; 6; 8	0	No ports. Algorithm not applicable



a. Evaluation metric per port (EM)

b. Rail-to-Truck mode share ratio (RT)

Figure 8. GMAP model evaluation results

2.2.3.2 GMAP+ Model Evaluation

Method The output of the GMAP+ model is the volume (in tons) of each commodity transported during each vessel trip. No direct validation measure is available as this data is not public. As an indirect measure, the output is evaluated based on the difference in model estimates and observations of the distribution of commodity volumes (in tons) observed at locks (LPMS). Commodity volumes are normalized to the total freight volume of the system (all commodities, trips, and locks aggregated) to eliminate scaling effects that would prevent a direct comparison, and presented as percentages of total freight, $V_{j,l}$ (Eq. 20). A single validation metric, V, averages $V_{j,l}$ for all commodities and all locks in the system (eq. 21).

$$V_{j,l} = \left| \left({LPMS_{j,l}} \Big/ {\sum_j \sum_l LPMS_{j,l}} \right) \times 100 - \left({\sum_t x_{t,j}^l} \Big/ {\sum_j \sum_l \sum_t x_{t,j}^l} \right) \times 100\% \right| \quad \forall j \in C, \forall l \in L \qquad 20$$

$$V = \frac{\sum_j \sum_l V_{j,l}}{L \times C} \qquad 21$$

Where,

$V_{j,l}$ is the model validation metric for tonnages of commodity group j and lock l,

$LPMS_{j,l}$ is the annual volume (in tons) of commodity j reported by LPMS for lock l,

$x_{t,j}^l$ is the annual volume (in tons) of commodity j carried by trips t (model results) observed at lock l.

To calculate $x_{t,j}^l$, a screenline approach is used such that trip path geometries of tugs/tows that intersected locks (represented by line segments) are counted as vessels in transit through the lock,

V = overall model validation metric (considering tonnages of all commodities, all locks),

C = number of commodity groups, and

L = number of locks within the study area.

Results The lower the validation metrics V and $V_{j,l}$, the better the model. Differences in the volume of commodity between LPMS and model results, $V_{j,l}$, range from 0.00% to 1.82% for each lock, with an average of 0.25% (**Table 9**).

Table 9. Model Validation Metric $V_{j,l}$ in percent for the Arkansas River for 2016

Commo-dity/Lock	Coal	Petrol	Che-micals	Crude Materials	Manu-factured	Food & Farm	Mach-inery	Waste	Unk-nown
85	0.15	0.08	0.65	0.74	0.17	0.63	0.02	0.00	0.12
88	0.20	0.03	0.47	0.61	0.29	0.73	0.02	0.00	0.13
89	0.20	0.00	0.48	0.62	0.30	0.72	0.02	0.00	0.13
90	0.11	0.01	0.01	0.21	0.25	1.82	0.01	0.00	0.15
91	0.10	0.00	0.12	0.21	0.27	1.79	0.02	0.00	0.14
92	0.07	0.00	0.00	0.25	0.19	1.39	0.01	0.00	0.15
93	0.08	0.00	0.00	0.25	0.19	1.39	0.01	0.00	0.15
105	0.01	0.06	0.27	0.25	0.21	0.95	0.02	0.00	0.22
101	0.01	0.05	0.24	0.22	0.20	0.97	0.01	0.00	0.22
102	0.02	0.01	0.35	0.24	0.22	0.79	0.03	0.00	0.22
104	0.00	0.17	0.40	0.25	0.16	0.69	0.03	0.00	0.21
103	0.03	0.24	0.53	0.52	0.54	0.08	0.03	0.00	0.22
106	0.03	0.25	0.49	0.52	0.52	0.15	0.03	0.00	0.22
107	0.03	0.26	0.50	0.53	0.52	0.14	0.03	0.00	0.22

Lower performance as measured by the model evaluation metrics can be attributed to several issues. First, the proposed validation methods assume that tug-trips carry freight along all their path, while freight might be carried only for a portion of the trip, e.g. between a port and an anchoring area. Second, the model input data is imperfect, even after data pre-processing. For example, it was observed that 2016 AIS data covers 91% of the vessel population on the Arkansas River (Asborno, Hernandez, and Yves, 2020). In addition, there could be issues with the commodity volumes manually reported in LPMS. Third, in terms of model characteristics, assumptions of tonnage capacities per trip plays a key role in model accuracy, despite the adoption of a stochastic approach that considers several scenarios of diverse trip capacity. The model may be improved by increasing the number of scenarios, as in a Monte Carlo simulation approach (Lin et al., 2018).

2.2.4 Multimodal port catchment area metrics

A freight port "catchment area" is defined as the region where the facility delivers and draws freight (Vadali et al., 2017). Based on this definition, catchment areas can be identified as the connected origin-destination pairs where the trips made by the vehicles that accessed the facility occur. In a freight supply chain, the catchment area contains several modes, freight facilities, and industries, which would be better represented (and linked together) by spatially and temporally continuous data, such as historical truck and vessel paths. Such trips are mined from vehicle tracking data, as explained in the data preparation methodology (Sections 2.1.2.3 for maritime AIS, and 2.1.3.3 for truck GPS). By selecting the trips with origin or destination in a given freight facility, its catchment area is identified and visualized.

To complement visual depictions of freight catchment areas, key quantitative indicators (**Table 7**) are calculated per mode and by combining all modes (e.g., multimodal). The indicators constitute performance of the freight activity associated with each facility. The catchment area size, population, number of business within the area, and location of unique TAZs serving as the origin or destination of trips to/from each port are derived using statistical packages and modeling tools in GIS platforms. The state-wide number of business within the catchment area is obtained by conflating the catchment areas with the County Business Patterns dataset from (U.S. Census Bureau, 2018), for the year of study. Similarly, the population is obtained by conflating the catchment area with the Arkansas TIGER/Line® Shapefiles: Census Tracts from (U.S. Census Bureau, 2019b). The TAZs shapefile is obtained from the State Travel Demand Model (Alliance Transportation Group, 2015). The VMT and VHT corresponding to all trips to and from each port, per mode, are calculated by aggregating the trip length (in miles) and duration (in hours) for all the trips with origin or destination in the said port (Eq. 22-25). The multimodal VMT and VHT is calculated by summating of the mode-specific VMT and VHT, respectively (Eq. 26-27)

$$VMT_i^{truck} = \sum_t k_{t,O=i}^{truck} + \sum_t k_{t,D=i}^{truck} \tag{22}$$

$$VMT_i^{vessel} = \sum_t k_{t,O=i}^{vessel} + \sum_t k_{t,D=i}^{vessel} \tag{23}$$

$$VHT_i^{truck} = \sum_t d_{t,O=i}^{truck} + \sum_t d_{t,D=i}^{truck} \tag{24}$$

$$VHT_i^{vessel} = \sum_t d_{t,O=i}^{vessel} + \sum_t d_{t,D=i}^{vessel} \tag{25}$$

$$VMT_i^{multimodal} = VMT_i^{truck} + VMT_i^{vessel} \tag{26}$$

$$VHT_i^{multimodal} = VHT_i^{truck} + VHT_i^{vessel} \tag{27}$$

Where,
$k_{t,O=i}$ is the mileage of trip t, with origin in port i
$k_{t,O=i}$ is the mileage of trip t, with destination in port i
$d_{t,O=i}$ is the duration (in hours) of trip t, with origin in port i
$d_{t,O=i}$ is the duration (in hours) of trip t, with destination in port i

2.2.5 Dwell time and travel time from AIS data

2.2.5.1 Dwell time

Dwell time is the amount of time a vessel or truck spends at a port facility and can include loading/unloading operations, and wait time. For this project, the dwell time is calculated as the average duration of all stops made by all vessels visiting the facility during the study period (Eq. 28). Notably, on U.S. inland waterways, AIS transponders are onboard tugs that push barges carrying freight, but barges do not have an AIS transponder (Kruse, et al. 2018). Thus, AIS transponders track the position of tugs not cargo. In addition, the operation of loading and unloading freight from barges does not necessitate the presence at the dock of the tug that pushes such barges through the river. In a typical operation, for example, a tug pushing loaded barges would arrive at a dock, maneuver to position the barges at the dock, and once the barges are safely moored, the tug would leave the dock and the unloading of the barge(s) would start. Thus, the "dwell time" calculated for the purpose of this work constitutes the time spent by the tug or towboat at the port terminal to position or pick up barges, differing from the traditional definition of dwell time, which refers to the time incurred to load and unload cargo.

$$W_i = \frac{\sum_v \sum_s d_{s,i}^v}{S_i} \tag{28}$$

Where,
W_i is the Annual average dwell time for port i
$d_{s,i}^v$ is the duration (in hours) of stop s made by vessel v at port i

S_i is the number of stops at port i (by all vessels)

2.2.5.2 Travel time share on the multimodal transportation system

For each port terminal, the travel time share within the multimodal transportation system is calculated by first summing the maritime VHT, dwell time, and roadway VHT corresponding to each port terminal, and then calculating the percentage of share that each of those metrics have on the summation (Eq. 29-31).

$$TS_i^{vessel} = \frac{VHT_i^{vessel}}{VHT_i^{truck} + VHT_i^{vessel} + W_i} \times 100 \quad 29$$

$$TS_i^{truck} = \frac{VHT_i^{truck}}{VHT_i^{truck} + VHT_i^{vessel} + W_i} \times 100 \quad 30$$

$$TS_i^{w} = \frac{W_i}{VHT_i^{truck} + VHT_i^{vessel} + W_i} \times 100 \quad 31$$

Where,

VHT_i^{vessel} is the vehicle hours travelled for vessel (or truck) visiting port i,

TS_i^{vessel} is the maritime travel time share for port i,

TS_i^{truck} is the truck travel time share for port i,

TS_i^{w} is the dwell time share for port i, and

All other terms as previously defined.

3 Results: Commodity-based Performance Measures for the Arkansas River

The methodologies presented in Section 2 were applied to the Arkansas River, including 43 freight port terminals. This section summarizes: i) performance measure for six sample freight port terminals; ii) tabular results of port throughput by commodity for the 43 freight port terminals within the project scope, iii) maps of detailed commodity flow in the Arkansas River, and iv) annual average dwell time per port terminal.

3.1 Port Terminal Performance Summaries

The port terminal performance summaries are presented for six select port terminals (see Appendix A). The sample facilities was made considering their varied location along the river (i.e. avoid including more than two terminals within a single port authority), and the variability in commodities handled per terminal (i.e. avoid including in the sample more than two terminals shipping a single same product). Notably, most of the 43 port terminals are dedicated to shipping or receiving a single commodity (such as aggregates, steel structures, grain, etc.).

The port performance summaries include:

1. Map of the freight catchment areas,
2. Map of the Traffic Analysis Zones (TAZs) associated with each port,
3. Population, Businesses, and Area of TAZs visited by trucks and vessels associated with the port,
4. Vehicle Hours Travelled and Vehicle Miles Travelled of trucks and vessels visiting each port
5. Travel time for trucks and vessels for each port, and
6. Distribution of commodities estimated for each port.

3.2 Port Throughput by Commodity

Table 10 and Table 11 summarize the results of applying the GMAP model to the eight sections of the Arkansas River where the 43 freight ports are located, closing a critical data gap previously unavailable in the public domain.

Table 10. 2016 McClellan Kerr-Arkansas Upriver Freight Transloaded per Port, Commodity, and Mode (Annual Tons)

Section	Port	Coal	Petrol	Chemicals	Crude Materials	Manufactured	Food & Farm	Machinery	Waste	Unknown	Truck Transload	Rail Transload	Port total
3	3001	15,293		69,414	31,404	67,029	3,574				186,714		186,714
	3002						6,469				6,469		6,469
	3003		14,896								14,896		14,896
4	4001						109,273				109,273		109,273
5	5001						63,534				63,534	34,887	98,421
	5002				0	0					0		0
	5003		27,582	0		0	0				27,582		27,582
	5004			138,749			0				138,749	0	138,749
	5005			0	29,344	0				1,787	31,130	0	31,130
	5006						0				0	0	0
	5007					14,681		3,596			18,277		18,277
	5008					9,576		0			9,576		9,576
	5009			0		0	0				0		0
	5010				12,443	0					12,443		12,443
	5011					59,955					59,955		59,955
	5012						0				0		0
	5013						0				0		0
7	7001-2			0	0	0					0	45,200	45,200
	7003		0								0	0	0
	7004			145	0	0	0			0	145		145
	7005				0						0	0	0
	7006	239									239		239
	7007		137,646								137,646		137,646
	7008			0			51,308				51,308	0	51,308
	7009			0	0	0	0		0	10,251	10,251	0	10,251
	7010-11			0	17,509	541,310	13,280		0	0	572,099		572,099
	7012		0	192,253	182,050		0				374,302		374,302
	7013				334						334		334
9	9001				33,915						33,915		33,915
	9002				0	42,419					42,419		42,419
	9003			64,801			26,060				90,862		90,862
10	10001				92,529						92,529	10,647	103,175
	10002			147,897	0	43,162	30,053				221,113	0	221,113
11	11001					34,262		2,198			36,460		36,460
	11002				10,526			0			10,526		10,526
	11003	0		0	0	0				0	0		0
	11004									0	0	175,957	175,957
13	13001				14,315	0			0	0	14,315		14,315
	13002					56,362					56,362		56,362
	13003-4	13,993		242,891	154,515	121,982					533,381	7,637	541,019
	13005						65,449				65,449		65,449
	13006				0						0	0	0
	13007		19,422	0	0	0					19,422	0	19,422

Note that blank cells in the tables denote that the port did not handle a specific commodity or serve a given mode.

Table 11. 2016 McClellan Kerr-Arkansas Downriver Freight Transloaded per Port, Commodity, and Mode (Annual Tons)

Section	Port	Coal	Petrol	Chemicals	Crude Materials	Manufactured	Food & Farm	Machinery	Waste	Unknown	Truck Transload	Rail Transload	Port total
3	3001	20,755		128,109	225,177	5,353	98,946				478,340		478,340
	3002						179,082				179,082		179,082
	3003		10,016								10,016		10,016
4	4001						251,922				251,922		251,922
5	5001						158,703				158,703	31,116	189,819
	5002				0	0					0		0
	5003		1,335	0		0	0				1,335		1,335
	5004			37,173			0				37,173	0	37,173
	5005			0	98,573	0				0	98,573	0	98,573
	5006						0				0	0	0
	5007					1,524		4,074			5,598		5,598
	5008					994		0			994		994
	5009			0		0	0				0		0
	5010				41,797	0					41,797		41,797
	5011					6,224					6,224		6,224
	5012						0				0		0
	5013						0				0		0
7	7001-2			0	0	0					0	27,775	27,775
	7003		0								0	0	0
	7004			67	0	0	0			0	67		67
	7005				0						0	0	0
	7006	270									270		270
	7007		7,868								7,868		7,868
	7008			0			207,603				207,603	0	207,603
	7009			0	0	0	0		4,785	0	4,785	0	4,785
	7010-11			0	20,569	25,837	53,735		0	0	100,142		100,142
	7012		0	89,639	213,874		0				303,513		303,513
	7013				392						392		392
9	9001				84,479						84,479		84,479
	9002				0	2,135					2,135		2,135
	9003			39,810			99,530				139,340		139,340
10	10001				72,667						72,667	7,758	80,426
	10002			71,908	0	4,889	60,581				137,378	0	137,378
11	11001					3,666		2,997			6,663		6,663
	11002				158,892			0			158,892		158,892
	11003	0		0	0	0				0	0		0
	11004									0	0	421,510	421,510
13	13001				4,080	0			0	0	4,080		4,080
	13002					2,795					2,795		2,795
	13003-4	6,897		118,462	44,040	6,049					175,448	4,108	179,556
	13005						136,099				136,099		136,099
	13006				0						0	0	0
	13007		14,840	0	0	0					14,840	0	14,840

Note that blank cells in the tables denote that the port did not handle a specific commodity or serve a given mode.

3.3 Maps of Detailed Commodity Flow in the Arkansas River

Existing maps of freight flow on inland waterway are limited to lock locations. However, locks are not the true origin or destination of freight, and there are several port terminals located between each pair of consecutive locks. This significant limitation is addressed by this project. By mapping the true origin and destination of each vessel trip characterized by commodity, e.g., a port, and aggregating the volume of each commodity (in tons) of all vessel trips that transit through each inland navigable waterway network link, we are able to generate maps that depict commodity flows along river segments. The maps (**Figure 9**) allow for highly disaggregated commodity flow depictions on regional inland waterways.

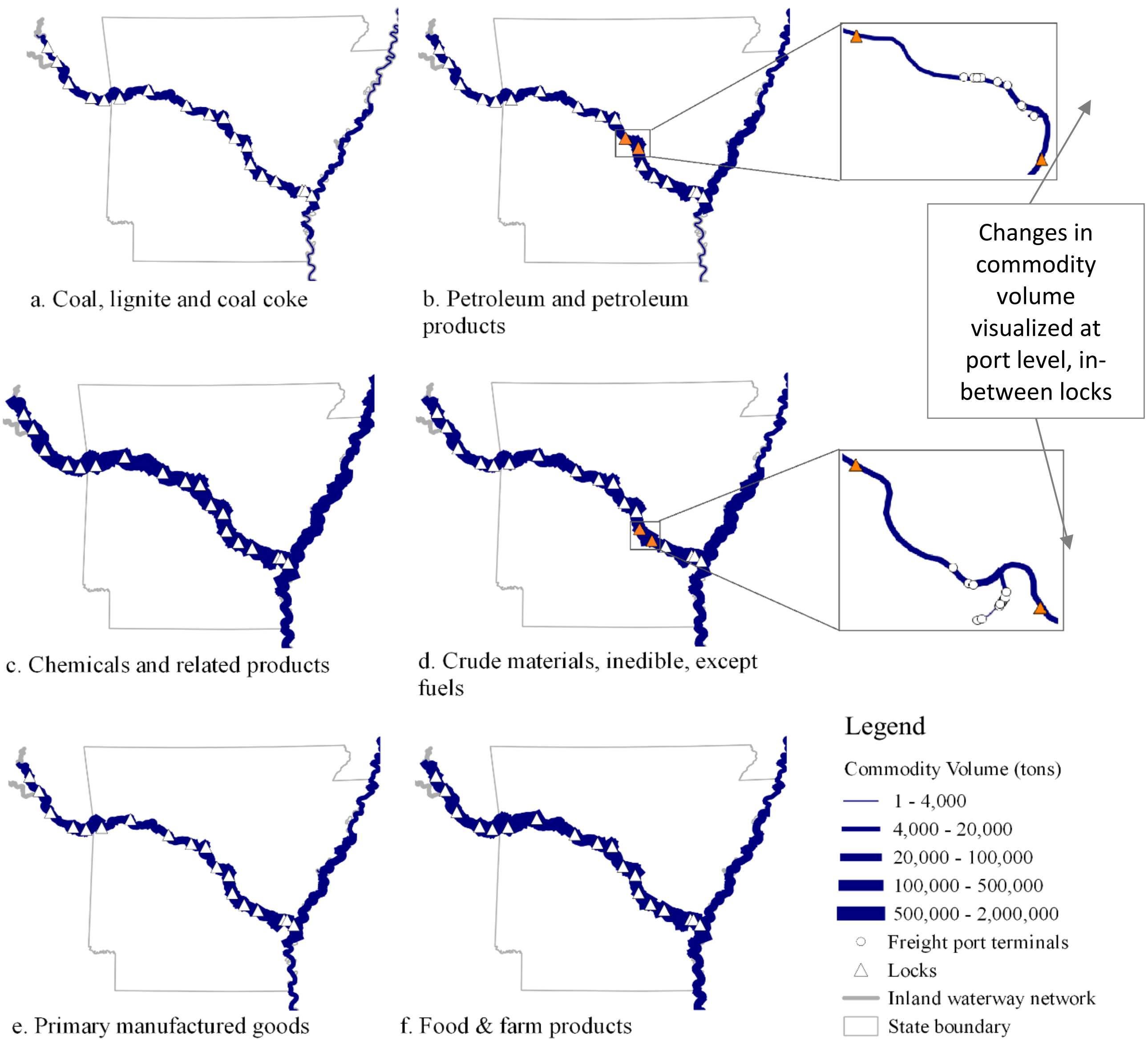


Figure 9. Commodity flow mapped to a highly disaggregated inland navigable waterway network in Arkansas, 2016

3.4 Port Terminal Dwell Time

The average dwell time for the 43 freight port terminals on the Arkansas River, as well as the number of stops identified during 2016 is shown in Figure 10. Dwell time is an indication of the time spent by tugs and towboats to maneuver while approaching the terminal, to safely moor barges, and load/unload cargo. Considering all of the 43 freight port terminals, the average dwell time on the Arkansas River during 2016 was 4.8hrs, with a minimum of 0.2hrs, a maximum of 30.5hrs, and a standard deviation of 5.8hrs.

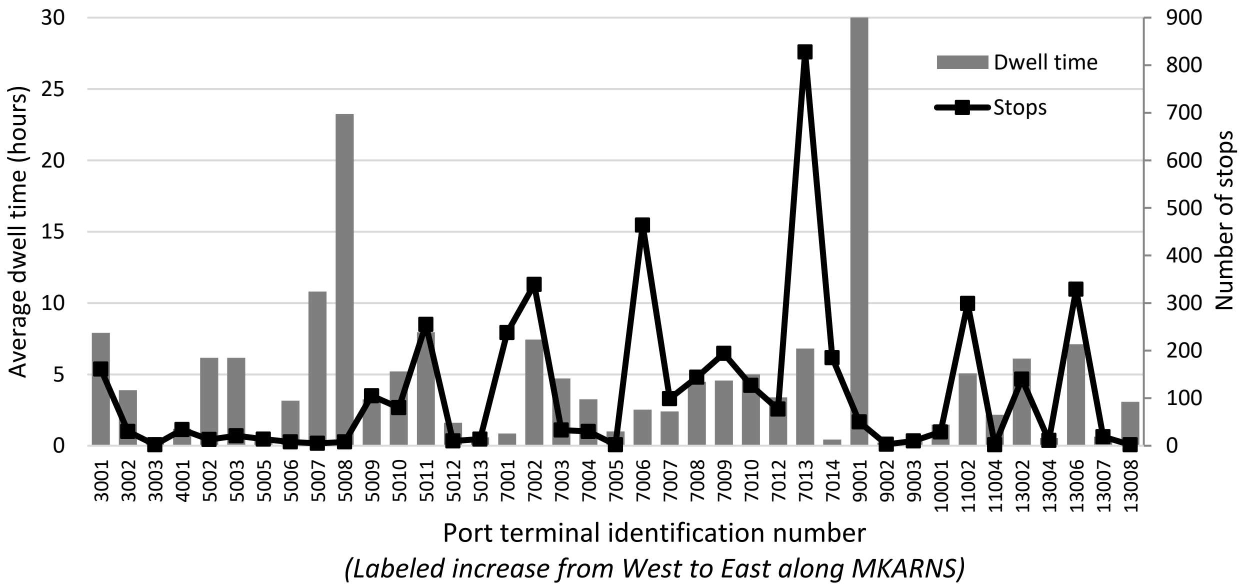


Figure 10. Average dwell time and number of stops per freight port terminal on the Arkansas River in 2016

4 Impacts/Benefits of Implementation

This section presents a discussion of the results of the port and vessel commodity assignment models, focusing on the anticipated impacts and benefits of implementation of this project.

Multimodal Catchment Areas The multimodal catchment areas defined by the truck and vessel data can be associated with potential investments on freight facilities. By using a data driven approach, rather than solely using professional judgement or targeted surveys, we present a consistent method to estimate port performance and impacts. The use of ubiquitous data in time and space, such as AIS and truck GPS, provides a more accurate depiction of the catchment area (or impact area) of a freight facility (when compared to the naïve assumption of radial impact areas around the facility). The unique impact areas could not be visualized by relying solely on surveys which may be untimely and costly or static traffic data which may be available at the study site. Even though truck trip paths (and thus, areas of impact) may be visualized from the output of a travel demand model, such models are based, in large part, on survey data. Waterway trip paths cannot be visualized from travel demand models that do not represent the navigable waterway network. In this context, vehicle tracking data provides a viable alternative to the outputs of state travel demand models to analyze multimodal freight catchment areas for project evaluation and prioritization.

Project Evaluation and Prioritization Within the context of transportation infrastructure investment, several projects compete for a limited amount of resources, based on an estimation of project benefits relative to costs, e.g., 'B/C ratios'. To evaluate project benefits, it is important to understand the extent, location, and characteristics of a project's impact area, or "catchment" area, which can be defined as the region where the facility draws and delivers freight, or the OD pairs served by the facility. However, little has been written regarding systematic methods to identify multimodal catchment areas. State-of-the practice methods to identify the impact area of a facility consist of arbitrarily selecting a radial perimeter around the facility, ignoring complex interactions among freight modes and supply chains. By visualizing multimodal port catchment areas from ubiquitous, continuous AIS vehicle tracking data, all projects evaluated are subject to the same data and criteria to identify their impact area, providing a common basis for proper comparison and competition of funds.

The commodity-based characterization of vessel trips on an inland waterway network, made possible by the fusion of mode-specific datasets, constitutes a data-driven measure of performance of the maritime transportation system and a guide to strategic investment decision-making. In particular, the quantification and identification of the type of commodities transported on inland waterway network links, from highly disaggregated data, allows for the prioritization of projects such as dredging, based on the economic value of commodities transported. The geospatial, timestamped trip data characterized by commodity produced by our model can support planning and scheduling of transportation infrastructure investments. In particular, traffic-disruptive maritime operations can be scheduled based on the selection of the time of year when a given commodity has its lowest traffic on the link and node of the network where the infrastructure improvements are planned, thus minimizing construction and maintenance impacts on the economy. A similar analysis can be conducted on the roadways (Hernandez, Asborno and Burris 2018).

Exposure Statistics The identification and visualization of the geographic extent of multimodal freight catchment areas can be used to estimate population and business exposure statistics, such as exposure to emissions, by super-imposing census and business locations to the catchment areas. For example, the number and location of unique TAZs that constitute the origin and destination of trips to and from each port, derived from multimodal vehicle tracking data, can be used to support long-range transportation planning purposes, such as scenario planning. Scenarios simulating disruption of business in those zones might impact the port terminal economic activity, and vice-versa. For example, a severe weather event such as a flooding affecting a port in Little Rock, located in Central Arkansas, may have an impact on freight flows observed as far as Northwest Arkansas, encompassing a total area of 10,500 thousand acres. While an event affecting traffic flows in Northwest Arkansas, such as an accident at a highway/rail crossing, may have an impact on the economic activity of a port located as far as Little Rock.

Mode Competition The visualization of the multimodal catchment areas identified by mode serve to individualize corridors of modal competition. For example, for the port terminal located southeast of Little Rock towards the eastern boundary of Arkansas (Port Performance Summary #1, see Appendix A), the freight catchment area map shows that both maritime and roadway catchment areas overlap between Pine Bluff and Little Rock, constituting a corridor of modal competition, where food and farm products are transported to and from the facility (as per the port throughput pie chart). Thus, policy to shift food and farm products from truck to vessel on this particular corridor may alleviate unnecessary truck trips from the highway system. Knowledge of this modal overlap for this particular port and corridor can lead to more targeted investment or policy than if a broad policy were to be implemented across Arkansas.

Port Performance Statistics The quantification of port terminal throughput by commodity and mode obtained by fusing truck GPS and LPMS data fills a critical gap by providing data that was not previously publicly available. Such data complements the port performance freight statistics program, limited to the top-25 ports by tonnage, and constitutes a key portion of freight fluidity performance measures. Moreover, it can be used to support location selection for multimodal freight facilities on inland waterways. For example, from Table 10 and Table 11, we observed that there is a relatively high volume of food and farm products transported annually along river section 13, but there is only one port terminal capable of handling such products (due to loading equipment and storage availability). In the event this particular port terminal is out of operation (flooding, for example), the next port terminal with capability to transload food and farm products might be redirected to river section 10. Alternatively, policy may target an incentive to increase the number of port terminals or the acquisition of equipment to handle food and farm products on existing terminals. The multi-commodity assignment model can be further used to perform scenario planning, simulating partial or permanent port closures for resilience evaluations, and quantify to which extent existing facilities may absorb the displaced commodity flows.

Demand Modeling The potential incorporation of the detailed waterway network (with commodity-flow) representing the Arkansas River on the multimodal statewide freight travel demand model would further improve the capabilities of such model, currently limited by the lack of a waterway network. For example, it would permit the comparison and prioritization of multimodal investments. In the absence of a detailed waterway network, state-of-the-practice freight Travel Demand Models (TDMs) cannot assign number of vessels per draft and cargo to the network, preventing a true multimodal comparison of capacity upgrade needs and benefits among roadways (by the addition of travel lanes) and inland waterways (by dredging). The proposed methodologies can be applied to identify areas with maritime freight activity that are not currently designated as loading/unloading areas in public databases, based on vessel stop clusters and satellite imagery. This can further refine TDM network representation.

5 Recommendations and Conclusions

Fusion of "big data" sources not typically used for freight transportation planning, such as maritime Automatic Identification System (AIS), truck Global Positioning System (GPS), and Lock Performance Monitoring System (LPMS) data, provides a consistent and novel data source for multimodal, long-range freight planning. The methods developed for this work describe, quantify, and characterize commodity-based freight activity on a multimodal transportation system, with focus on inland waterway networks.

One of the limitations discovered during this project is the lack of information on the number of barges pushed per tug. To overcome such limitation, it would be desirable to recommend the use of AIS transponders on barges. Practical examples of mandatory AIS transponders of barges can be found in the Port of Antwerp (Port of Antwerp 2012) with its main purpose being safety (collision avoidance). The use of AIS on barges on inland waterways would serve a dual purpose of safety and information to support freight planning. Alternatively, an AIS message to report the number of barges pushed per tug would be desirable, as it is required in Europe (Javor, et al. 2013). However, this reporting method is not ideal due to its manual nature.

In future work, we will explore how the GMAP and GMAP+ models can be used as scenario analysis tools. For example, we can use the models or future variants to quantify the impacts of disruptions caused by flooding, port capacity and capability expansions, and investment decisions. While the current models can in some way mimic a scenario such as a port closure, they are not designed to serve as a decision making tool. In future work, we will determine in what ways we can expand the applicability of our models to better serve decision makers from the public and private sectors.

To conclude, the data fusion models and methods presented in this work support several long-range multimodal freight transportation planning applications, focusing on the evaluation of performance of inland waterway transportation system components. The methods developed and applied in this project close critical data gaps, such as throughput by commodity on inland waterway port terminals, and quantity and type of commodities transported per tug-trip, previously unavailable in the public domain. Moreover, this work presents a critical step towards the broader goal of representing robust inland waterway freight activity into multimodal transportation infrastructure management and strategic decision-making. Ubiquitous AIS and truck GPS data permit the transferability of the proposed model to other regions with waterways and aggregated commodity-flow data.

6 Future Work

Future work may improve and expand the methods presented in this work in several ways, such as: i) temporal disaggregation of the annualized port throughput by commodity obtained in this work, ii) development of a model that does not rely on truck GPS data, iii) temporal analysis of freight flows by commodity on inland waterways from automated data, , iv) further commodity disaggregation; an v) replacement of manually entered AIS fields by machine learning methods.

The multi-commodity assignment model presented in this work may be improved by adopting a time-expanded approach, in which a monthly analysis during a complete year is conducted. The results of a time-expanded multi-commodity assignment model would be the port throughput by commodity per month (instead of annual, as presented in this work). Such results would provide a more detailed input to the characterization and quantification per commodity type of cargo transported by vessel trips as identified on inland waterway networks, improving its results. Alternatively, LPMS commodity data may be directly disaggregated into the type and quantity of cargo transported by vessel trips transiting inland waterway locks (as observed from AIS data), and then use the paths, origin and destination of those trips to derive port throughput and highly disaggregated commodity flow on a detailed inland navigable waterway network. In this way, the truck GPS data, which is the most expensive source used in this work, would not be needed.

In this work, by mining AIS data, vessel trips were identified and characterized by place of origin (location as latitude and longitude, and port if applicable), destination, duration, length, timestamp, and most importantly, commodity carried. Based on this highly-disaggregated vessel trip characterization, future work may utilize unsupervised machine learning tools to find temporal and spatial patterns on commodity flows on inland waterways, taking one step further in the development of synthetic populations for activity-based freight travel demand models, for example.

Focusing on commodity-based planning, the nine commodity groups defined by LMPS were used in this work. However, it may be beneficial to further disaggregate commodities. For example, with the food and farm products category it would be valuable to know the breakdown of soybeans and rice, from other grains as they have different harvesting and shipment patterns as well as different constituent groups that lobby for their consideration in freight planning and policy development. The methods (e.g., GMAP) developed in this project can leverage additional, commodity-specific data sources for data fusion with the goal of commodity disaggregation. Such sources include the Agricultural Marketing Service data from Department of Agriculture (USDA), data from the National Agricultural Statistics Service, and data from the United States Energy Information Administration (EIA).

Lastly, this project focused primarily on the development of assignment models solved via optimization. Another possible modeling tool is that of machine learning (ML). ML tools are adept at finding patterns and making predictions from ubiquitous, highly disaggregated data like AIS. In particular, a drawback noted in the current publicly shared version of AIS data are the manually entered fields for commodity carried. As these fields were prone to human error, they were not used in this work. However, ML may be a promising tool to replace manually entered features. One such feature is the “status” of a vessel that indicates the type of activity in which a vessel is involved. To minimize human efforts and error, an unsupervised data mining algorithm (such as K-means clustering) could be applied to derive the activity based on features derived in this work from AIS data like trip length, duration, coverage, average speed, origin, and destination.

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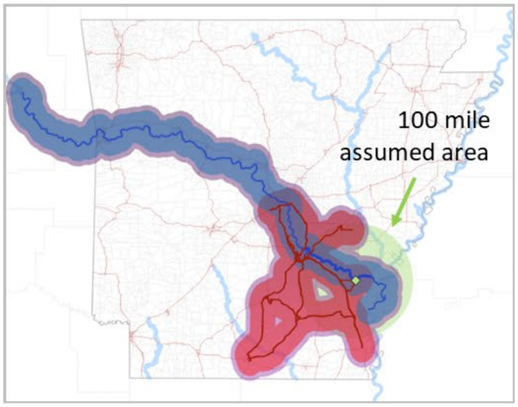
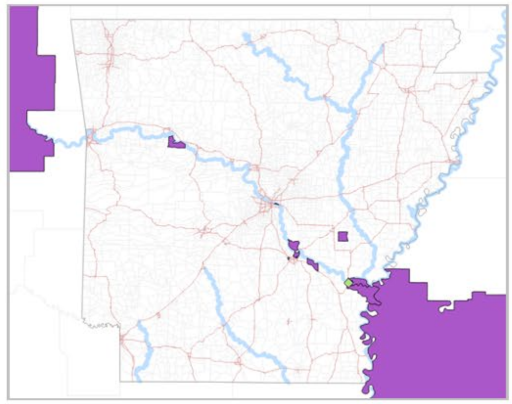
A1. Appendix A: Port Performance Summaries

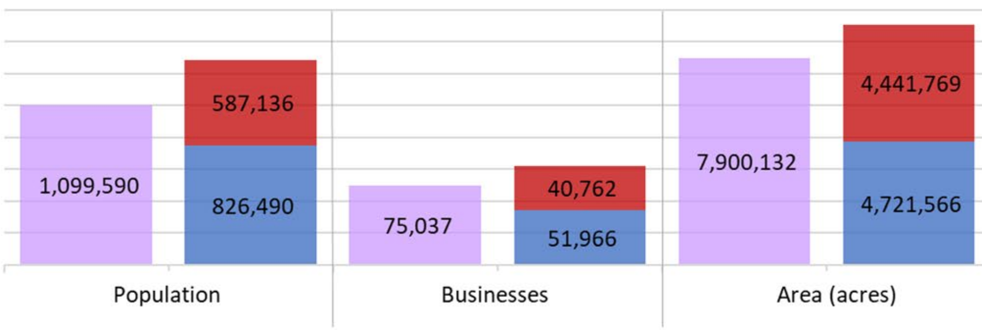
Port Terminal #1 Performance Measures
Annual Summary, 2016

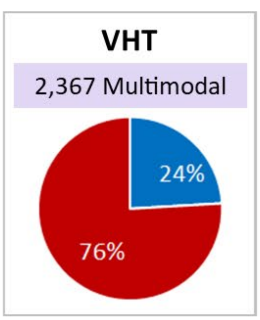


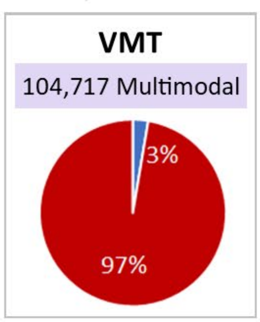


Freight catchment areas

13 unique TAZs as Origin or Destination of trips from/to this port terminal



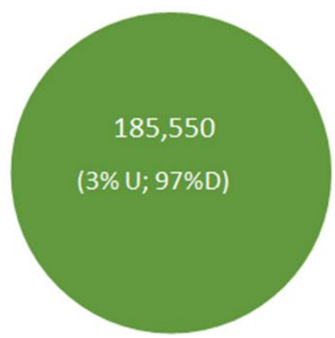




Travel time Dwell time

■ Multimodal ■ Maritime ■ Roadway

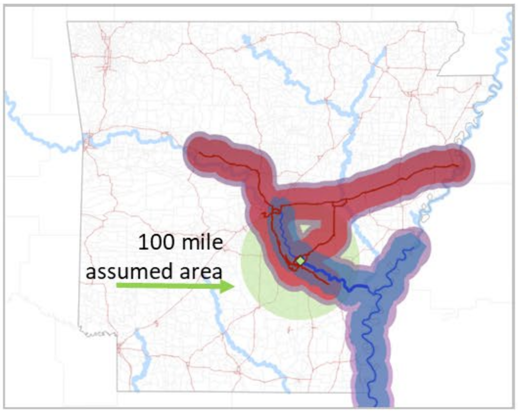
Port throughput by commodity



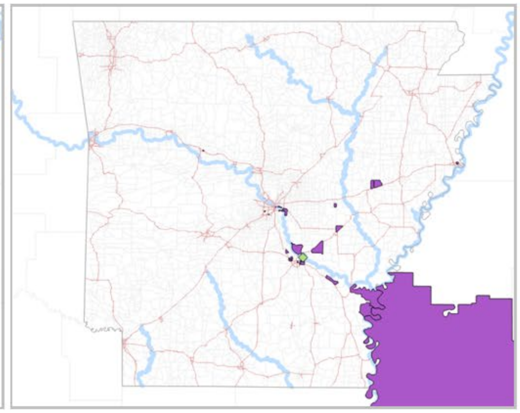
U: Upriver D: Downriver

■ Food & farm

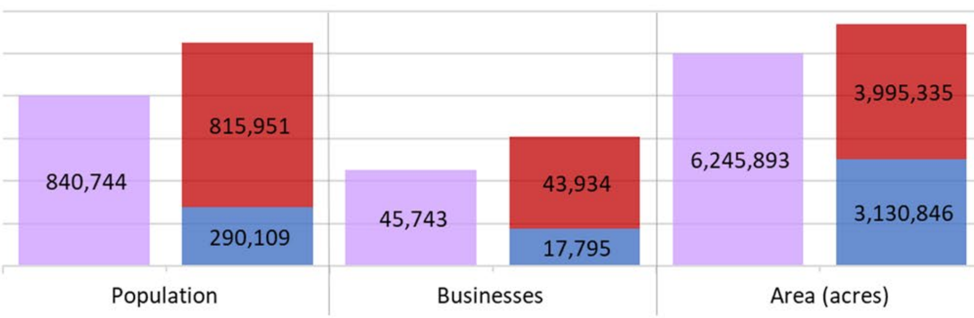
Port Terminal #2 Performance Measures
Annual Summary, 2016

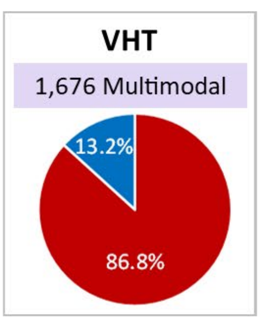


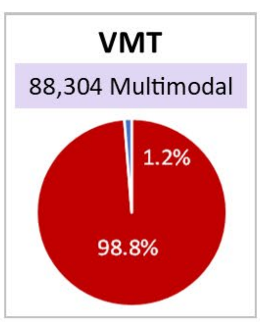
Freight catchment areas



29 unique TAZs as Origin or Destination of trips from/to this port terminal



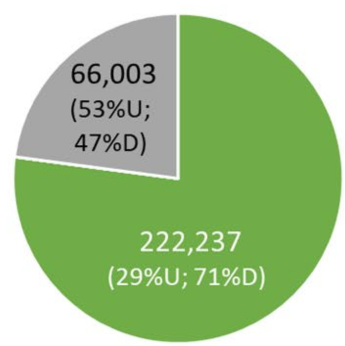




Travel time

■ Multimodal ■ Maritime ■ Roadway

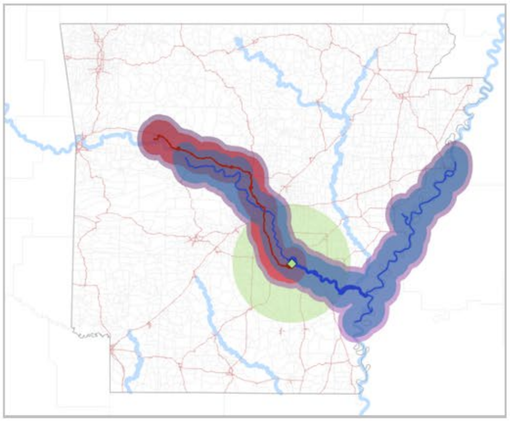
Port throughput by commodity



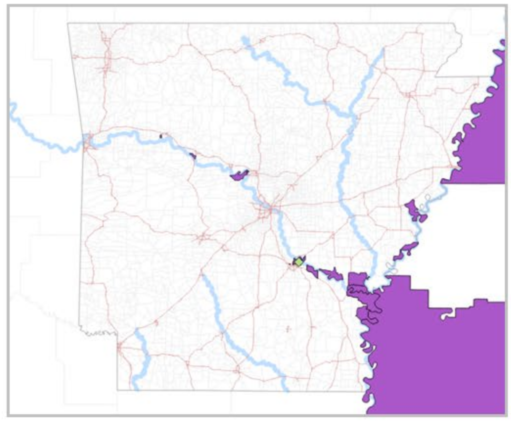
U: Upriver D: Downriver

■ Food & farm ■ Unknown by Rail

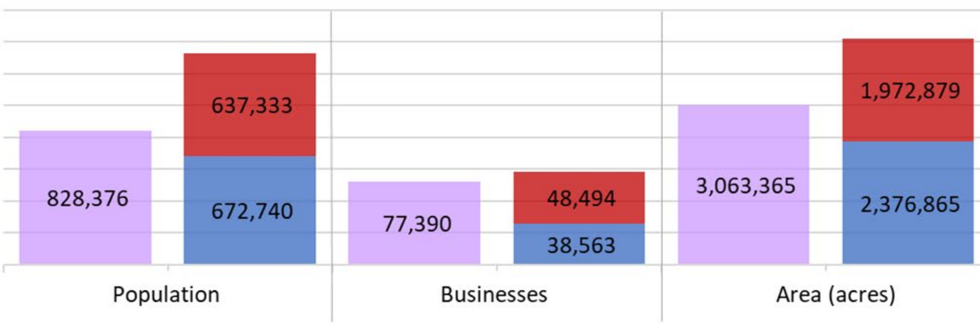
Port Terminal #3 Performance Measures
Annual Summary, 2016

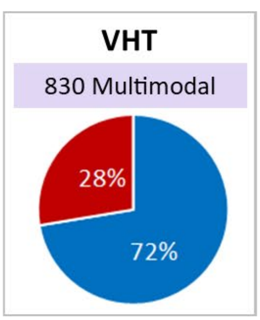


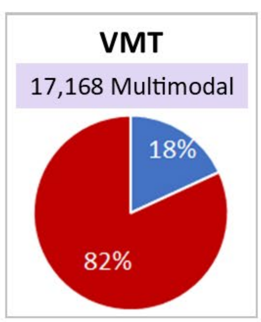
Freight catchment areas



9 unique TAZs as Origin or Destination of trips from/to this port terminal



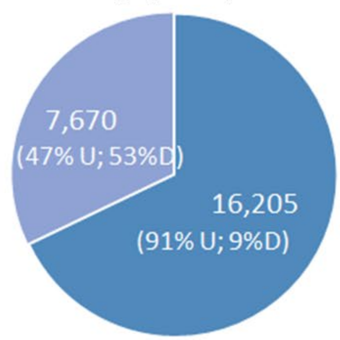




Travel time

Multimodal ■ Maritime ■ Roadway

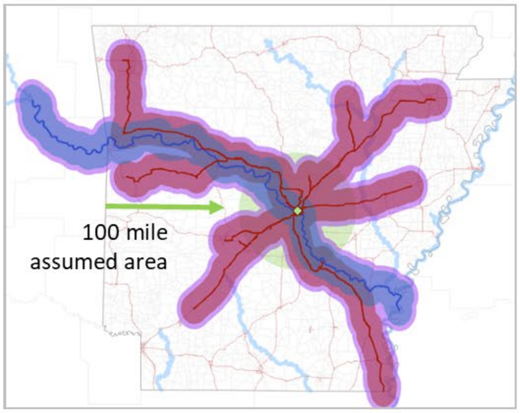
Port throughput by commodity



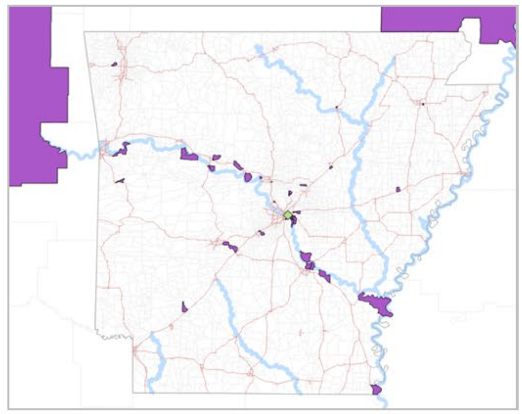
U: Upriver D: Downriver

■ Machinery ■ Manufactured

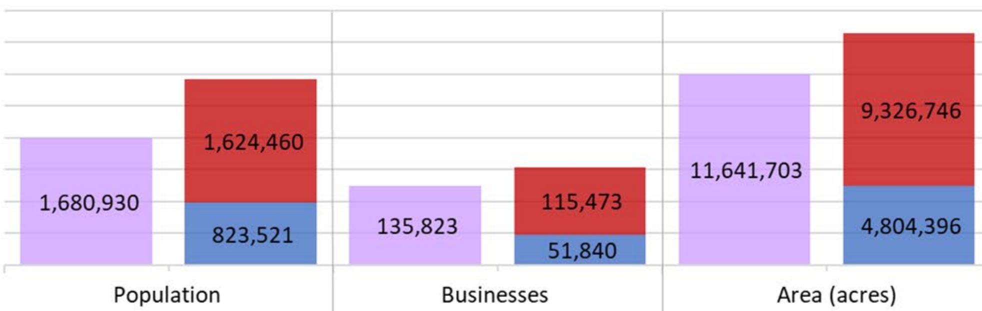
Port Terminal #4 Performance Measures
Annual Summary, 2016

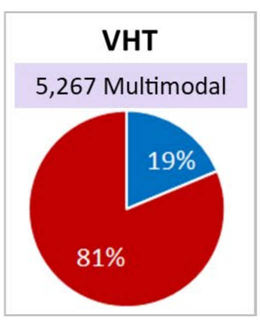


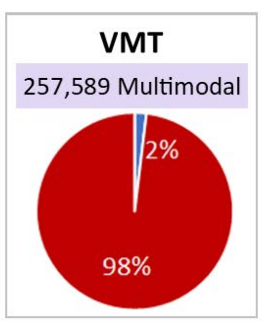
Freight catchment areas



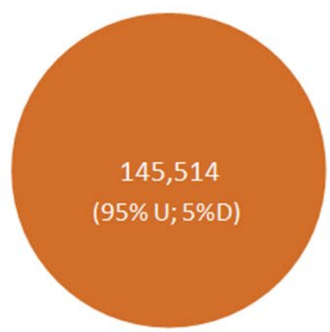
50 unique TAZs as Origin or Destination of trips from/to this port terminal







Port throughput by commodity



Travel time

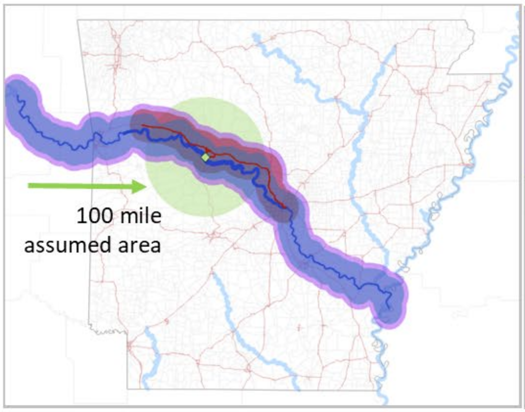
Dwell time

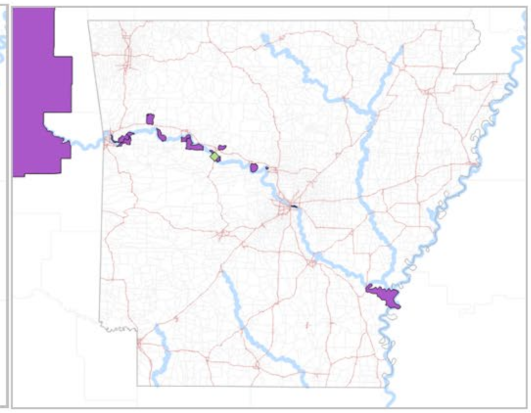
■ Multimodal ■ Maritime ■ Roadway

U: Upriver D: Downriver

■ Petrol

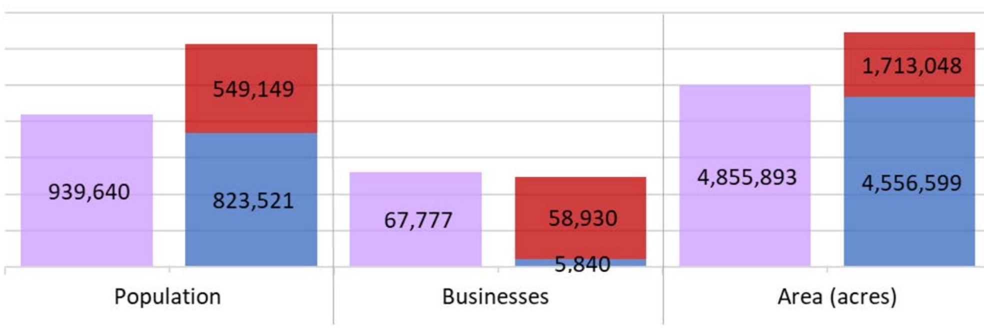
Port Terminal #5 Performance Measures
Annual Summary, 2016

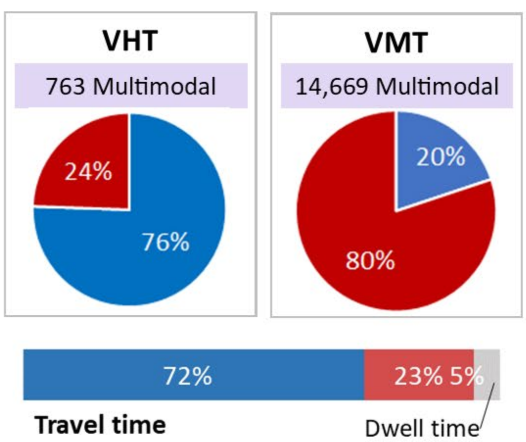




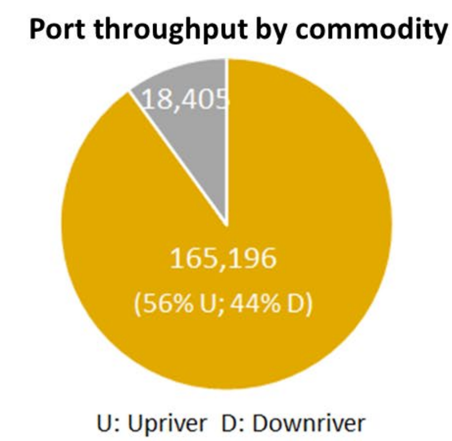
Freight catchment areas

19 unique TAZs as Origin or Destination of trips from/to this port terminal

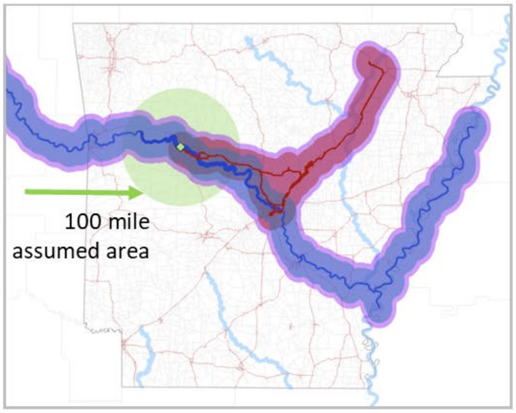


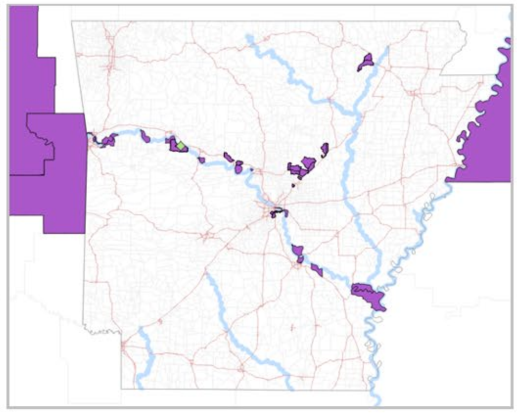


Multimodal Maritime Roadway



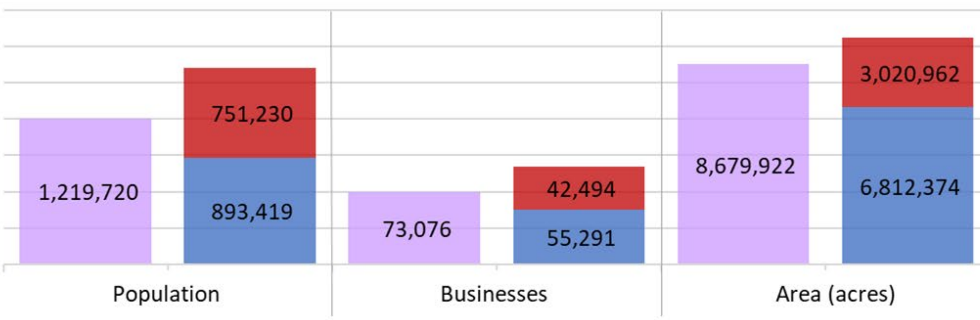
Port Terminal #6 Performance Measures
Annual Summary, 2016

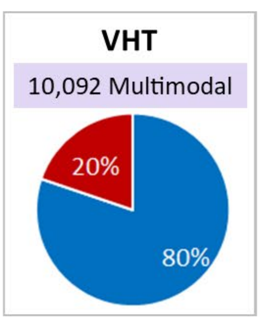


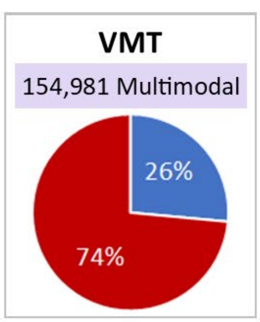


Freight catchment areas

56 unique TAZs as Origin or Destination of trips from/to this port terminal



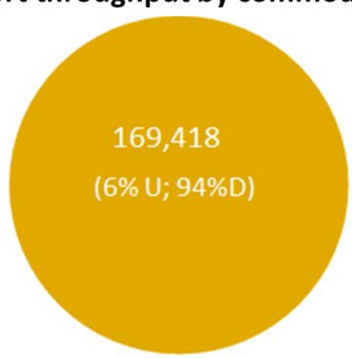




Travel time Dwell time

■ Multimodal ■ Maritime ■ Roadway

Port throughput by commodity



U: Upriver D: Downriver

■ Crude materials