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DISAGGREGATION OF FREIGHT FLOWS FOR TENNESSEE

FINAL REPORT

by

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EXECUTIVE SUMMARY

With the continuous increase of freight flows, environmental awareness, population, and an aging transportation infrastructure, the importance of reliable, sustainable, and safe freight transportation has grown substantially. Freight-related data (e.g., commodity flows, truck flows, freight facility economic and establishment data) have always been critical components for freight transportation planning at state, regional, and local jurisdictional levels and corridors. Commodity flow data allows transportation planning agencies to better understand freight movements and develop regional and state transportation plans for regional and local transportation projects. A variety of freight transportation data sources are currently available, both open source and proprietary. However, their application is limited due to a lack of geographic detail. Proprietary data at disaggregate levels do exist, but their cost is often prohibitive for statewide planning. Research efforts are needed to obtain high-resolution commodity flow data that would allow state Departments of Transportation (DOTs) and regional agencies to have a better understanding of freight movement and plan to provide the adequate infrastructure to meet the growing needs of freight demand and use in the travel demand model for planning and forecasting and policy decision making such as freight diversion studies.

This research addresses this issue by developing models and procedures to obtain regional, sub-regional, and jurisdictional level commodity flow data in Tennessee. The research objectives of this project were as follows:

1. Collect and compile a geodatabase with all the available freight flow, land-use, and economic activity data (open source and/or proprietary) for the state of Tennessee.
2. Develop the methodology and tools that can be used to disaggregate freight flows, land-use, and economic activity data in the state of Tennessee.
3. Apply the developed methodologies and tools to estimate and analyze freight flows, land-use, and economic activity data in the state of Tennessee at different disaggregation level.
4. Develop a comprehensive guidebook for the estimation of commodity flows, land-use, and economic activity and their applicability and use in freight planning.
5. Promote collaboration between the Piedmont Atlantic Megaregion states of freight planning, operations and management, and project selection.

To achieve the above objectives, the research team performed the following tasks:

1. Conducted a critical review summarizing published studies on freight, land-use, and economic data and how they can be applied and used for freight demand modeling and planning at various levels of aggregation (e.g., national, regional, state, local).
2. Collected and compiled into a geodatabase all the available freight flow, land-use, and economic activity data for the state of Tennessee.
3. Developed the methodology to estimate and disaggregate commodity freight flows (by mode), land-use, and economic activity data from the state/county level to the

zip code and Traffic Analysis Zone (TAZ) levels using employment codes as proxies to land use. This methodology will be able to disaggregate land use at any level the user requires.

4. Incorporated the commodity flow disaggregation methodologies into the ArcGIS software in the form of a series of toolboxes.
5. Developed a guidebook for the estimation of commodity freight flows, land-use and economic activity using the developed toolboxes to support development, implementation, and maintenance of a comprehensive freight plan and program to advance techniques and policies, to improve performance, reliability, safety, environmental sustainability, and direct capital investment for freight movements in Tennessee.
6. Developed a case study to showcase how state and local transportation agencies can utilize the guidebook and tools in innovative ways to support freight planning.
7. Identified new and emerging data sets and how they can be used independently or in association with the existing data for freight demand modeling, and short- and long-term decision making to address freight challenges.
8. Developed a searchable and straightforward application that would help identify how the available freight datasets have been used in freight planning by agencies and researchers.
9. Identified the effects of mega-trends on the structure and operations of supply chains, availability of data, and data needs by the public sector for efficient freight transportation planning.
10. Used truck Global Positioning System (GPS) data provided by the American Transportation Research Institute (ATRI) to update a 2018 truck parking congestion analysis and data analytics tools in Tennessee by including years 2019 and 2020.
11. Identified opportunities for freight collaboration across states that belong to the Piedmont Atlantic (PAM), Northeast and Florida Megaregions.
12. Planned and hosted a half-day virtual workshop to identify freight issues that are of concern and promote collaboration between the Piedmont Atlantic, Northeast, and Florida Megaregion states on freight planning, operations and management and project selection.

The research presented in this report implemented models and developed Geographic Information Systems (GIS) tools to disaggregate the IHS Global Insight's TRANSEARCH commodity freight database to any jurisdictional level. The IHS database was selected as it is the most comprehensive freight movement database at the county level. Two disaggregation methods were integrated into GIS tools. The first method relied on the industry proportional weighting and economic indicator regression. The second was based on industry and economic indicator proportional weighting. InfoUSA, a data package product of the Infogroup company, business and consumer contact database were used to obtain disaggregate-level zone economic indicators (employment, the value of sales, and sq. footage) values. Bureau of Economic Analysis (BEA) Input-Output Account Supply and Use tables were utilized to link industries that produce with industries that use the commodity and estimate their shares. The economic indicator regression was used to create a relationship between the aggregate zone economic indicators and freight flow productions and attractions. The economic indicator proportional weighting was employed to create a relationship between the disaggregate and aggregate zone freight flows using industry economic indicator shares. Three freight flow distribution methods were applied: the Gravity model, the Iterative Proportional Fitting, and Proportional Weighting. The developed ArcGIS tools were grouped into three sets: the preprocessing tools, the disaggregation tools, and the postprocessing tools. The preprocessing tools prepared the input data in disaggregation tools. The disaggregation tools were created for each of the disaggregate models. The postprocessing tools were created to provide the user with analytical and visualization capabilities. Analytical capabilities were achieved by giving users the ability to select the disaggregate flows by some condition or estimate disaggregate zone productions and attractions. The visualization was achieved by providing users with the ability to automate map creation to visualize either disaggregate Origin-Destination (O-D) flows or productions and attractions.

This research provides the Tennessee Department of Transportation (TDOT) and regional/local agencies in Tennessee with high-resolution (i.e., disaggregated in a finer geography) commodity freight flow data. This data can be utilized to better understand freight movements to plan for adequate infrastructure to meet the growing needs of freight demand, use in the travel demand model for planning and forecasting, and maintain a database of intra- and inter-regional commodity flows. Moreover, it helps obtain the growth and enhance policy decision-making such as expanding freight diversion opportunities, and develop and analyze links between commodity flows, economic activity, and land use. This research will also support freight planning by documenting and analyzing the strengths and limitations of emerging new freight flow, land-use, and economic activity data and their potential applications in freight planning and modeling.

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CHAPTER 1 INTRODUCTION

As freight transportation draws increasing attention, freight-related data (e.g., commodity flows, truck flows, freight facility economic, and establishment data) are becoming even more critical to conducting transportation planning at state, regional, and local jurisdictional levels. The purpose of using commodity flow data in transportation planning is to understand which industries and localities generate the most freight demand by mode on the transportation system and how to develop policies that would support the movement of certain commodities between various modes to minimize externalities and improve the efficiency of the transportation system. This data can provide a key link between economic trade relationships and freight demand. There are currently several useful commodity flow data sources (open source and proprietary) at the national level. However, their application is limited to the state, regional, and local planning because they lack the appropriate geographic detail (i.e., level of disaggregation). Many commodity flow data sources and survey techniques do not track cargo movements in a set of linked modal transfers from the point of production of a product to the point of consumption. This does not directly align with the desire of many State Departments of Transportation (DOTs) and Metropolitan Planning Organizations (MPOs) who want to use commodity flow data for modal diversion to study their impact on specific highways or rail lines, and as the primary freight, demand input to travel demand models. Commodity flow data often does not explicitly account for the intermediate handling of cargo in specifying origins and destinations. Furthermore, mode-specific information is not attached to the commodity flow data. Commodity flow, land-use, and economic activity data at a disaggregate-level are critical to conducting freight transportation planning at the state, regional, and local levels. Such data can provide links between the industries that generate and attract the demand and can provide critical information for freight demand modeling and modal diversion studies.

This research presents models and procedures that can be used to obtain regional, sub-regional, and jurisdictional level commodity flow data. Model strength to accurately obtain commodity flow data is demonstrated through case studies that will illustrate the applicability of commodity flow data in travel demand models in Tennessee. Finally, a guidebook was prepared that (1) details how commodity flow data should be collected and disaggregated to be used in local planning models for decision making and to understand freight movement in Tennessee better, and (2) identifies and categorizes the current and rapidly emerging data being collected or processed by the private sector for freight movements and outline approaches, methods, analytical techniques, and megatrends that enable local agencies, MPOs, and state DOTs to better understand freight planning, programming, and operations responsibilities. While initially, this research proposed to develop and host a summit, to present findings from this project and foster the beginning of dialog with regards to developing collaborations of the Piedmont Atlantic Megaregion (PAM) states for improvement of freight planning, operations and management, and project selection and funding, due to the COVID-19 pandemic crisis, an online workshop was instead developed and hosted by the research team.

The remainder of the report is structured as follows. Chapter 2 provides a review of studies that have employed freight flow disaggregation methods. Chapter 3 presents collected and compiled all the available freight flow, land-use, and economic activity data for the state of Tennessee into ArcGIS geodatabase accompanied with the developed application that would help identify how the available freight datasets have been used in freight planning by agencies and researchers. Chapter 4 presents the freight flow estimations and the disaggregating methods accompanied by a description of the method's advantages and disadvantages, the implemented methodology for the developed disaggregation models, and a simple numerical example showcasing the developed models. Chapter 5 presents the developed ArcGIS tools, their computational times, and case studies an example of map output showed. Chapter 6 identifies megatrends that affect the structure and operations of supply chains, availability of data, and data needs by the public sector for efficient freight transportation planning. Chapter 7 provides the results from the truck parking congestion analysis. Chapter 8 provides the results from the freight workshop and Chapter 9 concludes the report and provides a summary of future research avenues.

CHAPTER 2 LITERATURE REVIEW

As part of the study, the literature on freight flow disaggregation methods was reviewed. In total, 25 studies were reviewed with dating publication years from 2000 to 2020. A summary of studies that have used Proportional Weighting, Regression, and other methods are presented in the supplementary document that accompanies this report. The summary review table provides information on the applied methods, study objective, disaggregate zone spatial resolution, the types of modes modeled, commodity flow datasets utilized, and variables used to disaggregate commodity flow data. Among all applied disaggregation methods, the most applied was the proportional weighting, which accounted for 60 percent of all instances, followed by regression (23 percent). All other methods such as iterative proportional fitting, cross-classification, econometric, multinomial logit, behavior-based, and structural equations accounted for 3 percent of all instances. Employment was the most common variable used to disaggregate commodity flows summing up to 35 percent of all the cases, followed by population (27 percent), farm acreage (11 percent), the value of sales (5 percent), payroll (5 percent), vehicle miles traveled (VMT) (3 percent), and livestock (3 percent). Variables such as gross domestic product (GDP), electricity generated, the number of establishments, personal income, total make value, and fractional attraction and production levels accounted for 2 percent of all instances. Approximately 30 percent of studies used some variation of Input-Output (IO) model outputs in their studies. The most often adopted freight flow data source was the Freight Analysis Framework (FAF), which was used 35 percent of the time. TRANSEARCH (the Intermodal Transportation Management System (ITMS) also included), Impact Analysis for Planning (IMPLAN), and Commodity Flow Survey (CFS) were utilized 15 percent of the time, followed by Waybill (9 percent), and the Bureau of Transportation Statistics (BTS) Air Carrier Statistics (4 percent). Other data sources such as BTS Border Crossing Database, BTS Transborder Freight Database, and statewide models were employed 2 percent of all instances.

Proportional weighting

The proportional weight disaggregation method was found to be the most widely used freight flow allocation method. Typically, the aggregate-level zone values are allocated to disaggregate-level zones proportionally by some socioeconomic data variable or industry-specific or commodity-specific activity data. The Battelle Institute (1) developed a methodology (see Figure 2-1) to allocate Freight Analysis Framework version 2 (FAF2) data to the county-level. County freight tons generated by all combined commodities were estimated as a function of FAF2 zone all combined commodity tonnage, total truck VMT within the county, and FAF2 zones.

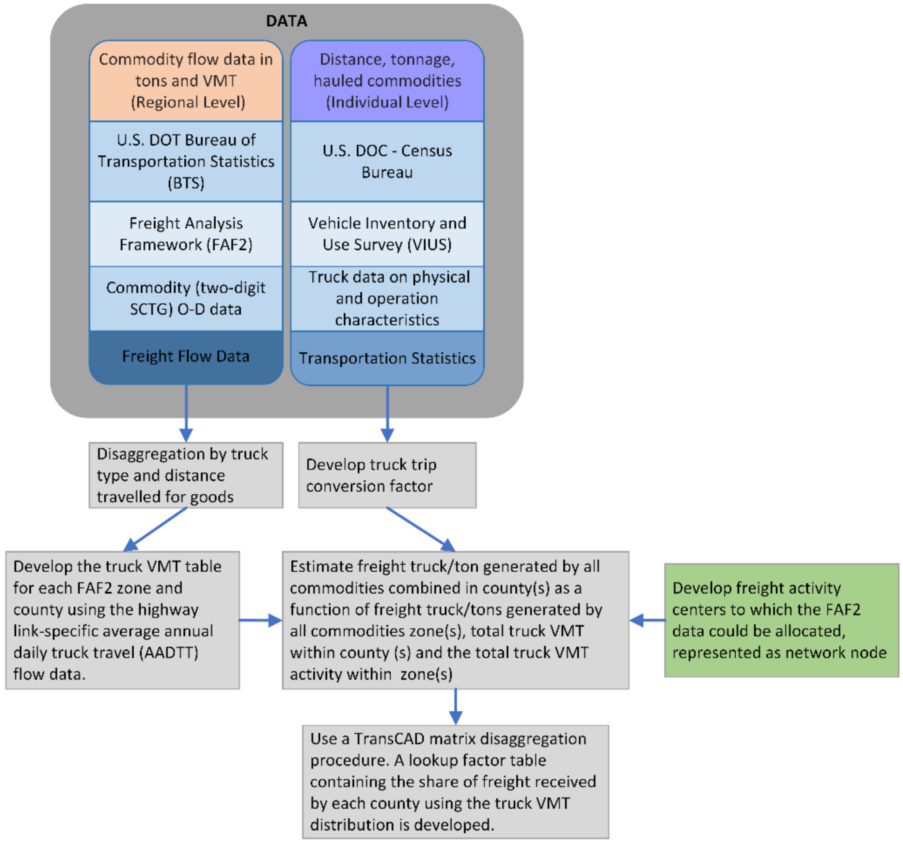

Figure 2-1 Development of County-to-County Freight O-D Matrix from 2002 FAF2 Freight Data

Zang et al. (2) disaggregated CFS down to Traffic Analysis Zone (TAZ) level by proportionally allocating commodity flow using employment and population. Opie et al. (3) developed thirteen methods to disaggregate FAF2 commodity data down to the county level for New Jersey. The authors used various socio-economical and transportation data to allocate data using proportional weight disaggregation. J. R. Wilburn and Associates (4) used the proportional weight disaggregation method to disaggregate FAF4 to county-level using employment data by industry. The data was further disaggregated at the census tract level by applying the shares of census tract to county employment. However, there was no way to differentiate the employment by North American Industry Classification System (NAICS) code at the sub-county level. Shin and Aultman-Hall (5) suggested using a five-digit Zip code Business Pattern (ZBP) from the U.S. Census Bureau to develop Freight Analysis Zones. The number of business establishments by zip codes was weighted by employee size and utilized as a proxy of freight activity to disaggregate the CFS dataset. The San Joaquin Valley Council of Governments, as described in National Cooperative Freight Research Program (NCFRP) Report 26 (6), proportionally allocated (see Figure 2-2) ITMS commodity flow data from county-level to zip code-level using industry employment and farm acreage for the agricultural industry.

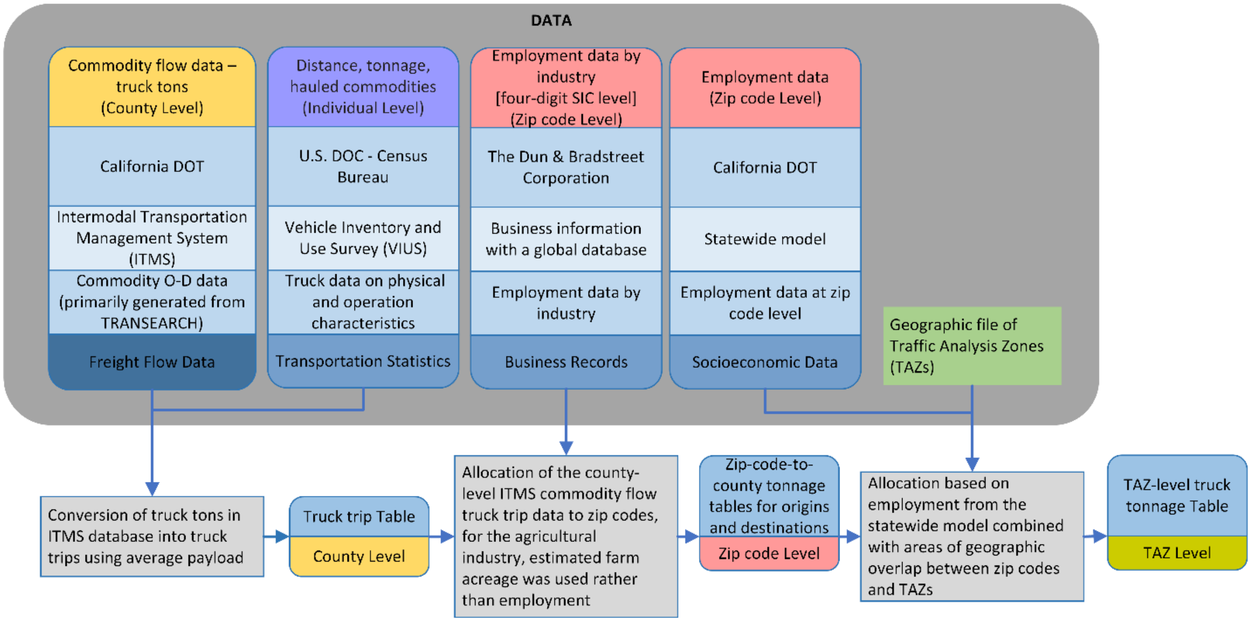

Figure 2-2 Proportional Weighting Allocation for San Joaquin Valley Truck Trip Table Development at the TAZ level

Southern California Association of Governments (*7*) developed model forecasts trips for three heavy-duty truck weight classes. The truck trips were generated and distributed using a combination of TRANSEARCH data and NAICS 2-digit employment or acreage data for allocating county data to TAZs (see **Error! Reference source not found.**).

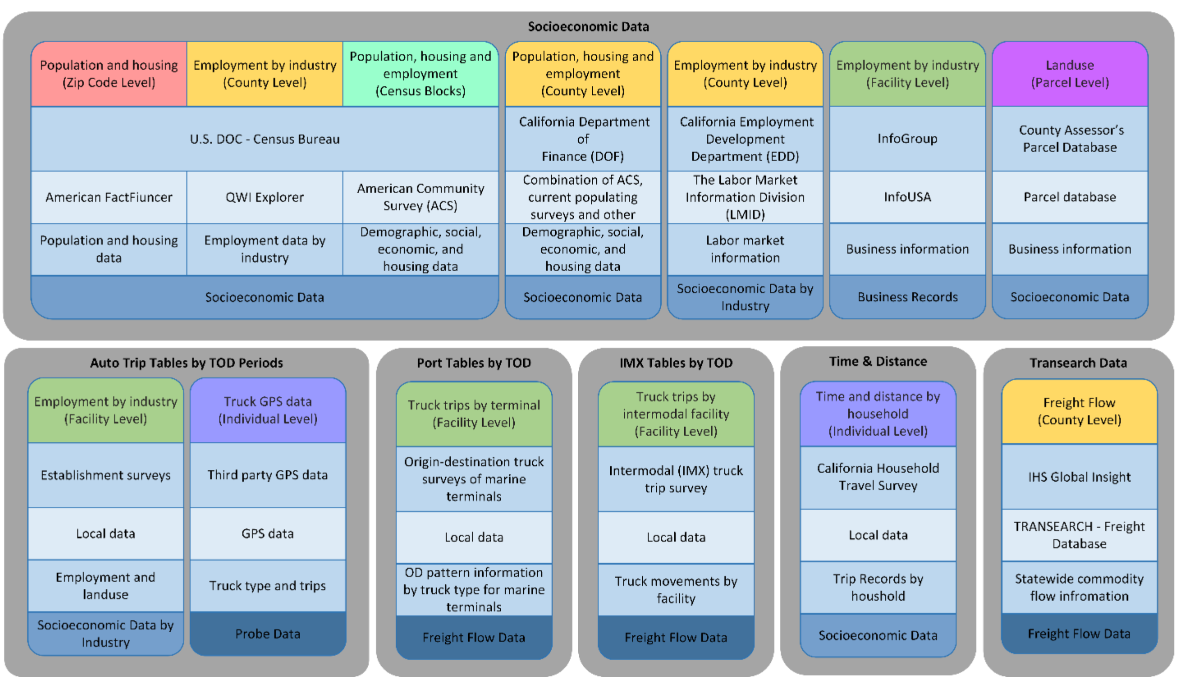

Figure 2-3 The Southern California Association of Governments Heavy Duty Truck Model Input Data

Jansuwan et al. (8) used the FAF3 database to allocate truck flows to internal and external state zones and then use the proportional weighting disaggregate commodity flow using employment and population.

Several studies utilized the outputs of Input-Output models with proportional weighting. These models can provide information on the economic outputs and inputs used in the production process. Commodity-based external urban truck trip models were developed by Fischer et al. (9). The authors used TRANSEARCH and Input-Output modeling data from IMPLAN to disaggregate the county-level commodity flows to the TAZ-level using employment data, land use data, and commercial facility data. Sorratini and Smith (10) used CFS, TRANSEARCH, and IMPLAN data to disaggregate truck flow down to TAZ-level. First, truck tons per employee for each sector at the county-level was estimated. Truck trip attractions were derived based on the IMPLAN model. The monetary values were converted to tons to obtain commodity attraction rates in tons per employee. The population was used to distribute the county-level truck tons to the TAZ-level. Mitra and Toliver (11) applied the proportional weighting method with outputs from the Input-Output Accounts to disaggregate FAF2 data to county-level using employment by industry obtained from County Business Patterns (CBP). The inbound flow was disaggregated to the TAZ-level based on the number of manufactures and other economic sectors in the TAZ. Freight flow distribution was performed using the Gravity model. Giuliano et al. (12) used IMPLAN in combination with import/export commodity flow data from secondary sources to estimate detailed commodity flow at the TAZ-level. Regional Input-Output tables were utilized to estimate commodity-specific trip attractions and trip productions. Estimates were further allocated to TAZs using employment by sector and proportional weight disaggregation method.

Regression

Another common method used in disaggregating freight flow data is regression. Regression models are used to establish a statistical relationship between commodity-specific freight flows and one or more explanatory variables. Viswanathan et al. (14) developed a methodology to disaggregate FAF2 data to the county-level. The CBP and Census PUMS files were used to create a relationship between employment by industry and the commodities those industries produce and consume. The industry's employment data was aggregated to develop mathematical relationships between the FAF2 commodity shipments to and from a FAF2 region. The employment data by industry was then used with these equations to estimate the expected production and attraction of freight tonnage in a FAF2 region and smaller geography units in that FAF2 region. Ruan et al. (15) explored three methodologies to generate county-level outbound shipment data (i.e., proportional weighting, direct regression, and optimal regression model). In the proportional weighting method, freight flow was allocated using employment by industry obtained from the CBP. In the regression method, employment, and the number of intermodal facilities, obtained from the National Atlas, was selected as the indicator of the total commodity outbound shipments in an area. First, regression equations were developed for the FAF regions and then applied to the counties of the FAF regions. The optimal regression method involved adding the direct regression and disaggregation matrix that guarantees that the county-level estimates will add up to the regional total. NCFRP Report 20 (16) described a disaggregation methodology (see Figure 2-4) developed by FHWA to divide FAF2 regional commodity O-D data to county-level O-D data using local economic data and regression. Employment, farm acreage, livestock, and electricity generation information data were aggregated to develop mathematical relationships between the FAF2 region commodity flows and the industries in that FAF2 region. The developed regression equations for the FAF regions were then applied to the counties inclusive in the FAF regions. Proportional weighting is then used to obtain the final flows at the county level.

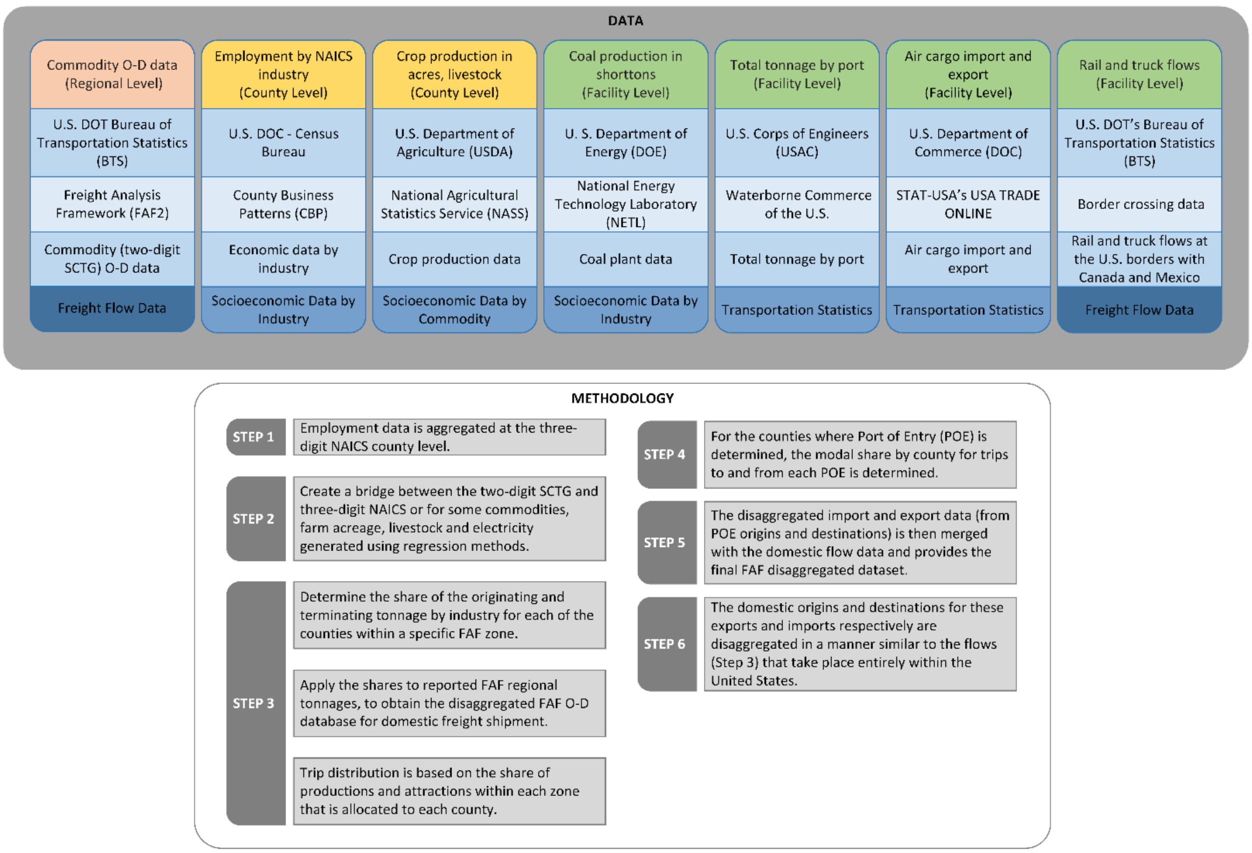

Figure 2-4 Disaggregation of FAF2 regional commodity O-D data to county-level O-D data using regression

Ross et al. (17) disaggregated the FAF3, first to the county level and then to TAZ-level. Spatial regression and nonlinearity transformation techniques were used to identify the relationship between commodity productions/attractions with employment and other explanatory variables like population and highway access. For each FAF region and commodity productions and attractions, regression equations were developed and used to estimate disaggregated produced and attracted tonnage and further used the proportional weighting method.

A few of the studies employed the regression method with outputs from Input-Output models. Chin and Hwang (18) used the cross-classification and regression to disaggregate the CFS data to county and zip code level (see Figure 2-5). The authors used ZBP data to estimate the number of business establishments weighted by employment size classes, which was used as a proxy of freight-related economic activities. Freight productions were modeled by quantifying the freight shipped value by industry sector from the CFS and an annual payroll by industry sector from BEA Input-Output Accounts. Freight attractions were modeled by quantifying the share of industry sectors that use the commodities produced by a given industry sector, the state-level of the total annual payroll from industry sectors that use the commodities produced by each industry sector.

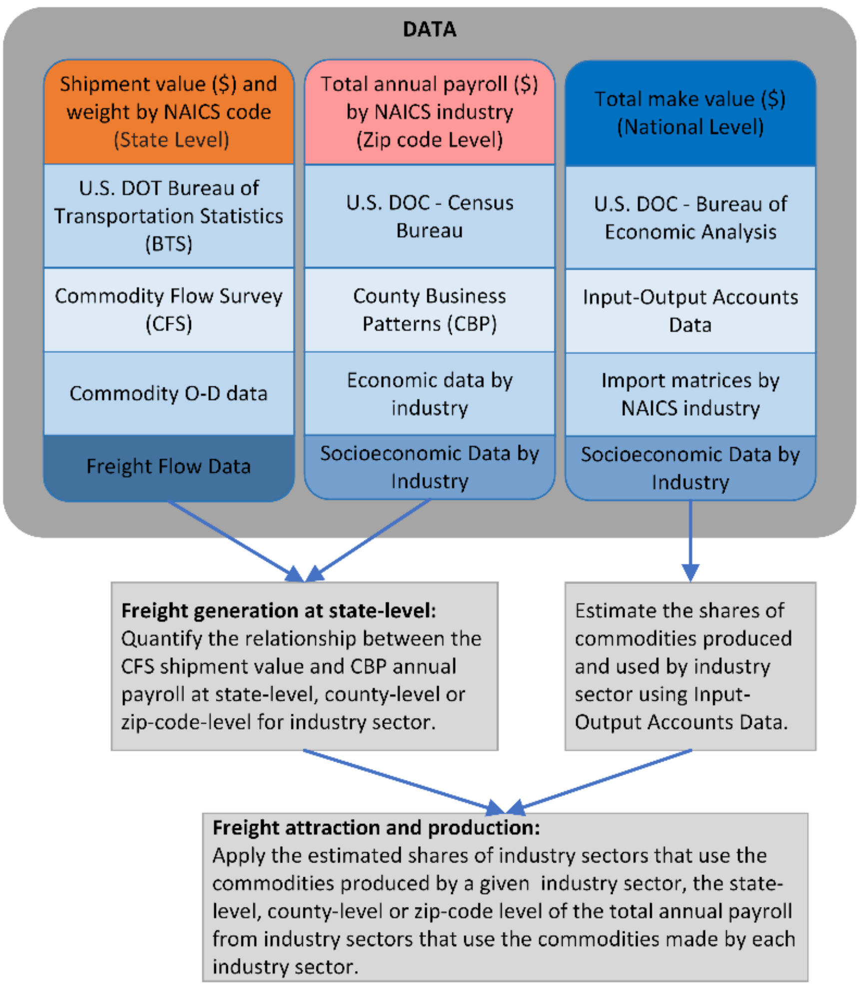

Figure 2-5 Disaggregation of CFS Data to County-Level or Zip Code-Level to Develop Freight Demand Models

Cambridge Systematics (19) disaggregated the FAF2 dataset to the county-level (see Figure 2-6). The FAF2 data was allocated by county using regression equations that link commodity productions and attractions to employment by industry, population, energy production, and agriculture data. Estimated county-level productions and attractions were then adjusted using IMPLAN productions and attractions.

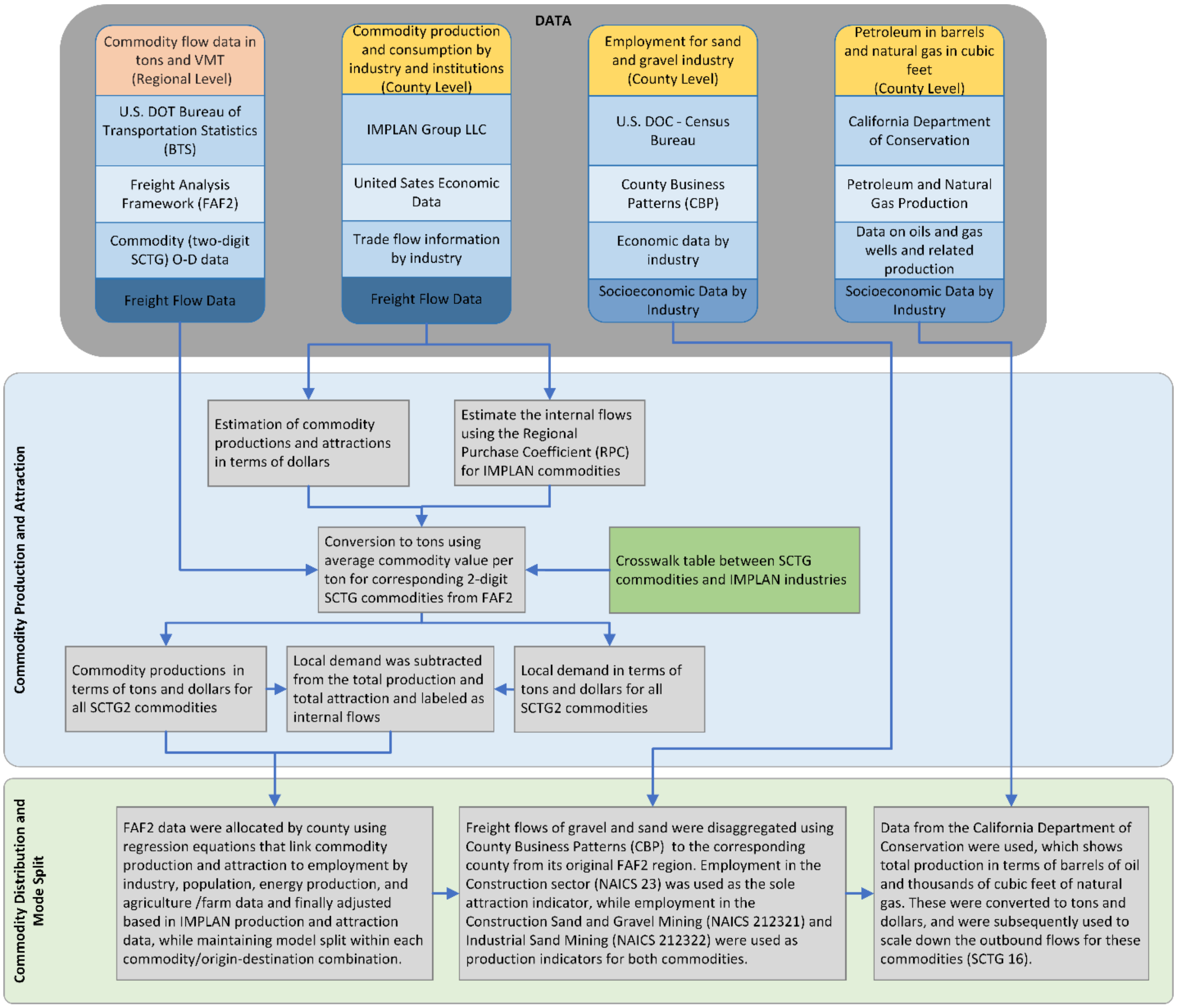

Figure 2-6 Commodity Flow Disaggregation for Central Coast of California

Parsons Brinckerhoff (20) disaggregated FAF2 zone flows to county-level by all freight modes and 2-digit commodity code classification (see Figure 2-7). Authors used employment by industry combined with inter-industry coefficients to allocate the origins and destinations flows to counties with corresponding employment type. Truck flows were disaggregated using county-level employment and IMPLAN inter-industry coefficients. Oliveira-Neto et al. (21) disaggregated FAF freight flow down to the county-level. The total employment payroll was used to estimate aggregate productions and attractions based on CFS data at the state level. The models were then associated with industry producers and consumers of commodities using Input-Output Accounts. County distance matrices were used not only to calculate ton-miles, but they were also applied to find the spatial distribution of freight generated using the Gravity model.

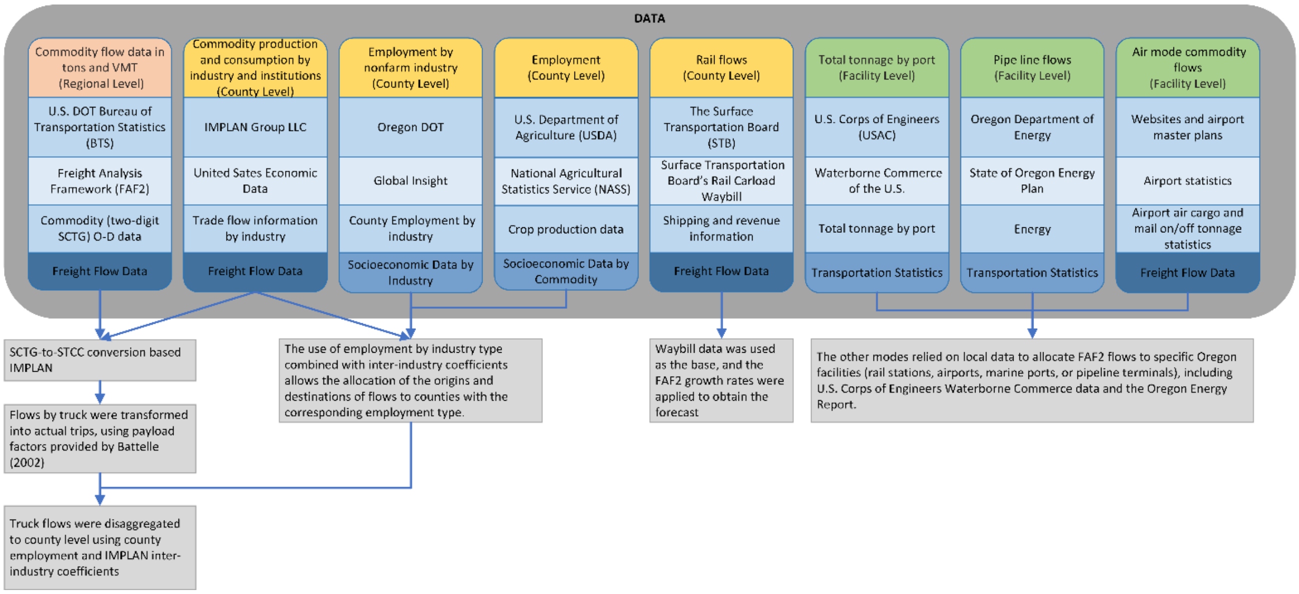

Figure 2-7 Oregon DOT Commodity Flow Database Development

Other Freight Flow Disaggregation Methods

Other methods have been proposed in the literature to disaggregate commodity freight flow data. Prozzi et al. (22) used a Multinomial (MNL) logit model to estimate county-level commodity-specific freight flows (see Figure 2-8). First, for each state, the total productions and attractions by commodity were estimated using the CFS and IMPLAN data and further converted to fractional productions and attractions levels of a commodity. Centroidal distances between zones were employed as the impedance measure affecting freight flow distribution. The production flow distribution of commodities was modeled as a function of the generalized cost of transportation and the relative attraction level of the destination zones. Similarly, the attraction flow distribution of commodities was modeled as a function of the generalized cost of transportation and the origin zone's relative production level.

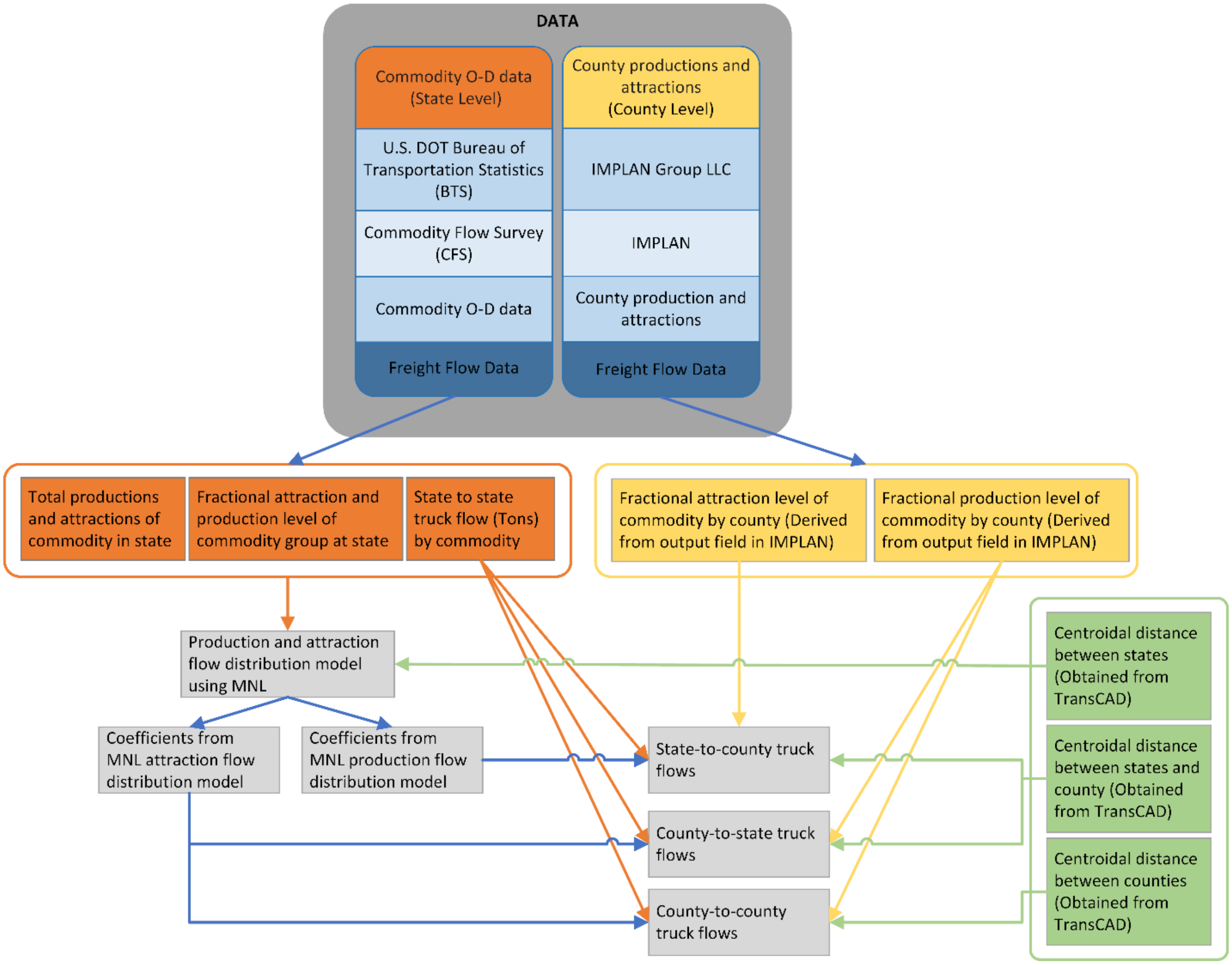

Figure 2-8 Multinomial (MNL) logit model to estimate commodity-specific freight flows at the county level

Harris et al. (23) developed a methodology (see Figure 2-9) to disaggregate the FAF2 to county-level using a national freight origin/destination database and various socioeconomic factors. The factors considered in this research included the value of sales, personal income, population, and employment. The value of sales was used as a predictor of freight generation activity. The methodology of disaggregation was based on iterative proportional fitting as follows.

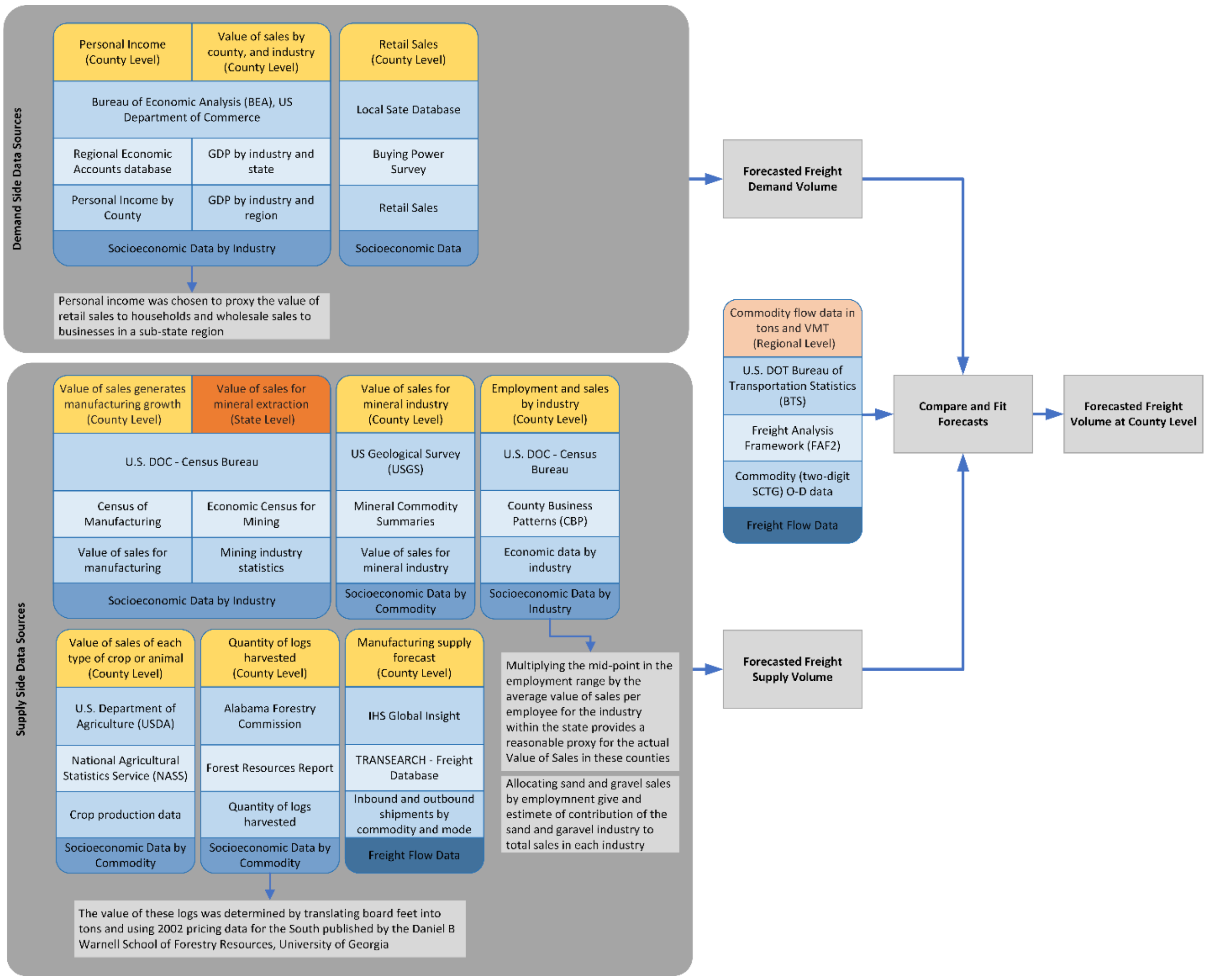

Figure 2-9 Disaggregation of Freight Analysis Framework Version 2 to County Level

Ranaiefar et al. (24) used a structural equation modeling (SEM) framework to capture relationships between commodities at aggregate-level with public data that can then be applied to disaggregate-level. Authors used employment, the number of establishments, population, farm acreages, GDP, capacities of refineries, annual consumption, and power plants' production to disaggregate FAF data to Freight Analysis Zones (FAZ)-level. Livshits et al. (25) developed a behavior-based freight model. The developed agent-based supply chain and freight transport model used disaggregate behavior-based logistics and transportation choice models to simulate commodity flows at the firm level. The model considers firms or business establishments as individual decision-making units in the freight transportation system. Momtaz et al. (26) developed a procedure to disaggregate FAF data and fusing with TRANSEARCH data. The authors formulated and estimated a joint econometric model framework with the maximum likelihood approach to estimate county-level commodity flows. TRANSEARCH and FAF were connected by generating potential paths between the origin and destination of interest of TRANSEARCH flows. The fused flows were further disaggregated using a proportional allocation framework. Population and employment were used as disaggregation variables. Total tonnages were also converted to truck flows using the payload factors.

CHAPTER 3 EVALUATION OF COMMODITY AND FREIGHT FLOW, LAND USE, ACTIVITY DATA

Introduction

As part of the project, the research team collected and compiled into an ArcGIS geodatabase (available for download through the website developed for this project) all the available freight flow, land-use, and economic activity data for the state of Tennessee, including proprietary data already purchased by TDOT. Metadata is provided for each identified data source that provides general data source descriptions and information regarding the data type, data output, spatial and temporal resolution, modes of freight, classification system, public or commercial availability, and hyperlink to the identified data source in the supplementary document that accompanies this report.

The research team has also developed a Microsoft Office Excel-based Freight Data Resource Matrix application (see Section 3.2). The developed application will evaluate available commodity and freight flow, land-use, and economic activity data. Finally, a description of utilized data sources to disaggregate commodity-specific freight flow data is presented in section 3.3.

Freight Data Resource Matrix

As a part of the study, the research team developed a Microsoft Office MS Access-based application (available for download through the website developed for this project) that identifies available commodity and freight flow, land-use, economic activity data, a summary of freight flow estimation and disaggregation methods, accompanied by description and method advantages and disadvantages, and finally the developed disaggregation methods.

Utilized Commodity Freight Flow and Economic Activity Data

The criteria for the commodity freight flow and economic activity data selection included the availability of the spatial coverage and resolution, selection of modes as well in what units the freight flow data is represented. TRANSEARCH data was selected from all available freight data sources. TRANSEARCH data provides the most comprehensive available information of commodity flow data at the county level and by multiple modes of freight (truck, rail, air, water, pipeline) (see Table I-1), by equipment (see Table I-2), and trade type (see Table I-3). Furthermore, TRANSEARCH represents flow not only in tons and value but also in units, which are the equivalents of truck trips. TRANSEARCH commodity flow data available for this research was given in Standard Classification of Transported Goods (SCTG) 3-digit code, instead of STCC code in which TRANSEARCH data is usually represented. Economic activity data was obtained from InfoUSA business and consumer contact database and BEA Input-Accounts. InfoUSA provides economic activity data (employment, the value of sales, square footage) at the establishment level, while BEA Input-Accounts provides measures of the relationships between various industries in the economy at the national level. Specifically, the BEA Input-Accounts tables show the commodity inputs used by each industry to produce its output, the commodities produced by each industry, and the use of commodities by final consumers.

CHAPTER 4 FREIGHT FLOW DISAGGREGATION METHODOLOGY

Introduction

This chapter presented the freight flow disaggregation methodology used in this research project. Section 4.2 will discuss how the freight flow estimation and disaggregation methodologies were selected. Section 4.3.1 presents the disaggregation methodology that uses regression, Section 4.3.2 presents the disaggregation methodology using proportional weighting. The supplementary document that accompanies this report presents the available freight flow estimation and disaggregation methods in detail, a description and advantages/disadvantages of each method, and a simple example showcasing the use of the developed models.

Selection of Freight Flow Estimation and Disaggregation Methodologies

While there are several freight flow estimation and disaggregation methodologies, many require large data samples, complex modeling, and increased computational effort that do not result, necessarily, in more accurate or reliable results. For example, the use of Artificial Neural Network (ANN) to disaggregate freight flow may lead to a higher degree of accuracy than regression methods, but it is hard to explain a model's assumptions and outputs. Also, ANN requires a large data sample, and the computational efforts are increased compared to the regression alternatives. As this research aims to find exact disaggregate flows, cross-classification will not be beneficial as the output takes class labels compared to the regression output that takes continuous values. As was discussed in the literature review, regression and proportional weighting were the most applied methods, with proportional weighting accounting and regression accounting for 60 percent and 23 percent of all freight disaggregation applications, respectively. Computational time was also an important parameter when selecting the methods to be implemented. TRANSEARCH commodity flow data is already an extensive database, available at the county-level for the state of Tennessee. Disaggregation to a TAZ level or even down to Census Block for 40 commodities by type of trade, mode, and equipment can lead to extensive computational times. Proportional weighting was selected to be one of the disaggregation methods as it has low computational complexity and limited data requirements. Also, the commodity flow allocation can be based on the physical size of the disaggregated geographies, socioeconomic data variables, industry-specific, and commodity-specific activity data within each of the sub-regions. Similarly, regression has relatively low modeling and computational complexity compared to other methods. In comparison, it has an advantage over the proportional weighting method as it can provide the ability to identify the relationship between demand generators, and it has statistical measures to evaluate the goodness-of-fit. Refer to the supplementary document that accompanies this report for a detailed summary of advantages and disadvantages of each disaggregation method.

Freight Flow Disaggregation Implementation

In this research, two methods were implemented to disaggregate commodity freight flows. The first method relied on the industry proportional weighting and economic indicator regression, where the industry proportional weighting utilizes the relationship between commodity-producing and using industries. The economic indicator regression utilizes the relationship between the aggregate zone economic indicators and freight flow productions and attractions. The second method is based on industry and economic indicator proportional weighting. Similarly, to the first method, the industry proportional weighting utilizes the relationship between commodity-producing and using industries. Economic indicator proportional weighting utilizes the relationship between the disaggregate zone freight flow to aggregate zone freight flow and is assumed to be proportional to the industry economic indicator shares. The following subsections present the methodology for the developed disaggregation models and a simple numerical example showcasing the developed models. Section 4.3.1 presents the disaggregation methodology that uses regression, Section 4.3.2 presents the disaggregation methodology using proportional weighting.

Disaggregation Method: Regression

The disaggregation method using regression disaggregates the TRANSEARCH freight flow data by commodity (SCTG 2-digit), from aggregate zone to disaggregate zones using the relationship between economic indicators (employment, value of sales, and sq. footage) by NAICS 3-digit or 2-digit industry code obtained from InfoUSA, and the type of commodity shipped by applying regression for each aggregate zone. First, the industries (NAICS 3-digit or 2-digit) that produce and use a commodity (SCTG 2-digit) were identified using two crosswalk tables. The first crosswalk table (see Table H-4) developed by Anderson et al. (39) was used to link the SCTG 2-digit commodity with NAICS 3-digit producing industry, and the second crosswalk table obtained from the Bureau of Economic Analysis (BEA) links Input-Output Account (IO) Codes with NAICS code. The same crosswalk table with NAICS-2-digit can be obtained from the original tables and can be used for disaggregation. By utilizing both crosswalk tables with BEA Input-Output Accounts Supply and Use tables, it was possible to identify for each commodity (SCTG 2-digit) the shares of industries (NAICS 3-digit or 2-digit) that produce the commodity and the shares of industries use of the commodity. Next, the regression equations were applied on total aggregate-level productions and attractions by commodity tons to estimate aggregate zone economic indicator coefficients for producing and using industries. Estimated aggregate-level regression coefficients, disaggregate-level industry economic indicator values, and the shares of commodity-producing and using industries were further used as inputs to estimate disaggregate-level commodity productions and attractions. Furthermore, for each aggregate zone and type of commodity, the estimated disaggregate zone productions and attractions were adjusted to meet the aggregate zone productions and attractions by proportional weighting. The disaggregate zone origin and destination freight flow by commodity estimation were performed using three freight flow distribution methods. The first method used the Gravity model to distribute disaggregate zone freight flow by commodity. The relative impedance was calculated as an exponential function of the negative distance between the disaggregate zone origins and destinations and the average distance by commodity, estimated using TRANSEARCH. The second method distributes disaggregate zone freight flow by commodity using the Proportionally Weighting, where disaggregate zone level freight flows by commodity are estimated by multiplying the aggregate level freight flow with the production and attraction ratios of the disaggregate to aggregate zone for each commodity. Finally, the third method uses Iterative Proportional Fitting. The disaggregate-level freight flows by commodity are estimated by distributing the freight flow to fit given disaggregate zone productions and attractions.

Notation	
Sets and Indices	
I, i	Set and index of aggregate zones
J, j	Set and index of disaggregate zones
J_i	Set of disaggregate zones in aggregate $i \in I$
C, c	Set and index of commodities
E, e	Set and index of economic indicators (employment, value of sales, sq. footage)
K	set of NAICS 3-digit industries, where industry $k \in K$
P	Set of producing NAICS 3-digit industries
U	Set of using NAICS 3-digit industries
$K^{Pc} \subseteq K$	Set of NAICS 3-digit industries producing commodity $c \in C$
$K^{Uc} \subseteq K$	Set of NAICS 3-digit industries using commodity $c \in C$
Parameters	
p_{kc}	The Gross Domestic Product of industry $k \in K^{Pc}$ producing commodity $c \in C$
u_{kc}	The Gross Domestic Product of industry $k \in K^{Uc}$ using commodity $c \in C$
x_{ake}	Value of economic indicator $e \in E$ for industry $k \in K$ at aggregate $a \in I$ or disaggregate $a \in J$ zone
d_{ab}	The distance between the disaggregate zone $a \in J_a$ and disaggregate zone $b \in J_b$
d_c	The average travel length by commodity $c \in C$
T_{AB}^c	Total tons of freight flow of commodity $c \in C$ from aggregate zone A $to\ B \in I$
U_{AB}^c	Total units of freight flow of commodity $c \in C$ from aggregate zone A $to\ B \in I$
V_{AB}^c	Total value of freight flow of commodity $c \in C$ from aggregate zone A $to\ B \in I$
Input Variables	
s_{kc}^P	Industries $k \in K^{Pc}$ share of producing commodity $c \in C$

s_{kc}^{U}	Industries $k \in K^{Uc}$ share of using commodity $c \in C$
γ_{ke}^{c}	The coefficient of aggregate zone annual tons of commodity $c \in C$ produced by one unit of NAICS 3-digit industry $k \in K^{Pc}$ economic indicator $e \in E$
δ_{ke}^{c}	The coefficient of aggregate zone annual tons of commodity $c \in C$ attracted by one unit of NAICS 3-digit industries $k \in K^{Uc}$ economic indicator $e \in E$
T_{ac}^{P}	Total tons of commodity $c \in C$ produces in aggregate $a \in I$ or disaggregate $a \in J$ zone
T_{ac}^{U}	Total tons of commodity $c \in C$ consumed in aggregate $a \in I$ or disaggregate $a \in J$ zone
f_{ab}^{c}	Commodity $c \in C$ specific friction factor between aggregate $a, b \in I$ or disaggregate $a, b \in J$ zones ($f_{ab} \leq=\geq f_{ba}$)
Output Variables	
T_{ab}^{c}	Total tons of freight flow of commodity $c \in C$ from aggregate zone $a\ to\ b \in I$ or disaggregate zone $a\ to\ b \in J$

Additional sets, input, and output variables will be defined as needed.

Commodity producing and using industry share estimation

Industries share of producing commodity:

$$s_{k}^{P} = \frac{p_{kc}}{\sum_{k \in K^{Pc}} p_{kc}}, \forall\ k \in K^{Pc}, c \in\ C$$

, where p_{kc} is the Gross Domestic Product of industry $k \in K^{Pc}$ producing commodity $c \in C$.

Industries share of using commodity:

$$s_{kc}^{U} = \frac{u_{kc}}{\sum_{k \in K^{Uc}} u_{kc}}, \forall\ k \in K^{Uc}, c \in C$$

, where u_{kc} is the Gross Domestic Product of industry $k \in K^{Uc}$ using commodity $c \in C$.

Regression coefficient estimation

Regression equation to estimate total tons of productions by commodity for the aggregate zones:

$$T_{ic}^{P} = \sum_{e \in E, k \in K^{Pc}} \gamma_{ke}^{c} * x_{ike} * s_{k}^{Pc}\ , \forall\ i \in I, c \in C$$

, where γ_{ke}^{c} is the coefficient of aggregate zone annual tons of commodity $c \in C$ produced by one unit of NAICS 3-digit industry $k \in K^{Pc}$ economic indicator $e \in E$, and x_{ike} is the explanatory variable of the aggregate zones $i \in I$ producing industries $k \in K^{Pc}$economic indicator $e \in E$.

Regression equation to estimate total tons of attraction by commodity for the aggregate zones:

$$T_{ic}^{U} = \sum_{e \in E, k \in K^{Uc}} \delta_{ke}^{c} * x_{ike} * s_{k}^{Uc} \ , \forall\, i \in I, c \in C$$

, where δ_{ke}^{c} is the coefficient of aggregate zone annual tons of commodity $c \in C$ attracted by one unit of NAICS 3-digit industries $k \in K^{Uc}$ economic indicator $e \in E$.

By applying the regression equation for each aggregate zone, the research team found the economic coefficients for producing and using industries, which will be used as input to estimate disaggregate-level commodity productions and attractions.

Disaggregate productions/attractions estimation

Regression equation to estimate total tons of productions by commodity for the disaggregate zones:

$$T_{jc}^{P} = \sum_{e \in E, k \in K^{Pc}} \gamma_{ke}^{c} * x_{jke} * s_{kc}^{P} \ , \forall\, j \in J_i, i \in I, c \in C$$

, where x_{jke} is the explanatory variable of the disaggregate zones $j \in I$ producing industries $k \in K^{Pc}$ economic indicator $e \in E$.

Regression equation to estimate total tons of attractions by commodity for the disaggregate zones:

$$T_{jc}^{U} = \sum_{e \in E, k \in K^{Uc}} \delta_{ke}^{c} * x_{jke} * s_{kc}^{U} \ , \forall\, j \in J_i, i \in I, c \in C$$

, where x_{jke} is the explanatory variable of the disaggregate zones $j \in I$ using industries $k \in K^{Uc}$ economic indicator $e \in E$.

Disaggregate zone production and attraction adjustment

Next, the research team proportionally adjusted the disaggregate-level commodity productions and attractions to meet the aggregate-level productions and attractions.

The sum of disaggregate zone productions should equal to productions of the aggregate zone:

$$\sum_{j \in J_i} T_{jc}^{P} = T_{ic}^{P} \ , \forall\, i \in I, c \in C$$

The sum of disaggregate zone attractions should equal to attractions of the aggregate zone:

$$\sum_{j \in J_i} T_{jc}^{U} = T_{ic}^{U} \ , \forall\, i \in I, c \in C$$

Adjusted disaggregate zone productions:

$$T_{jc}^{P} = \frac{T_{jc}^{P}}{\sum_{j \in J_i} T_{jc}^{P}} * T_{ic}^{P} \ , \forall\, j \in J_i, c \in C, i \in I$$

Adjusted disaggregate zone attractions:

$$T_{jc}^{U} = \frac{T_{jc}^{U}}{\sum_{j \in J_i} T_{jc}^{U}} * T_{ic}^{U} \ , \forall\, j \in J_i, c \in C, i \in I$$

Production and attraction distribution methods

Several methods to estimate freight flow distribution between the disaggregate origins and destinations were applied: Iterative Proportional Fitting (IPF), Gravity model, Proportional weighting.

Iterative Proportional Fitting

Iterative Proportional Fitting can also be used to adjust freight flow distribution to fit given productions and attractions as follows. Initially, matrix flows from disaggregate zone $a \in J_A$ to disaggregate zone $b \in J_B$ are equal to 1, as there is no information. At the first iteration, the origin row values are adjusted proportionally to each row cell value to row total (productions). At the second iteration, destination column values are adjusted proportionally to each column cell values to column total (attractions) (Cambridge Systematics et al. (*13*)).

Initial disaggregate zone freight flow distribution values:

Step 1: $$T_{ab}^{c} = 1, \forall\, a \in J_A, b \in J_B, c \in C, n = 0$$

Adjusted disaggregate zone freight flow distribution by commodity by origin row values:

Step 2: $$T_{ab\,(n+1)}^{c} = \frac{T_{ab}^{c}}{\sum_{b \in J_B} T_{ab}^{c}} * T_{ac}^{P}, \forall\; a \in J_A, c \in C$$

Adjusted disaggregate zone freight flow distribution by commodity by destination column values:

Step 3: $$T_{ab\,(n+2)}^{c} = \frac{T_{ab\,(n+1)}^{c}}{\sum_{a \in J_A} T_{ab\,(n+1)}^{c}} * T_{bc}^{U}, \forall\, b \in J_B, c \in C$$

Check if percent tolerance (ε) has been met:

Step 4: If $\frac{\sum_{b \in J_B} T_{ab\,(n+2)}^{c}}{T_{ac}^{P}} * 100 \le \varepsilon, \forall\, a \in J_A, c \in C$ and $\frac{\sum_{a \in J_A} T_{ab\,(n+2)}^{c}}{T_{bc}^{U}} * 100 \le \varepsilon, \forall\, b \in J_B, c \in C$

end, else set $T_{ab}^{c} = T_{ab\,(n+2)}^{c}, n = n + 1$ and go to Step 2

Gravity Model

The freight flow distribution method uses the Gravity model, which was applied to distribute freight flow by commodity between disaggregate zone origins and destinations. Disaggregate zone freight flow distribution by commodity using the Gravity model method:

$$T_{ab}^{c} = T_{ac}^{P} * \frac{T_{bc}^{U} * f_{ab}^{c}}{\sum_{b \in J_B} T_{bc}^{U} * f_{ab}^{c}}, \forall\, a \in J_A, b \in J_B, c \in C$$

, where f_{ab}^{c} is the friction factor of trip interchange between the origin disaggregate zone $a \in J_A$ and destination disaggregate zone $b \in J_B$ by commodity $c \in C$. Zone-to-zone friction factors by commodity type were estimated using an exponential function of the distance between the disaggregate zone od pairs and the average commodity-specific travel length.

Friction factor function by commodity type (QRFM Third Edition, 40):

$$f_{ab}^{c} = e^{-\frac{d_{ab}}{d_c}}, \forall\, a \in J_A, b \in J_B, c \in C$$

, where e is the exponential function, d_{ab} is the distance between the disaggregate zone $a \in J_A$ and disaggregate zone $b \in J_B$ and d_c is the average travel length by commodity

$c \in C$ of the Internal-Internal (I-I), Internal-External (I-E), External-Internal (E-I) flows for the state of Tennessee, estimated using the TRANSEARCH database.

After initial flow allocation, the freight flow distribution is adjusted to fit given productions and attractions using the Iterative Proportional Fitting Method starting from Step 2.

Proportional Weighting

Proportional weighting was also applied to distribute freight flow by the type of commodity between disaggregate zone origins and destinations. The following method allocates freight flow proportional to the disaggregate zone's production and attraction ratio to aggregate zone, by each commodity (*14*).

Disaggregate zone freight flow distribution by commodity using Proportional Weighting method:

$$T_{ab}^{c} = T_{AB}^{c} * \frac{T_{ac}^{P}}{\sum_{a \in J_A} T_{ac}^{P}} * \frac{T_{bc}^{U}}{\sum_{b \in J_B} T_{bc}^{U}}, \forall\, a \in J_A, b \in J_B, c \in C$$

, where T_{AB}^{c} is the total tons of freight flow of commodity $c \in C$ from aggregate zone A $to\ B \in I$.

Total tons of the disaggregate zone freight flow conversion to units and value

Disaggregate zone freight flow conversion to units:

$$U_{ab}^{c} = \frac{U_{AB}^{c}}{T_{AB}^{c}} * T_{ab}^{c}, \forall\, a \in J_A, b \in J_B, c \in C$$

, where U_{AB}^{c} is the total units of freight flow of commodity $c \in C$ from aggregate zone A $to\ B \in I$.

Disaggregate zone freight flow conversion to values:

$$V_{ab}^{c} = \frac{V_{AB}^{c}}{T_{AB}^{c}} * T_{ab}^{c}, \forall\, a \in J_A, b \in J_B, c \in C$$

, where V_{AB}^{c} is the total value of freight flow of commodity $c \in C$ from aggregate zone A $to\ B \in I$.

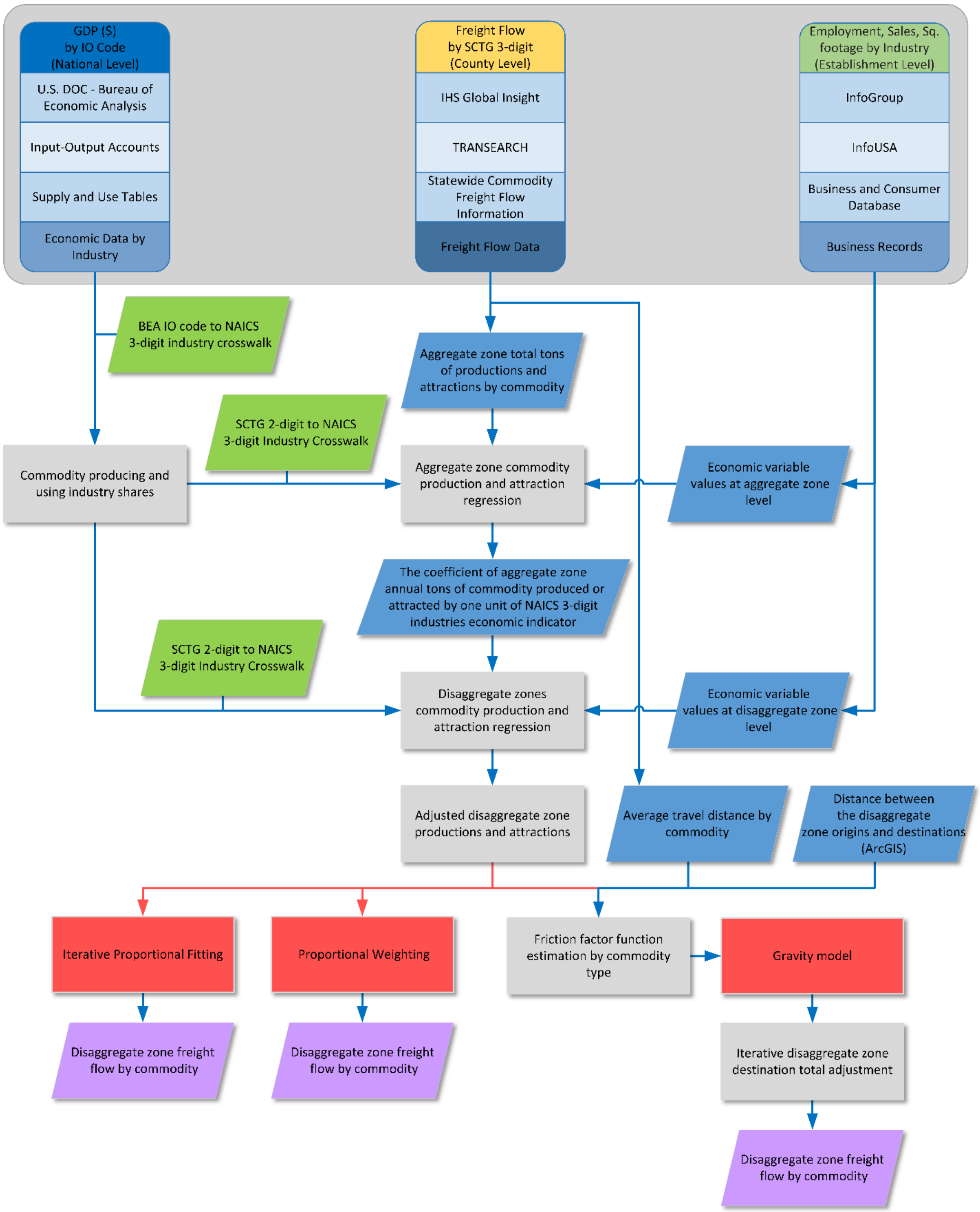

Figure 4-1 Freight Flow Disaggregation by Commodity Using Regression and Distribution Using Gravity model, Proportional Weighting, and Iterative Proportional Fitting

Disaggregation Method: Proportional Weighting

The following method disaggregates freight flow (TRANSEARCH) by commodity type (SCTG 2-digit), from aggregate zones to disaggregate zones by allocating commodity freight flow of each aggregate-level origin-destination pair by the share of commodity-producing and using industries (NAICS 3-digit or 2-digit) and the ratio of the disaggregate-level origin and destination economic indicator (employment, value of sales, sq. footage) to the aggregate-level origin and destination economic indicator obtained from InfoUSA. Similar to the disaggregation method using regression, the NAICS 3-digit or 2-digit industry shares that produce and use the commodity were identified by utilizing the relationship between the two crosswalk tables and Input-Output Account Supply and Use tables. Next, the research team estimated, for each NAICS 3-digit or 2-digit industry and economic indicator, the disaggregate zone to aggregate zone shares. Finally, the disaggregate zone freight flow by commodity are estimated by multiplying aggregate zone origin-destination commodity freight flow by the estimated shares of commodity-producing and using industries and disaggregate zone to aggregate zone economic indicator shares of the commodity-producing and using industries. In the case when the commodity-producing and using industry is not identified in the disaggregate zone, the shares of commodity-producing and using industry are proportionally adjusted.

Notation	
Sets and Indices	
I, i	Set and index of aggregate zones
J, j	Set and index of disaggregate zones
J_i	Set of disaggregate zones in aggregate $i \in I$
C, c	Set and index of commodities
E, e	Set and index of economic indicators (employment, value of sales, sq. footage)
K	set of NAICS 3-digit industries, where industry $k \in K$
P	Set of producing NAICS 3-digit industries
U	Set of using NAICS 3-digit industries
$K^{Pc} \subseteq K$	Set of NAICS 3-digit industries producing commodity $c \in C$
$K^{Uc} \subseteq K$	Set of NAICS 3-digit industries using commodity $c \in C$
Parameters	
p_{kc}	The Gross Domestic Product of industry $k \in K^{Pc}$ producing commodity $c \in C$
u_{kc}	The Gross Domestic Product of industry $k \in K^{Uc}$ using commodity $c \in C$

x_{jke}	Value of economic indicator $e \in E$ for industry $k \in K$ at disaggregate j∈ J zone
T_{AB}^{c}	Total tons of freight flow of commodity $c \in C$ from aggregate zone A $to\ B \in I$
U_{AB}^{c}	Total units of freight flow of commodity $c \in C$ from aggregate zone A $to\ B \in I$
V_{AB}^{c}	Total value of freight flow of commodity $c \in C$ from aggregate zone A $to\ B \in I$
Input Variables	
s_{kc}^{P}	Industries $k \in K^{Pc}$ share of producing commodity $c \in C$
s_{kc}^{U}	Industries $k \in K^{Uc}$ share of using commodity $c \in C$
r_{jke}	Disaggregate zones $j \in J_i$ industries $k \in K$ economic indicator $e \in E$ share
Output Variables	
T_{ab}^{c}	Total tons of freight flow of commodity $c \in C$ from disaggregate zone $a\ to\ b \in J$

Commodity producing and using industry share estimation

Industries share of producing commodity:

$$s_k^P = \frac{p_{kc}}{\sum_{k \in K^{Pc}} p_{kc}}, \forall\ k \in K^{Pc}, c \in C$$

, where p_{kc} is the Gross Domestic Product of industry $k \in K^{Pc}$ producing commodity $c \in C$.

Industries share of using commodity:

$$s_{kc}^U = \frac{u_{kc}}{\sum_{k \in K^{Uc}} u_{kc}}, \forall\ k \in K^{Uc}, c \in C$$

, where u_{kc} is the Gross Domestic Product of industry $k \in K^{Uc}$ using commodity $c \in C$.

Disaggregate zone industry economic indicator share estimation

Disaggregate zones industries share of the economic indicator:

$$r_{jke} = \frac{x_{jke}}{\sum_{j \in J_i} x_{jke}}, \forall\ k \in K, j \in J_i, i \in I$$

, where x_{jke} is disaggregate zones $j \in J$ industries $k \in K$ economic indicator $e \in E$ value.

Disaggregate zone freight flow distribution

Disaggregate zone freight flow distribution by commodity using economic indicator Proportional Weighting method:

$$T_{ab}^{ce} = T_{AB}^{c} * \Big(\sum_{k^P \in K^{Pc}} s_{kc}^{P} * r_{ak^P e}\Big) * \Big(\sum_{k^U \in K^{Uc}} s_{kc}^{U} * r_{bk^U e}\Big), \forall\ a \in J_A, b \in J_B, c \in C$$

, where T_{AB}^{c} is the Total tons of freight flow of commodity $c \in C$ from aggregate zone A $to\ B \in I$.

Total tons of the disaggregate zone freight flow conversion to units and value

Disaggregate zone freight flow conversion to units:

$$U_{ab}^{c} = \frac{U_{AB}^{c}}{T_{AB}^{c}} * T_{ab}^{c}, \forall\ a \in J_A, b \in J_B, c \in C$$

, where U_{AB}^{c} is the total units of freight flow of commodity $c \in C$ from aggregate zone A $to\ B \in I$.

Disaggregate zone freight flow conversion to values:

$$V_{ab}^{c} = \frac{V_{AB}^{c}}{T_{AB}^{c}} * T_{ab}^{c}, \forall\ a \in J_A, b \in J_B, c \in C$$

, where V_{AB}^{c} is the total value of freight flow of commodity $c \in C$ from aggregate zone A $to\ B \in I$.

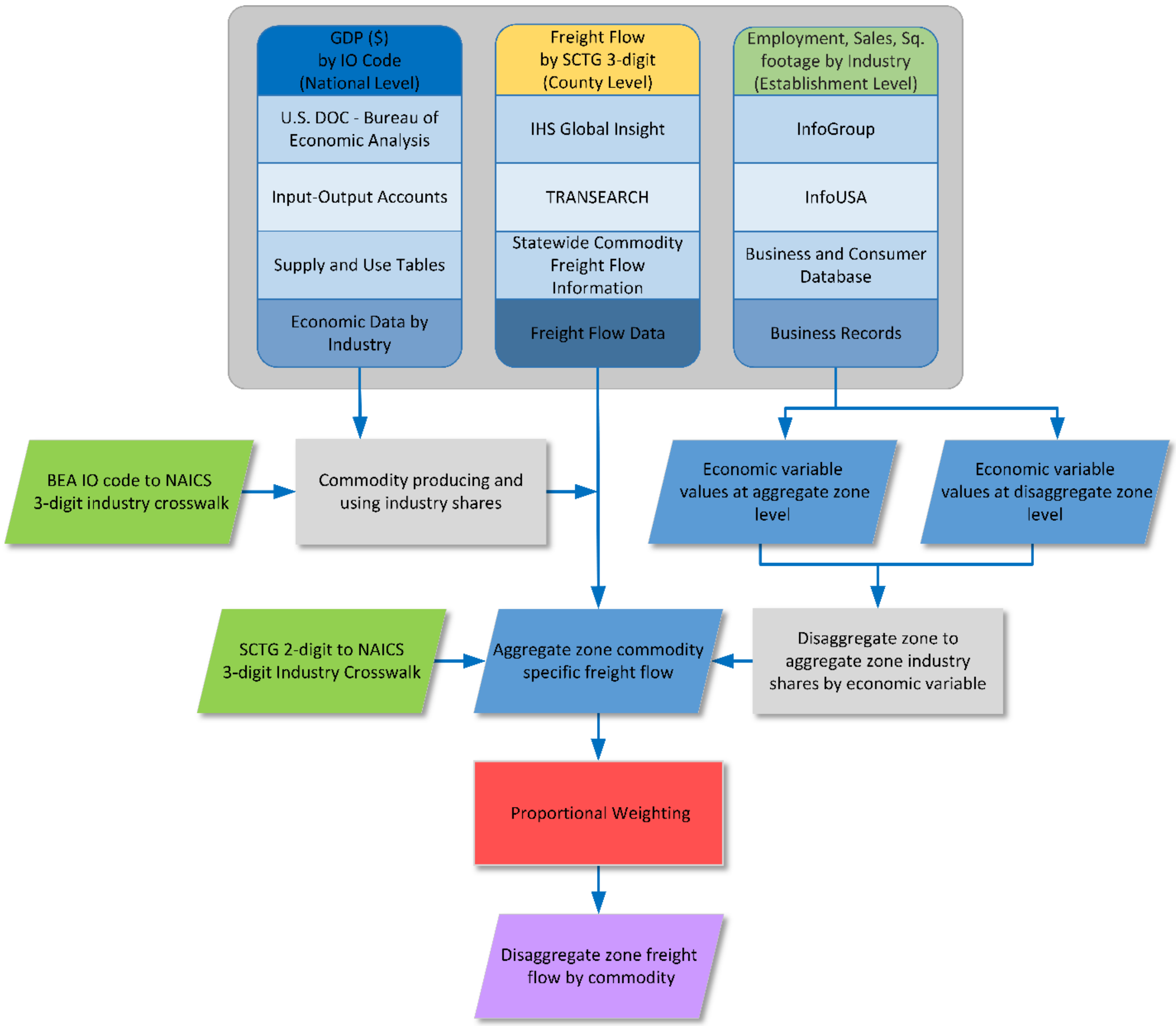

Figure 4-2 Freight Flow Disaggregation by Commodity Using Industry Economic Indicator Proportional Weighting

CHAPTER 5 FREIGHT DISAGGREGATION GIS TOOLS

Introduction

This section of the report presents the ArcGIS tools developed, their computational times, and example map outputs. In total, eight tools were developed: i) three data preprocessing tools, ii) two disaggregation tools, and iii) three postprocessing tools. The preprocessing tools were developed to prepare data inputs for the disaggregation tools. The TRANSEARCH Preprocessing Tool was used to preprocess TRANSEARCH data. Spatial and Economic Data Preprocessing Tool was employed to preprocess InfoUSA data. Input-Output (IO) Accounts Supply and Use Table Conversion Tool was developed to preprocess Input-Output Accounts data. For each developed disaggregation method, an ArcGIS tool was developed. The IO Accounts and Regression Disaggregation Method Tool was developed to apply the Regression disaggregation method. The IO Accounts and Proportional Weight Disaggregation Method Tool was developed to use the Proportional Weighting method. The postprocessing tools were created to provide the user with analytical and visualization capabilities. The PA Estimation OD Selection Tool provides the capabilities to output specific disaggregate OD flow and estimate productions and attractions. The PA MAP Tool and OD MAP Tool provides the capability to visualize either origin-destination or production and attraction flows by creating ArcMap Map Exchange Document (MXD) export maps as PDF and JPG files. The supplementary document that accompanies this report discusses the tools in a more detailed matter and showcases the tool interface.

Case Studies

As part of the research, the Tennessee Statewide Model network was used to disaggregate the TRANSEARCH freight flow data for the state of Tennessee and for Davidson County down to the TAZ-level. The research team compiled the results in a geodatabase that can be downloaded from the website developed for this project. The rationale for performing disaggregation for one county was to provide computational time comparisons. The Tennessee Statewide Model network (see Figure 5-1) has 3,293 zones, while Davidson County is composed of 231 TAZs. The total time to process the TRANSEARCH data for the state of Tennessee using all six disaggregation outputs (three for each method) ended to be 264.5 hours or 11 days. Computer used to process data had Intel(R) Core (TM) i7-7700 CPU @ 3.60GHz 3.60 GHz processor and 16 GB RAM. It is possible to reduce the processing times using three computers simultaneously, instead of one. In that case, the processing time can be reduced to 109.5 hours or 4.6 days. Next, tool processing times (see Figure 5-2) of the selected datasets for the forty 2-digit SCTG commodities, fifteen modes, eight equipment types, and eight trade types and showcase examples of map outputs are presented.

Figure 5-1 Tennessee Statewide Model TAZ Map

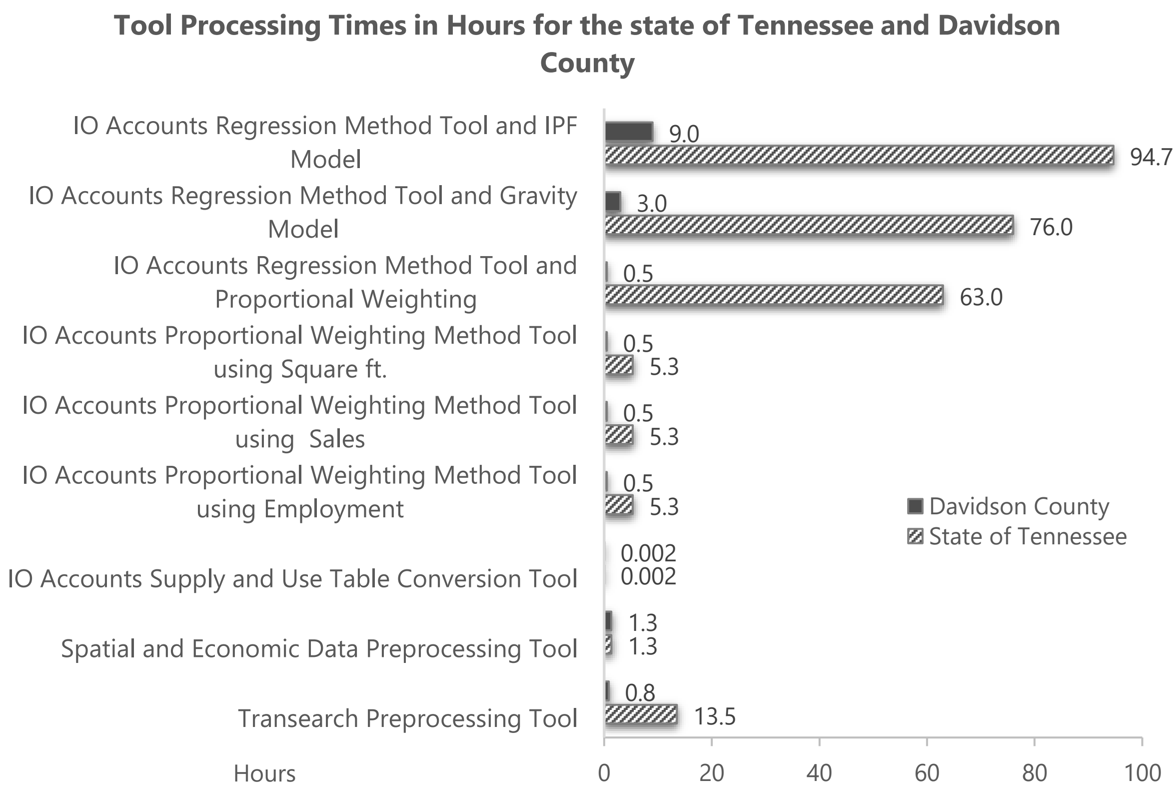

Figure 5-2 Tool Preprocessing Computational Time in Hours: state of Tennessee and Davidson County

Example Map Outputs

Examples of disaggregate zone flow maps were created using OD MAP Tool and Tennessee Statewide Model TAZ network and are presented herein. Multiple maps are available in the geodatabase that was created as part of the project. Figure 5-3 is an example of the TAZ 1657 in Davidson County for motorized and other vehicles, including parts, that originates and destines in the Tennessee, with inbound and internal flows by trucks mode group. Example map of disaggregate zone internal flows utilizing the regression disaggregation method and distributing flow using the Gravity model is shown in Figure 5-4 and internal and external flows is shown in Figure 5-10. Using the Iterative proportional fitting distribution is shown in Figure 5-5 and for internal and external flows is shown in Figure 5-1. Using the proportional weighting distribution is shown Figure 5-6 and for internal and external flows is shown in Figure 5-12. A map of disaggregate zone flows using the proportional weighting disaggregation method using employment is shown in Figure 5-7 and for internal and external flows is shown in Figure 5-13. Using the value of sales is shown in Figure 5-8 and for internal and external flows is shown in Figure 5-14. Using square footage is shown in Figure 5-9 and for internal and external flows is shown in Figure 5-15.

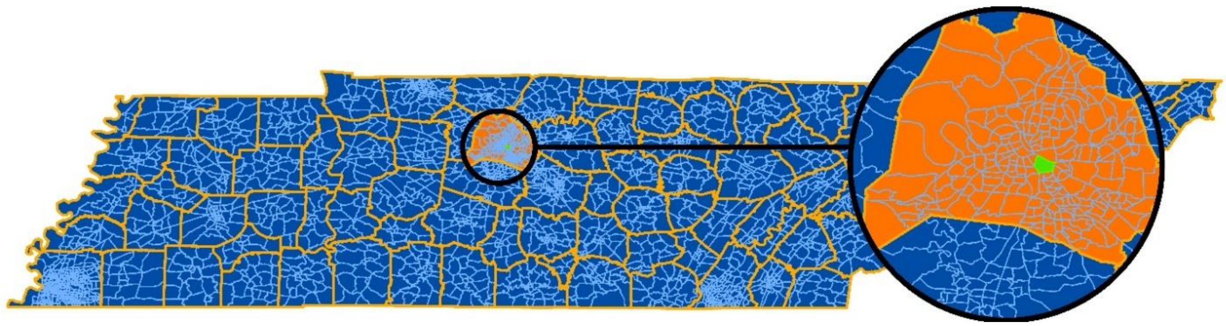

Figure 5-3 Tennessee Statewide Model TAZ Network and Selected TAZ: 1657

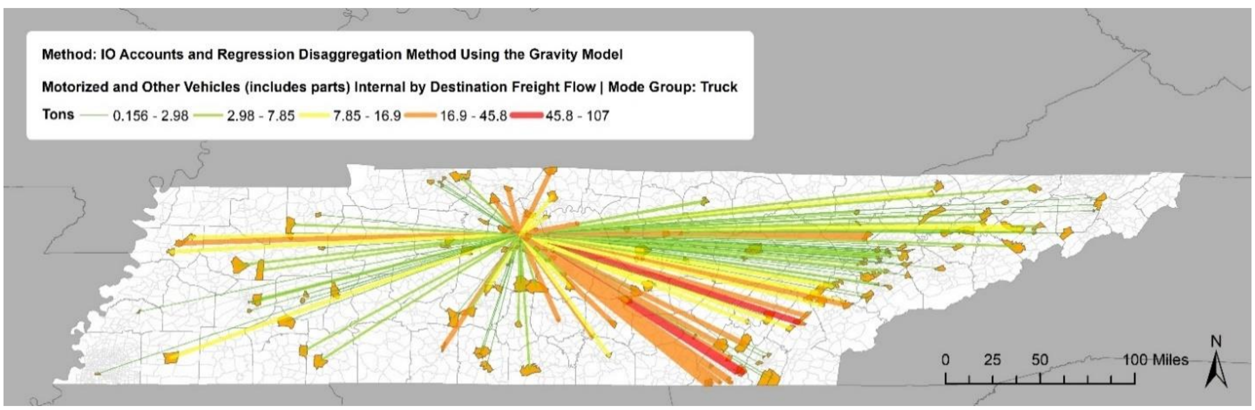

Figure 5-4 Example Internal OD Flow Visualization for a Selected TAZ (Regression Disaggregation Method and the Gravity Model Distribution)

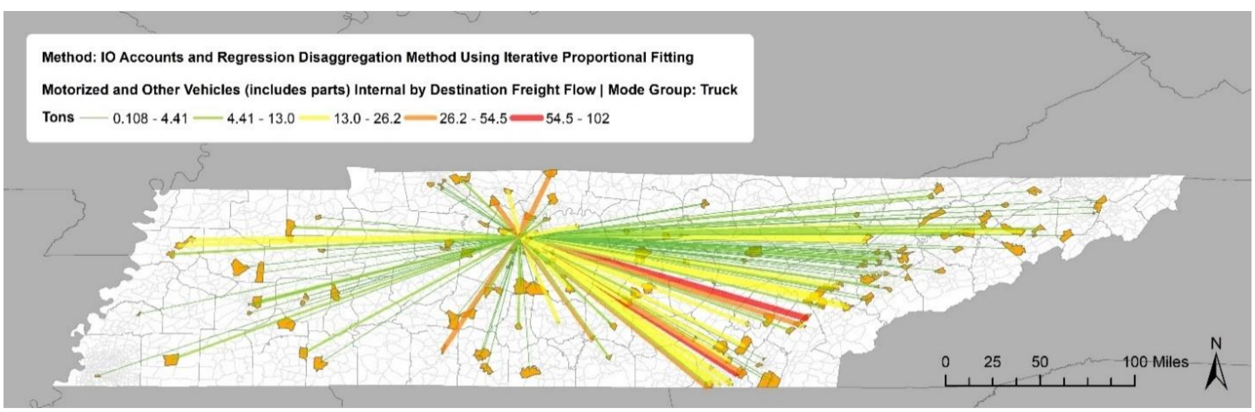

Figure 5-5 Example Internal OD Flow Visualization for a Selected TAZ (Regression Disaggregation Method and Iterative Proportional Fitting Distribution)

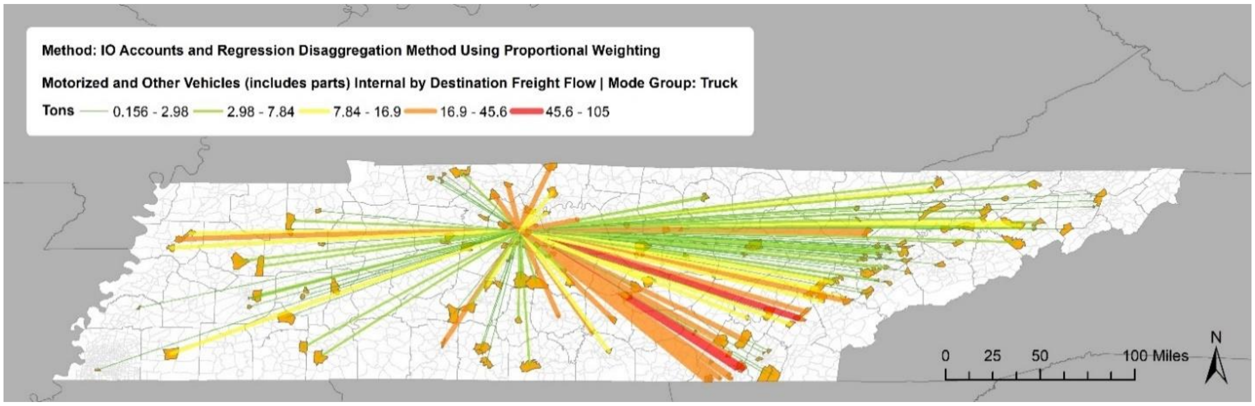

Figure 5-6 Example Internal OD Flow Visualization for a Selected TAZ (Regression Disaggregation Method and Proportion Weighting Distribution)

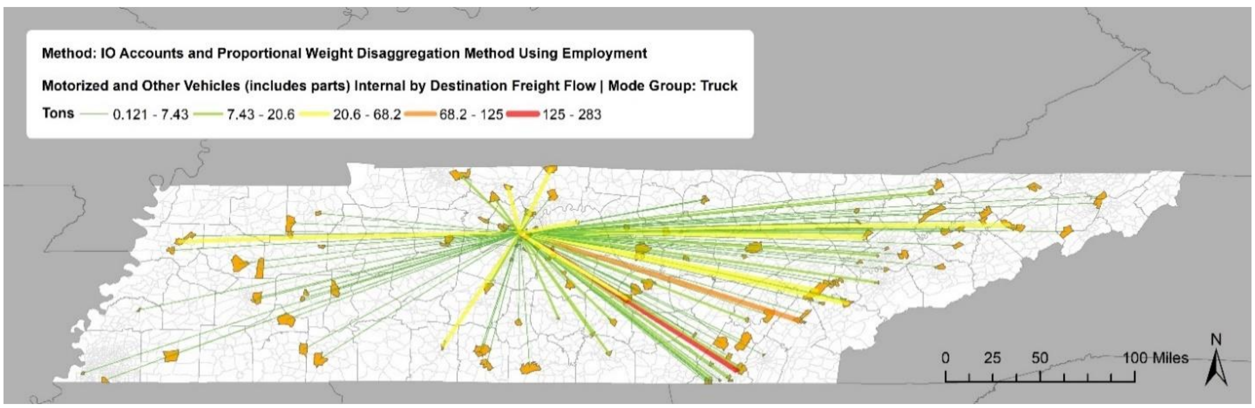

Figure 5-7 Example Internal OD Flow Visualization for a Selected TAZ (Proportion Weighting Disaggregation Method with Employment)

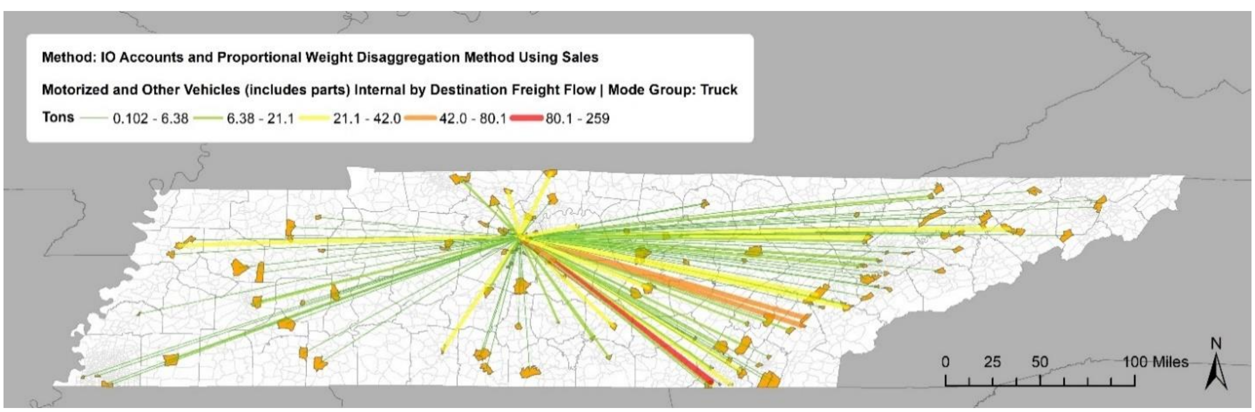

Figure 5-8 Example Internal OD Flow Visualization for a Selected TAZ (Proportion Weighting Disaggregation Method with the Value of Sales)

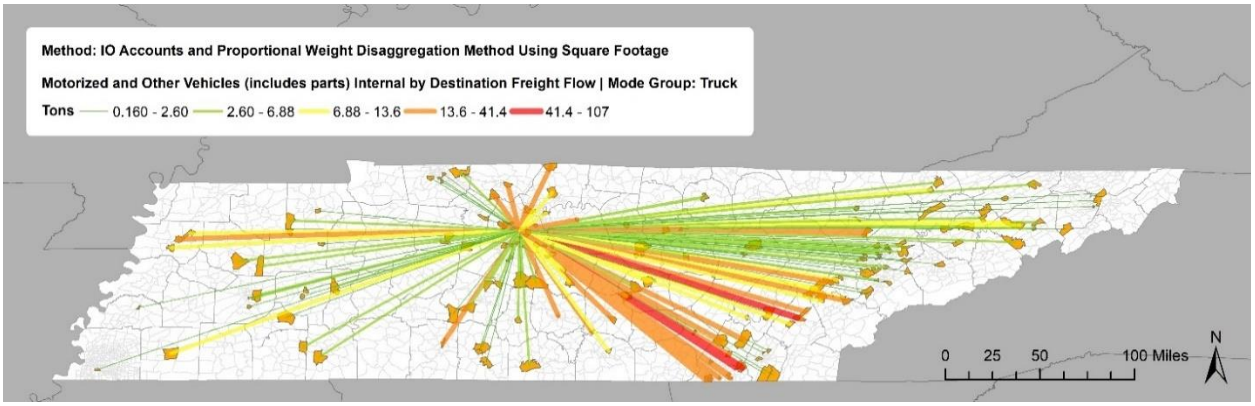

Figure 5-9 Example Internal OD Flow Visualization for a Selected TAZ (Proportion Weighting Disaggregation Method with Square Footage)

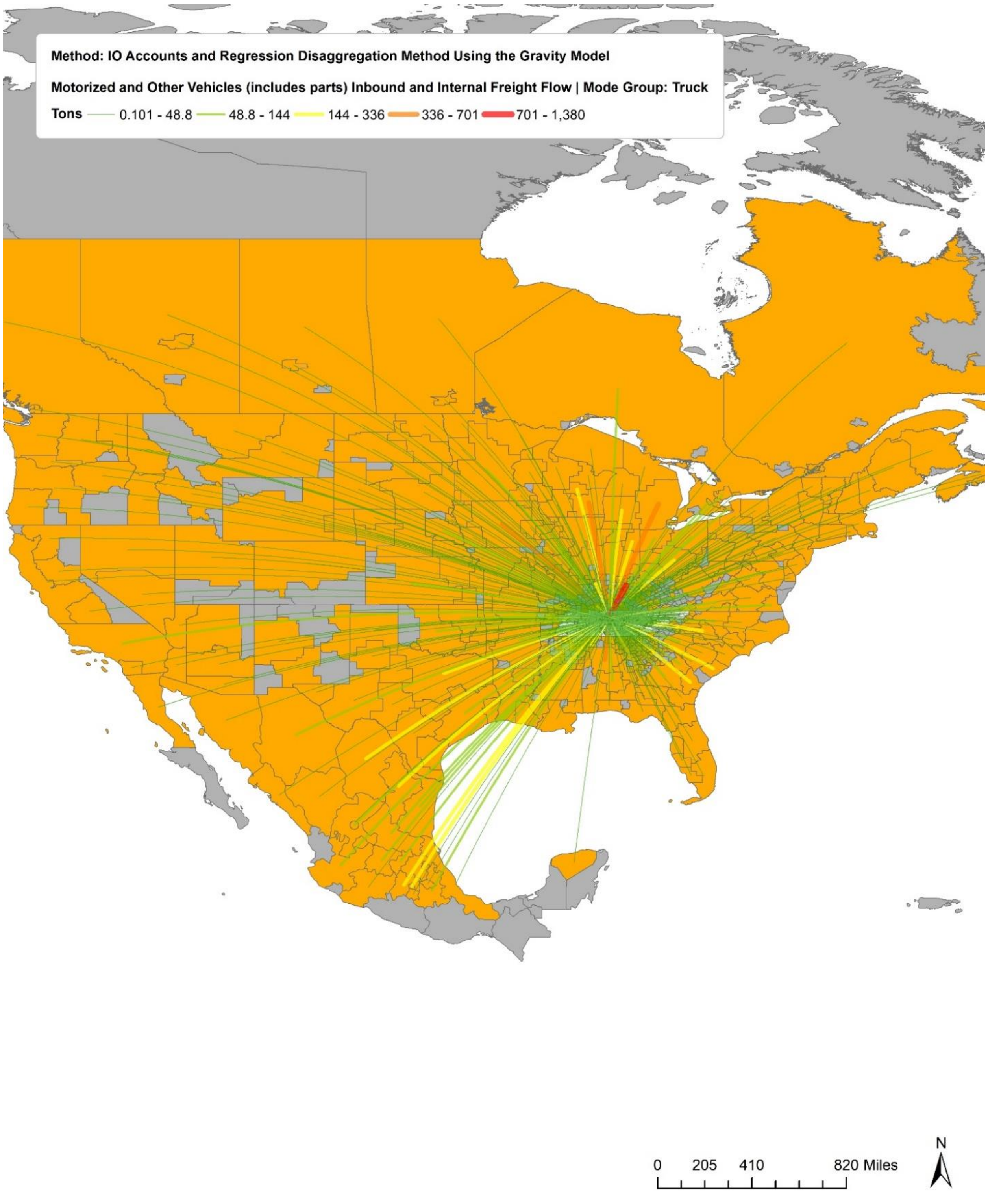

Figure 5-10 Example Internal and External OD Flow Visualization for a Selected TAZ (Regression Disaggregation Method and the Gravity Model Distribution)

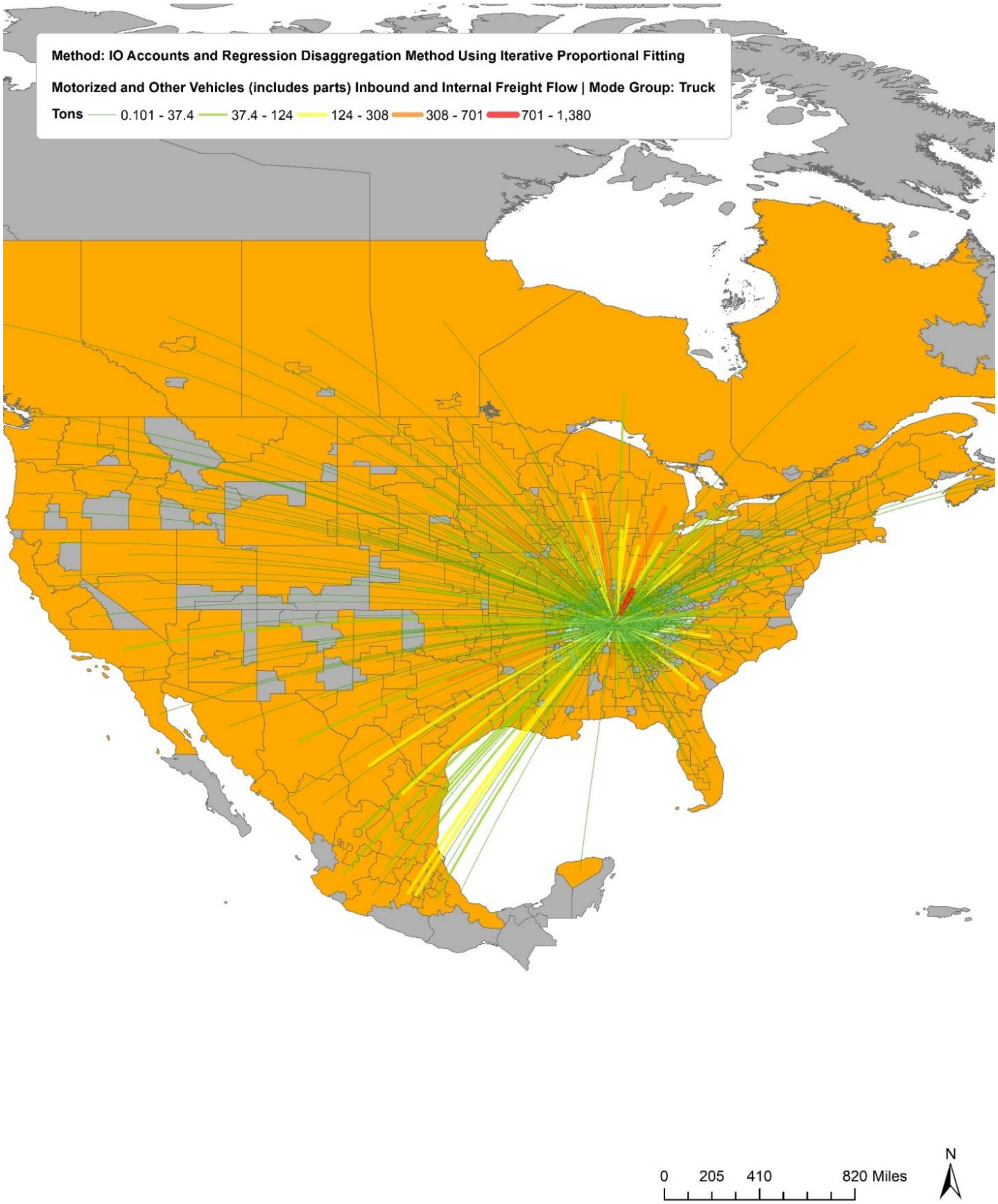

Figure 5-11 Example Internal and External OD Flow Visualization for a Selected TAZ (Regression Disaggregation Method and Iterative Proportional Fitting Distribution)

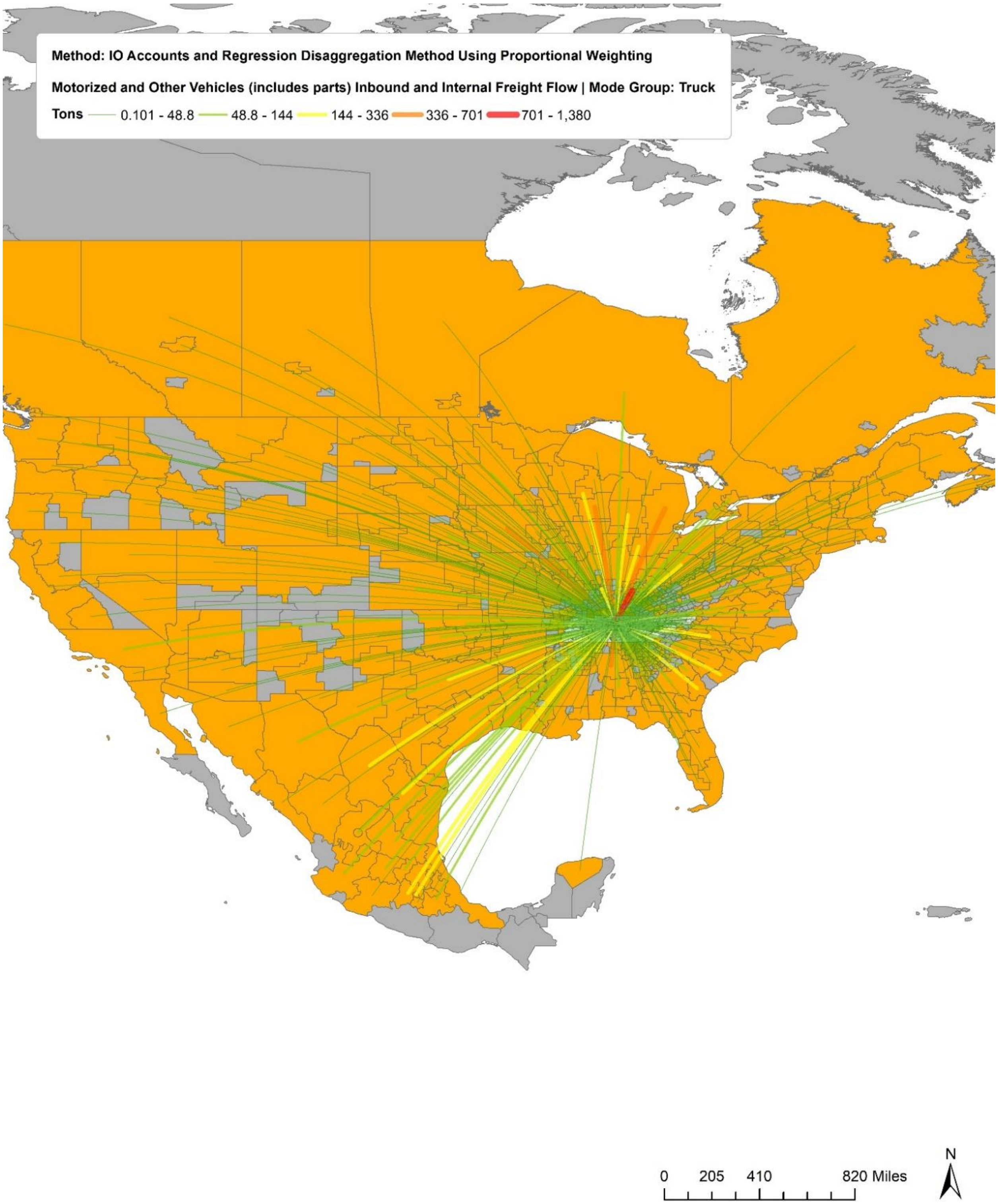

Figure 5-12 Example Internal and External OD Flow Visualization for a Selected TAZ (Regression Disaggregation Method and Proportion Weighting Distribution)

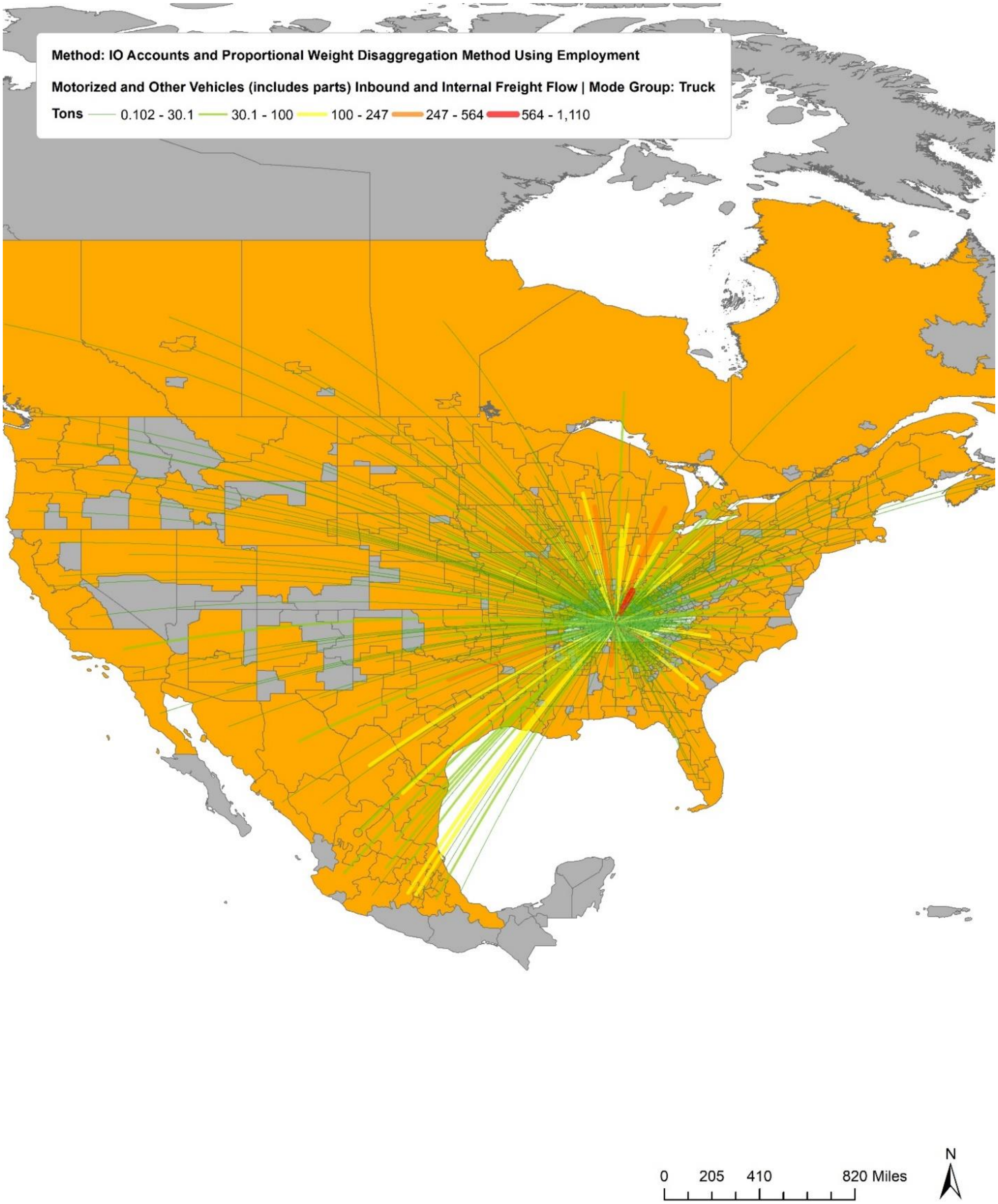

Figure 5-13 Example Internal and External OD Flow Visualization for a Selected TAZ (Proportion Weighting Disaggregation Method with Employment)

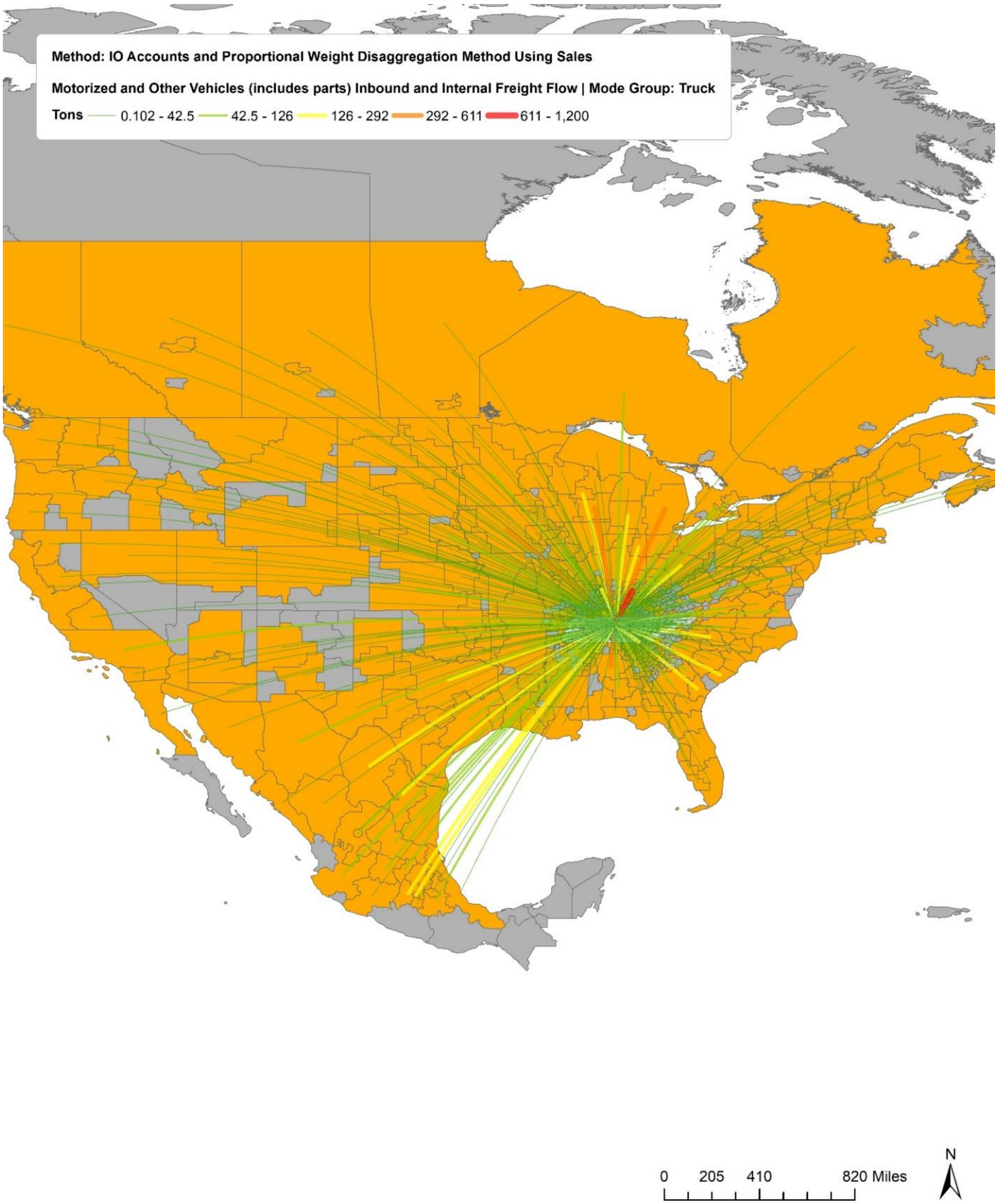

Figure 5-14 Example Internal and External OD Flow Visualization for a Selected TAZ (Proportion Weighting Disaggregation Method with the Value of Sales)

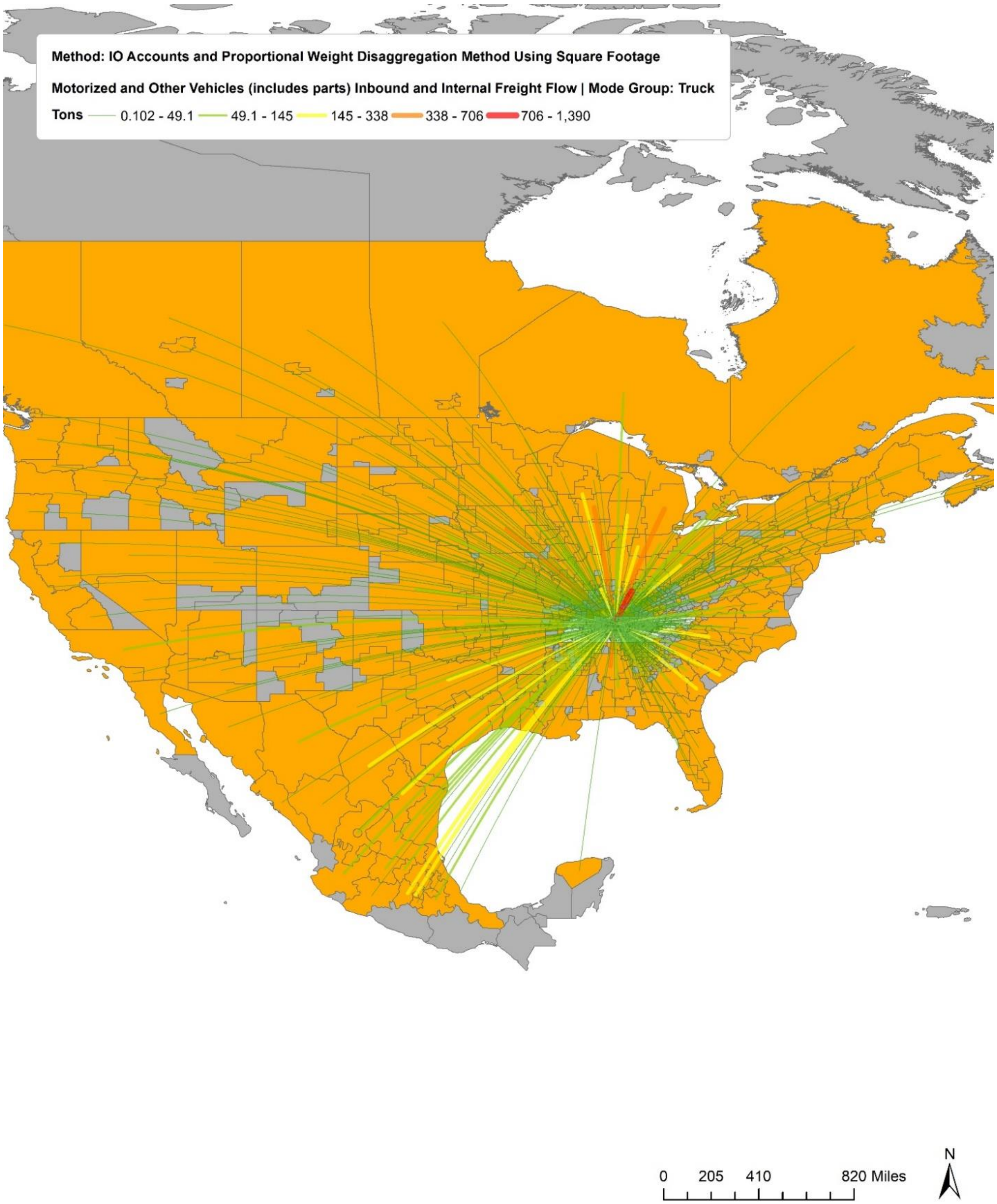

Figure 5-15 Example Internal and External OD Flow Visualization for a Selected TAZ (Proportion Weighting Disaggregation Method with Square Foot)

CHAPTER 6 MEGATRENDS

Megatrends are patterns or changes in activity, which take place over a long time and have a major impact on business and society globally. They often lead to significant opportunities and potentially disruptive impacts. Maraš et al. (*57*) identified the key megatrends affecting future passenger and freight transportation systems by reviewing existing literature with a time frame up to year 2050. Most important megatrends were identified if at least 70 percent of the reviewed literature described a particular megatrend. Figure 6-1 and 6-2 presents the percentage of identified megatrends described in the reviewed literature for freight and passenger transportation, respectively. In total, 26 reviewed sources related to passenger transportation and 14 sources related to freight transportation. The key megatrends with the most significant influence in freight transportation's future development were key resource scarcity and climate change (environmental challenges). In passenger transportation, urbanization and megacities and climate change were identified as the most important megatrends.

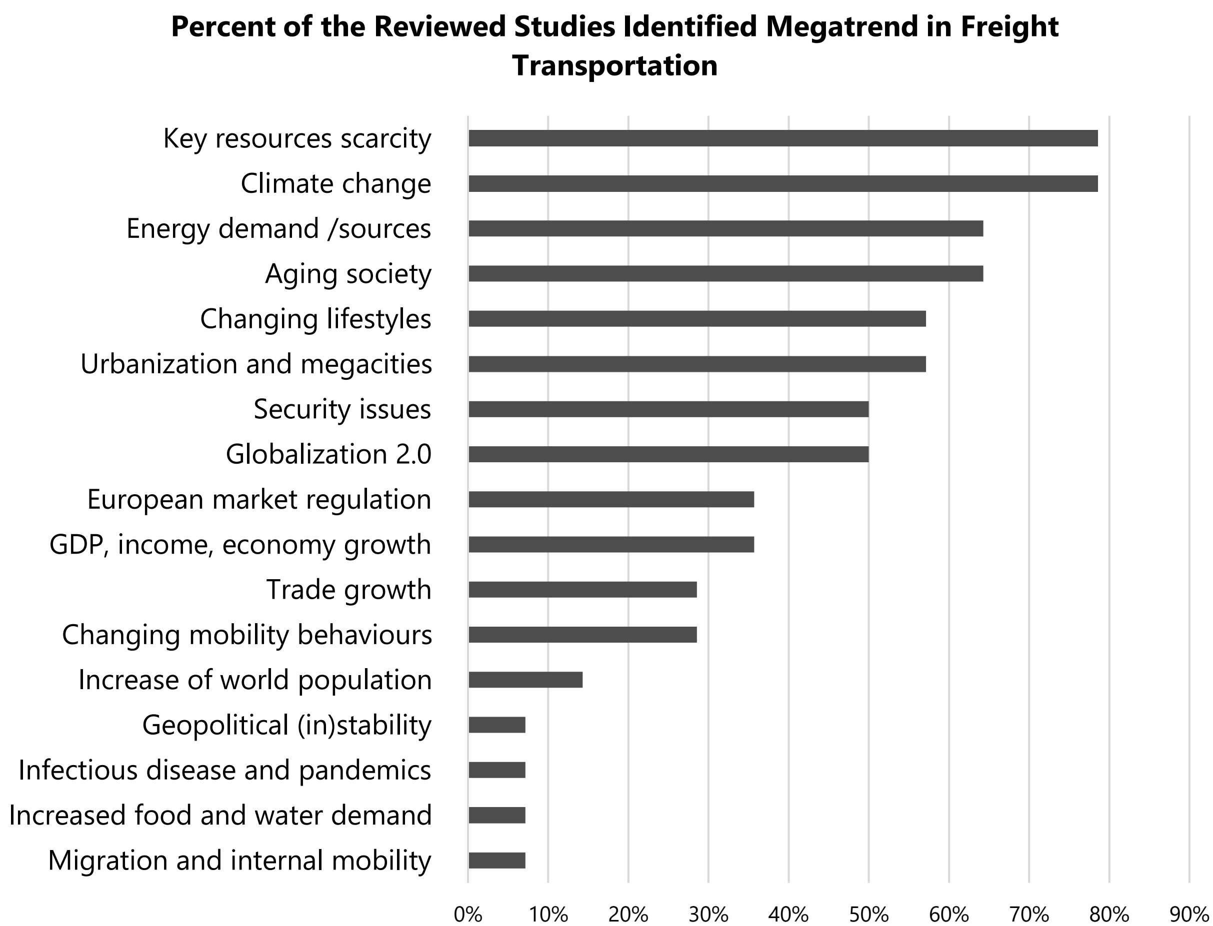

Figure 6-1 Percent of the reviewed studies identified megatrend in freight transportation (Adopted from Maraš et al. (57))

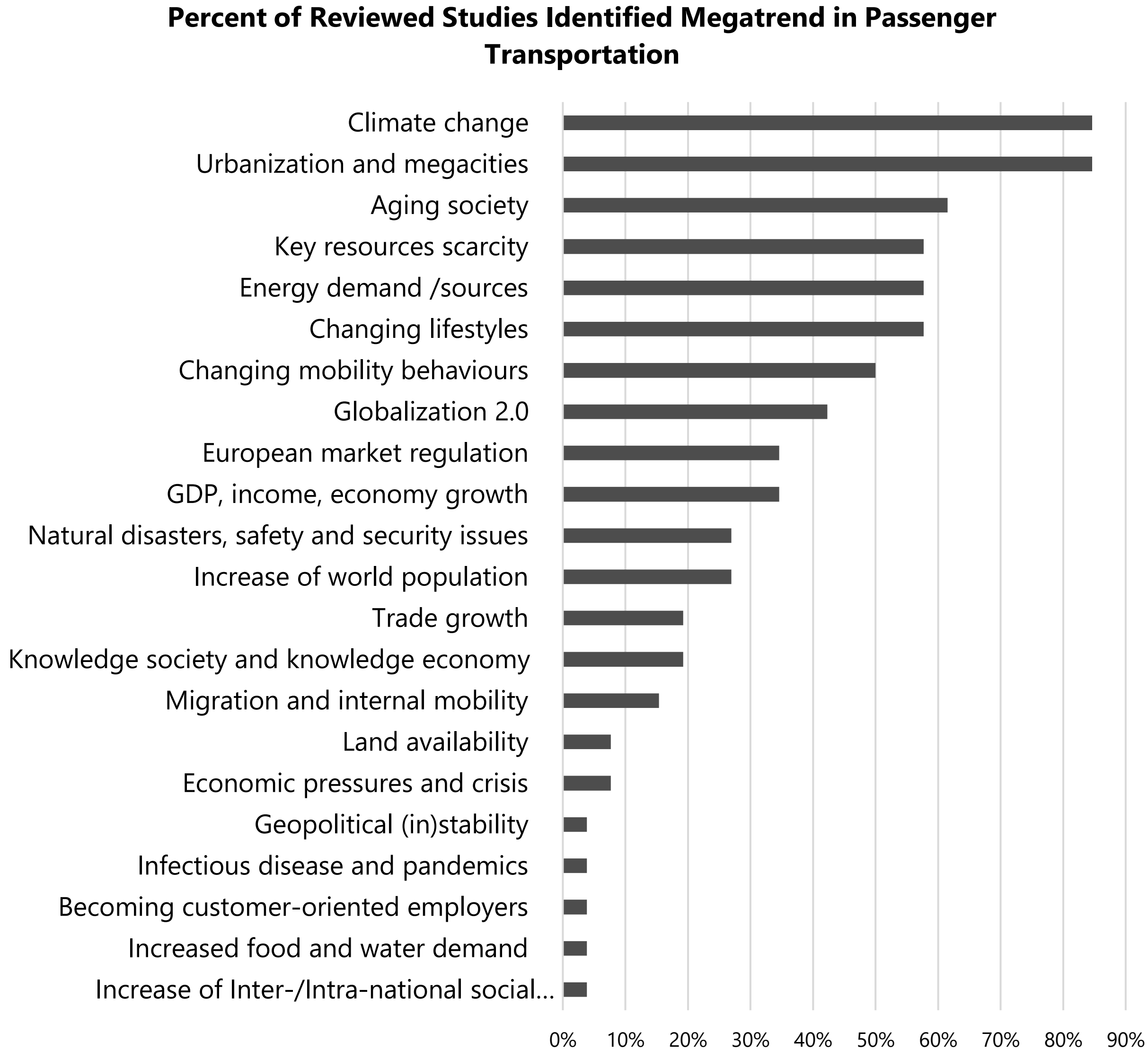

Figure 6-2 Percent of the reviewed studies identified megatrend in passenger transportation (Adopted from Maraš et al. (*57*))

Dia et al. (*58*) noted that one of the megatrends that will profoundly impact city transportation is rapid urban population growth. By 2050, it is estimated that an additional 2.5 billion people will move into urban areas (*59*). With the growing population, traffic congestion will continue to be a major challenge faced by the world's cities. It is a global problem with high costs to society resulting in delays, emissions, disruptions to commercial vehicle movements, lost productivity, and adverse effects on public health (*59*). Aging infrastructure is another problem faced around the world that needs to be addressed to support transport and urban mobility while also improving global connectivity. Transportation activity is a major source of pollution and currently accounts for half of the world's oil consumption (*59*). However, transport dependency on oil is likely to reduce gradually because of superior technologies and business models such as electric vehicles (EV), mobility as a service (MaaS), electric autonomous on-demand shared fleets, and similar emerging technologies (*58*). As environmental awareness is growing on the global scale, emission reductions will be taking place to reduce carbon emissions which will help in climate change. Furthermore, identifying measures to improve international freight transport efficiency and modeling global transport processes will become increasingly important (*57*). Climate change is projected to increase the frequency and intensity of extreme events, such as high-intensity rainfall and hurricanes, resulting in structural damages and disruption in transport services. Transportation resilience of urban areas and infrastructure should be improved to combat the extreme events that may arise with the changing climate.

In recent years there has been research on health problems induced by transport-related activities, such as stress, cardiovascular diseases, physical inactivity, and obesity (*59*, *60*). Furthermore, the recent pandemic crisis of COVID-19 has profoundly impacted people and goods movement across the world. Karabag (*61*) identified the coronavirus crisis not only as a disruptive period but also as a period of accelerated adoption of digital technologies, micro-level initiatives, and resource-intensive forms. The speed of digital technology adoption such as 3D printing, digital solutions, digital currencies, and AI has increased immensely during the COVID-19 crisis. The restrictive movement of people and goods across borders and the world could have potential revitalizing local industries (*62*). A recent example of the potentials of 3D printing was demonstrated by an American supercar company called Czinger. The company has revolutionized a new car manufacturing process by employing 3D printing (5). In 2020, the company has designed and built a hyper car, the 1250hp Czinger 21C, using AI, computational engineering, and 3D printing. This new method eliminates large amounts of production processes, reducing material costs, and the manufacturing time by creating efficient designs.

Today's advances as a new revolution was first labeled in 2016 by Klaus Schwab (*63*), Founder and Executive Chairman of the World Economic Forum. The author believes that we are witnessing the beginnings of the Fourth Industrial Revolution due to the historical changes, in terms of the size, speed, and scope, of the ways we live, work, and relate to each other. The author characterized the Fourth Industrial Revolution as a fusion between technology innovations (artificial intelligence (AI), robotics, the Internet of Things (IoT), autonomous vehicles, 3-D printing, nanotechnology, biotechnology, materials science, energy storage, and quantum computing, etc.) that will dissipate the boundaries between the physical, digital, and biological worlds. The author also believes that the technological innovation will also lead to a supply-side advancement, with long-term gains in efficiency and productivity. Transportation and communication costs will drop, logistics and global supply chains will become more effective, and the cost of trade will diminish, all of which will open new markets and drive economic growth. Additionally, the author has grave concerns: that organizations might be unable to adapt; governments could fail to employ and regulate new technologies to capture benefits; shifting power will create important new security concerns; inequality may grow; and societies fragmented. The impact of information technology implies major challenges in freight demand modeling and planning especially as the impact of new technologies is difficult to estimate and integrate. Freight transport models currently don't account for or consider the impact of technology innovations, nor do they account for the behavior of supply chains. Dia et al. (*58*) provided emerging trends and approaches for tackling the global transport challenges (see Table 6-1).

Table 6-1 Emerging trends and approaches for tackling the global transport challenges (Source: Dia et al. (58))

Traditional Approaches	Emerging Trends
Focus on supply and building additional infrastructure and capacity	Focus on demand management, maximizing efficiency, reliability, and resilience of transportation systems
Physical dimensions	Social dimensions (mobility benefits are equally and fairly distributed; fair access to transport services for all income groups)
Focus on mobility or physical movement from an origin and destination	Accessibility: Focus on the mobility required to access employment, opportunity, goods, and services
Large in scale	Local-scale - precinct level
Street as a road for vehicles	Street as space to be shared between all modes
Vehicle-oriented	People-oriented and customer-focused. Balanced development for all transport modes
Motorist transport	All modes of transport in a hierarchy with priorities for walking and cycling
Transport modeling approaches	Scenario development and modeling
Reacting to congestion and disruptions	Focus on positive business and operational outcomes
Travel as a derived demand	Travel as a valued activity as well as a derived demand
Minimization of travel times	Reliability of travel times
Key performance indicators: Traffic throughput and speeds	Key performance indicators: Accessibility, sustainability, social equity, environmental quality, health and well-being, and quality of life
Planning by experts	Planning through transparent and comprehensive stakeholder consultations
Segregation of people and traffic	Integration of people and traffic
Funds raised through petrol taxes, vehicle registration, and licensing fees	Congestion and road pricing and user-pay models
Private car ownership	New business models that promote a shift to car-sharing and ride-sharing solutions enabled by technology platforms
Emphasis on "knowing and seeing" and measuring past performance	Emphasis on "predicting and anticipating" to improve resilience and avoid disruptions

There is a need for freight demand modeling that goes beyond the traditional passenger four-step model and creates a new paradigm (*64*) that accounts for the various logistics and supply chain parameters that affect freight movements, including unreliable demand and supply, costs incurred when crossing boundaries (physical, regulatory, or administrative), possible efficiencies provided by economies-of-scale or hybrid networks, behavior-based modeling to identify emergent structures in policy and decision making, utilization of big data and data mining techniques, and smart city logistics to name a few (*65*). The purpose of these models would be to estimate the changes in transport costs and times as freight technology continues to evolve through truck platooning, truck automation, alternate fuel vehicles, and new modal choices and uses. Research along these lines should focus on: (i) models for choice problems where there is little or no track record, such as supply chain type choice (function, number, and location of inventories) and vehicle type choice (in particular, light vehicles vs. heavy-duty trucks); (ii) joining different models to link supply and demand at different levels, either within a multi-stage framework or a hyper network model; (iii) extending the spatial and dynamic reach of models to allow studying the evolution of global logistics networks and their interaction with systems at a national and regional level; (iv) deploying, transitioning, and assessing the benefits of information technology and automation (e.g., omnichannel logistics, dynamic delivery systems, and pick-up/drop-off freight networks, delivery to the trunk as opposed to home, public and freight transport network integration, mobility and sustainability, cooperation, etc.) for city logistics (*66*).

Another challenge to freight transport modeling identified by Meersmana et al. (*67*) is the inclusion of increasing scarcity of various resources and the internalization of external effects. The author noted a limitation in capturing the complexity of international freight transport structures' interdependencies and its actors’ motivations and behavior. The authors highlighted the importance of a better understanding of international freight transport's complexity and the need for a broader approach than modelling transport alone, let alone international freight transport separately. The authors identified the need to develop international freight models in the context of optimization of the efficiency of transport chains and their sustainability and to understand and simulate impacts of possible future development and steering measures. The authors stated that there is no international standard for the calculation of emissions, standardized data, and data formats. Furthermore, Savelsbergh and Van Woensel (*66*) identified that the volume, velocity, and variety of data arriving in real-time and containing high-value information continues to accelerate and is a key technological enabler for improving city logistics. Challenges that needed to be overcome are extraction and analysis in real-time, which requires advanced data analytics methods (i.e., optimization). Additionally, embedding and effectively using high-quality information and insights (e.g., dynamically updating distributions associated with any system uncertainty – demand, supply, travel times, etc.) in decision support (systems) is critical but nontrivial. In the context of city logistics, this may lead, for example, to systems that re-route in-route transport vehicles and/or re-sequence stops, based on current congestion information, pickup requests as they come in, and pickup requests that are anticipated. The information value of the incoming data is converted in near real-time into (autonomous) operational decisions.

The authors also identified several automotive technology developments that have a significant impact on city logistics. Alternative fuel vehicles (AFVs) are a small but becoming increasingly important part of the transportation system and autonomous or self-driving vehicles. The questions that researchers should address are the following: how to assess the benefits of self-driving vehicles for city logistics, how to most effectively employ self-driving vehicles, and how to best transition from an environment with 0 percent self-driving vehicles to 100 percent self-driving vehicles. Another useful innovation by the authors was the noted ability to access the trunk of your car, making it possible to allow companies to deliver to the trunk of your car (rather than to the door of your home). Interestingly, delivering to the trunk of a customer's car leads to a fundamentally different variant of the vehicle routing problem (VRP). As well, unmanned aerial vehicles (UAVs) will significantly enhance company supply chains and logistic operations by delivering smaller items within the last mile of the transportation system. The authors highlighted as opportunities two-echelon routing problems (in their setting, deliveries can only be made from satellite facilities, but by allowing an urban distribution center and a satellite facility to be co-located the more general setting can be handled as well), is still a relatively unexplored area as most of the existing research has focused on basic problem variants, as well the topics of dynamic delivery routing and crowd shipping are virtually unexplored and offer fertile ground for groundbreaking research. Furthermore, they stated that they only now recognize the various pricing issues that can arise in crowd shipping[1]. Relatively little research has been done on how to best design and operate pickup point networks and quantify their benefits. Successful research along these lines may enhance pickup point networks' effectiveness and their adoption (and the rate of their adoption). Surprisingly, given its practical importance, there is little or no research on the implications and the effective management of omnichannel logistics. The authors highlighted the enormous potential for research bridging two domains: freight logistics and public transit. Tavasszy et al. (*64*) advocate further integrating models to recognize super- and hyper-networks, spatial interactions, and inventory choice models. The purpose of these integrated models would be to estimate the changes in transport costs and times as freight technology continues to evolve through truck platooning, truck automation, alternate fuel vehicles, and new modal choices. Three further avenues of research are proposed:

- Models for choice problems where there is little or no track record, such as supply chain type choice (function, number, and location of inventories) and vehicle type choice (in particular, light vehicles vs. heavy-duty trucks)
- Joining different models to link supply and demand at different levels, either within a multi-stage framework or a hyper network model
- Extending the spatial and dynamic reach of models to allow studying the evolution of global logistics networks and their interaction with systems at the national and regional level

[1]Crowd shipping or Crowdsourced delivery is a sustainable method of employing contractors to handle deliveries using their own vehicles, going from warehouses, stores or centers to the end customer

CHAPTER 7 TRUCK PARKING CONGESTION AND UTILIZATION

With Tennessee possessing considerable freight congestion (#8 in the country for overall state-level truck congestion, and the Nashville region ranked #10 in metropolitan truck congestion) that is difficult to measure, the research team used truck GPS data provided by the American Transportation Research Institute (ATRI) and National Performance Management Research Data Set (NPMRDS) data from TDOT to conduct a state wide truck congestion analysis (including capacity analysis of truck parking facilities and undesignated parking rates at on- and off-ramps)– which documented and highlighted both state-level truck congestion analyses, as well as those of major metro areas (Memphis, Nashville, Knoxville and Chattanooga). The national NPMRDS also allowed the research team to provide more detailed information on truck congestion as it relates to national truck flows that enter/exit Tennessee. ATRI worked with the University of Memphis (UofM) to provide this strategic analysis TDOT at no cost. The data was also used to update the latest TN Truck Parking Study (RES 2019-16) results and provided additional insight into truck parking demand in Tennessee.

State of Truck Parking in the state of Tennessee

Under this task, the research team implemented methodology developed as part of RES2019-16. Then, after collecting and processing additional truck data for years 2019 and 2020, the truck parking utilization and violations (i.e., truck parking at on- and off-ramps) were estimated and a comparison for the period 2018 through 2020 in the state of Tennessee was developed. More information on the methodology and data is available in the final report of RES2019-16. Next, a discussion on the main results of this task is presented. The desktop and web-based data analytics tools developed as part of this task are available through the website developed as part of this project.

Parking Duration: Initial analysis of parking duration data showed parking durations were not normally distributed, as shown in Figure 7-1. Parking duration is best characterized by mean, median, and interquartile range values (Table 7-1). Parking durations at designated public and private rest areas did not significantly vary year over year in this study, implying COVID-19 had negligible effect on parking duration (Figure 7-2). Parking duration in 2020 did not differ markedly from previous years with regards to the trucks' arrival time at the parking facility.

Table 7-1 Summary of parking duration (hours).

		Truck Count	Mean	1st Quartile	Median	3rd Quartile
Private	All Years	1,079,730	4.44	0.47	0.83	10.15
	2018	372,956	4.35	0.47	0.80	10.08
	2019	283,611	4.67	0.48	0.90	10.28
	2020	423,163	4.37	0.47	0.82	10.08
Public	All Years	151,655	3.42	0.50	0.67	6.75
	2018	46,885	3.32	0.45	0.65	6.07
	2019	42,597	3.54	0.50	0.70	8.00
	2020	62,173	3.41	0.50	0.68	6.32
Total		1,231,385	4.32	0.48	0.82	10.03

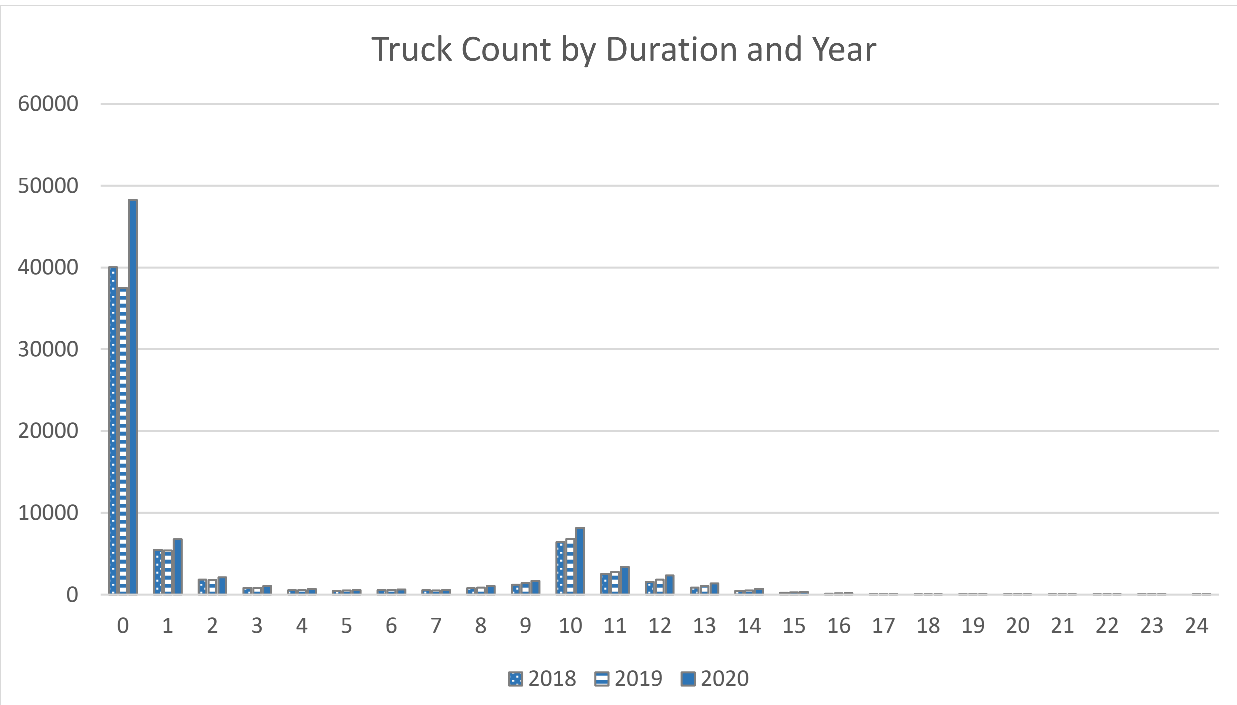

Figure 7-1 Histogram of parking durations, 15 minutes - 24 hours.

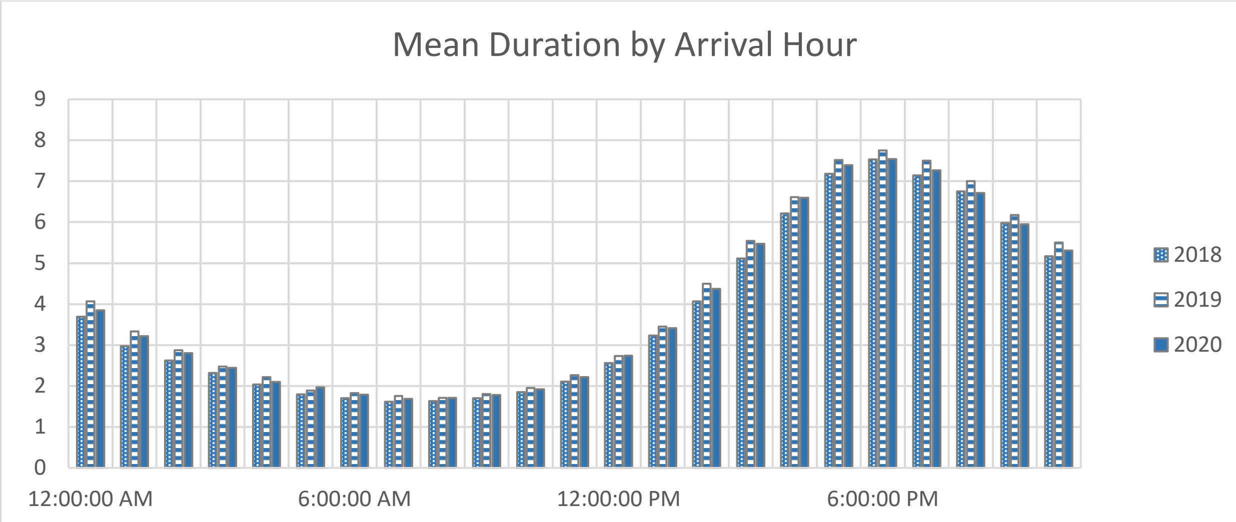

Figure 7-2 Mean parking duration (hours) by arrival time.

Occupancy: Rest area occupancy as determined by GPS transponder data presents ambiguous results. Occupancy appears higher in 2020 than in previous years, but 2020 is slightly overrepresented (39.4 percent) in sample data. Thus, it is not immediately clear whether the apparent rise in occupancy represents an increase in truck parking. This ambiguity extends into peak hour occupancy (peak hours are defined here as 8:00 PM – 4:00 AM, when drivers generally have taken off-duty breaks). Peak hour occupancy at private parking facilities for 2020 (Table 7-2) suggests increased truck parking, but hourly trends in mean occupancy remained stable from year to year (Figure 7-3).

Table 7-2 Summary of total and peak hour (PH) rest area occupancy (trucks per hour).

		Truck Count		Mean		1st Quartile		Median		3rd Quartile	
		Total	PH	Total	PH	Total	PH	Total	PH	Total	PH
Private	All Years	1,079,730	220,193	15.53	18.68	1	1	6	9	26	33
	2018	372,956	77,976	15.47	18.81	1	1	6	9	27	33
	2019	283,611	54,458	12.83	15.57	1	1	5	8	22	27
	2020	423,163	83,759	18.28	21.64	1	2	8	10	32	39
Public	All Years	151,655	30,504	1.31	1.84	0	0	0	0	2	2
	2018	46,885	10,565	1.10	1.63	0	0	0	0	1	2
	2019	42,597	8,361	1.18	1.63	0	0	0	0	1	2
	2020	62,173	11,578	1.67	2.27	0	0	0	0	2	3
Total		1,231,385	250,697	7.57	9.26	0	0	1	2	6	9

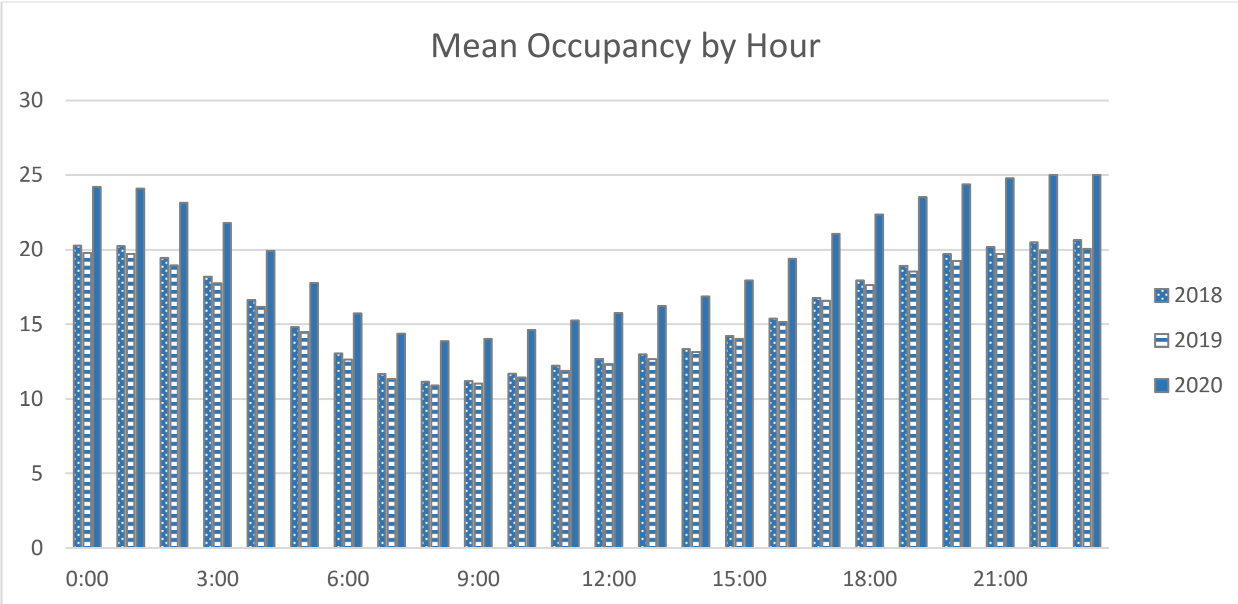

Figure 7-3 Mean rest area occupancy by hour.

Ramp Parking Violations: Trucks illegally parked on public rest area ramps often indicates parking shortages, especially during peak demand hours when occupancy is highest. Since ramp parking is somewhat a matter of drivers' preferences, only peak-hour data when scarcity is of higher concern is considered here. Parking data indicates illegal parking (shown in Figures 7-4 and 7-5) as a percentage of all peak-hour parking increased in 2020. This suggests the increase in occupancy noted in Table 7-2 and Figure 7-3 is not entirely a statistical number and reflects higher demand for parking. Increased off-ramp parking is especially noteworthy since it indicates drivers parked before passing through the designated parking area, i.e., before confirming the designated parking area was full.

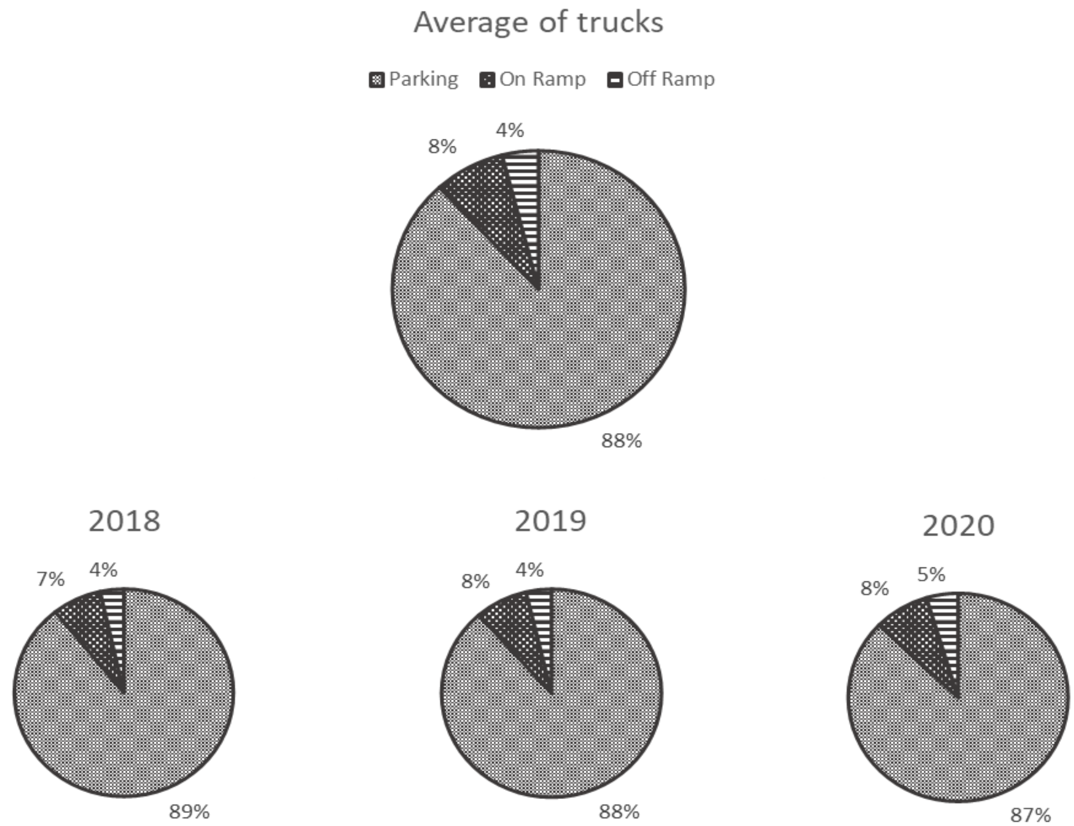

Figure 7-4 Ramp parking violations during peak demand hours.

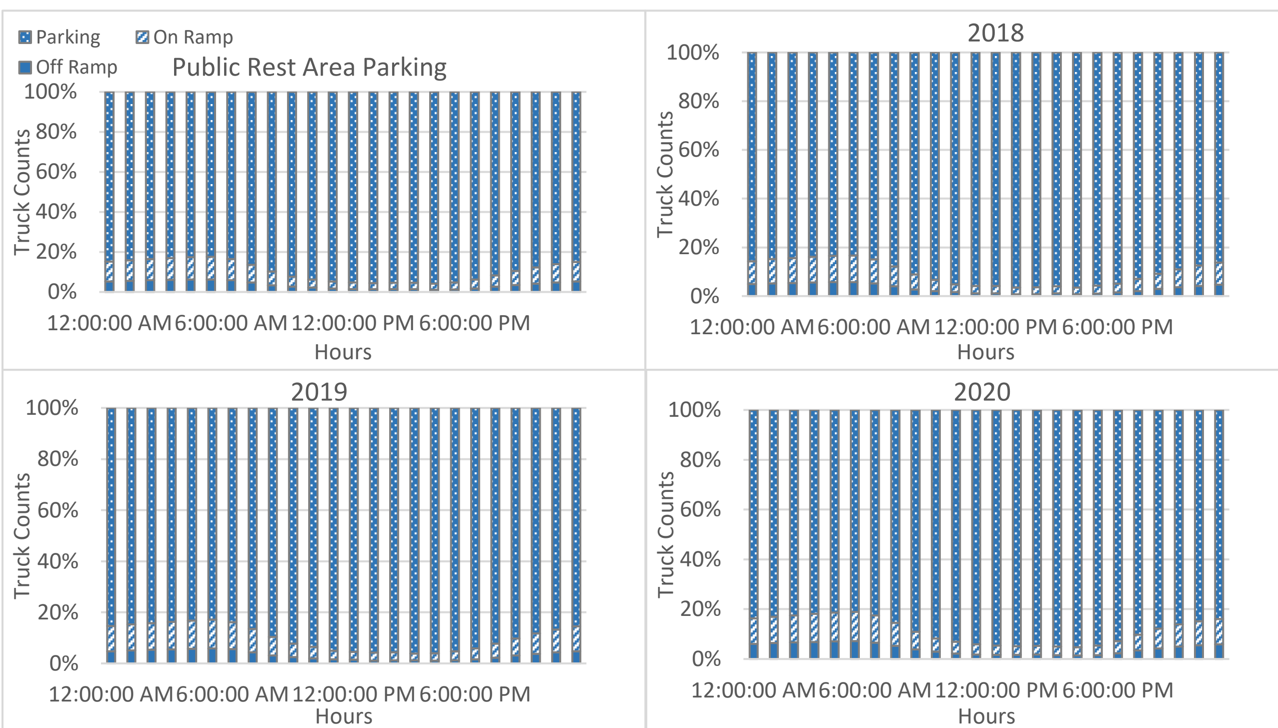

Figure 7-5 Mean ramp parking violations by hour as a percentage of all parking.

Discussion

By focusing on infrastructure investment at both federal and state levels, this study can provide an important blueprint for truck parking strategies which can provide the greatest value to policy makers. More specifically, by addressing strategic truck parking needs through the utilization of truck GPS data, policy makers can play an integral role in supporting hours-of-service compliance, unauthorized truck parking and the economic gains that come from highly efficient supply chains – particularly those that are becoming increasingly reliant on the evolution of e-commerce. Recognizing that truck parking is one of the most influential factors for route selection decisions, and that lack of truck parking has safety and economic ramifications, this study can be a key component for freight planning and investment activities, as well as a template on how to utilize GPS data to produce various performance measures regarding truck parking. Finally, the innovative use of GPS data for truck parking analysis can become a “best practice” for policy makers and researchers.

CHAPTER 8 COLLABORATION OPPORTUNITIES FOR REGIONAL FREIGHT PLANNING IN THE PIEDMONT ATLANTIC, NORTHEAST, AND FLORIDA MEGAREGION STATES WORKSHOP

As part of the study, the research had proposed to host an in-person summit to present its findings from the project and foster the beginning of dialog with regards to developing collaborations of Piedmont Atlantic, Northeast, and Florida Megaregion states for improvement of freight planning, operations, and management. Unfortunately, due to the COVID-19 pandemic, the format of the summit was changed to an online workshop. A half-day virtual workshop was held to promote collaboration between the Piedmont Atlantic, Northeast, and Florida Megaregion states on freight planning, operations and management, and project selection. In preparation for the workshop, a short survey was distributed to the participants to identify freight issues that are of concern to their state and rank their importance. An additional purpose of the survey was to identify areas where it would be possible to collaborate with researchers and DOT personnel from other states to study the problems. The results of this survey formed the basis for discussion during a half-day virtual workshop that took place in Summer 2021. The survey questionnaire, meeting minutes, agenda and a summary of the survey results are available in the supplementary document that accompanies this report,.

The research team surveyed representatives of the different State DOT officials from 24th June 2021 to 12th July 2021. The purpose of the survey was to identify freight issues of concern to a particular state and rank their importance. An additional objective was to identify areas where it would be possible to collaborate with researchers and DOT personnel from other states to study the problems.

A total of eight officials from seven DOTs (two from Tennessee) participated in the survey (Table 8-1). The average response time was 10 minutes. Most DOT officials who responded to the survey were involved in Planning divisions in their respective DOT (Figure 8-1). Every state DOT has a freight plan, and majority of DOTs updated the plan in 2017, as shown in Figure 8-2.

DOT officials were asked about their perceptions towards the different freight related issues including truck parking, dedicated freight infrastructure, urban freight access and delivery, truck related accidents, last mile access, railroad crossing accidents, and freight planning. The survey also included additional freight issues related to infrastructure preservation and environmental issues. First, the survey asked DOT officials to rate all issues from 1-worst to 10-best from the state’s perspective. The results are shown in Figures 8-3 and 8-4. All officials have mixed opinions about all freight issues. The officials were also asked to write out additional issues not mentioned. One of the DOT officials added *Public and Management education regarding the importance of freight, Public and Management education regarding the importance of freight* and *Impact of freight in state economy*.

DOT officials were also asked to rate the possibility of their respective states collaborating on these freight related issues on a scale of Low-Medium-High. The results are shown in Figures 8-5 and 8-6. Most of the issues were categorized under medium category for the collaboration. One of the DOT officials specified *economic development opportunity* as additional issue and rated it as medium on the scale. Finally, DOT officials were asked to rate the duration of such collaboration of the states on a scale of Short-Medium-Long and the distribution of responses is delineated in Figures 8-7 and 8-8. Majority of DOTs are in favor of a medium duration of collaboration among states.

Table 8-1 Distribution of DOT officials participated in the survey

S. No.	State DOT	Number of officials participated
1	Alabama (AL)	1
2	Connecticut (CT)	1
3	Georgia (GA)	1
4	Maryland (MD)	1
5	North Carolina (NC)	1
6	Rhode Island (RI)	1
7	Tennessee (TN)	2

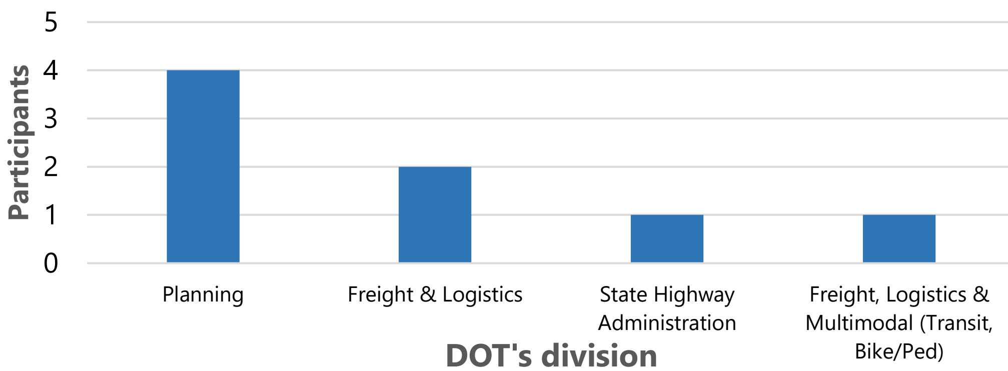

Figure 8-1 Participants' DOT division (N=8)

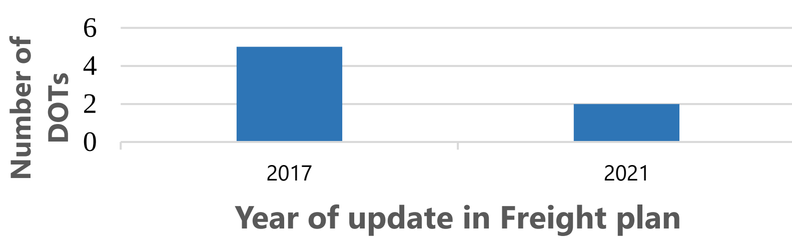

Figure 8-2 Year of update in Freight Plan (N=7)

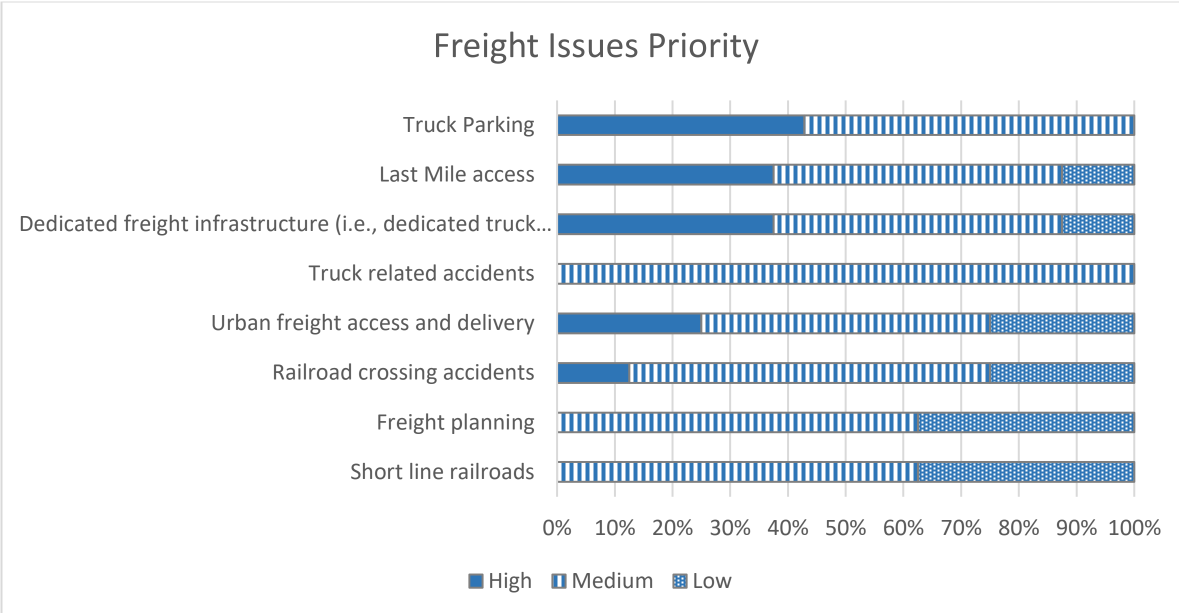

Figure 8-3 DOT officials' rating towards different freight related issues

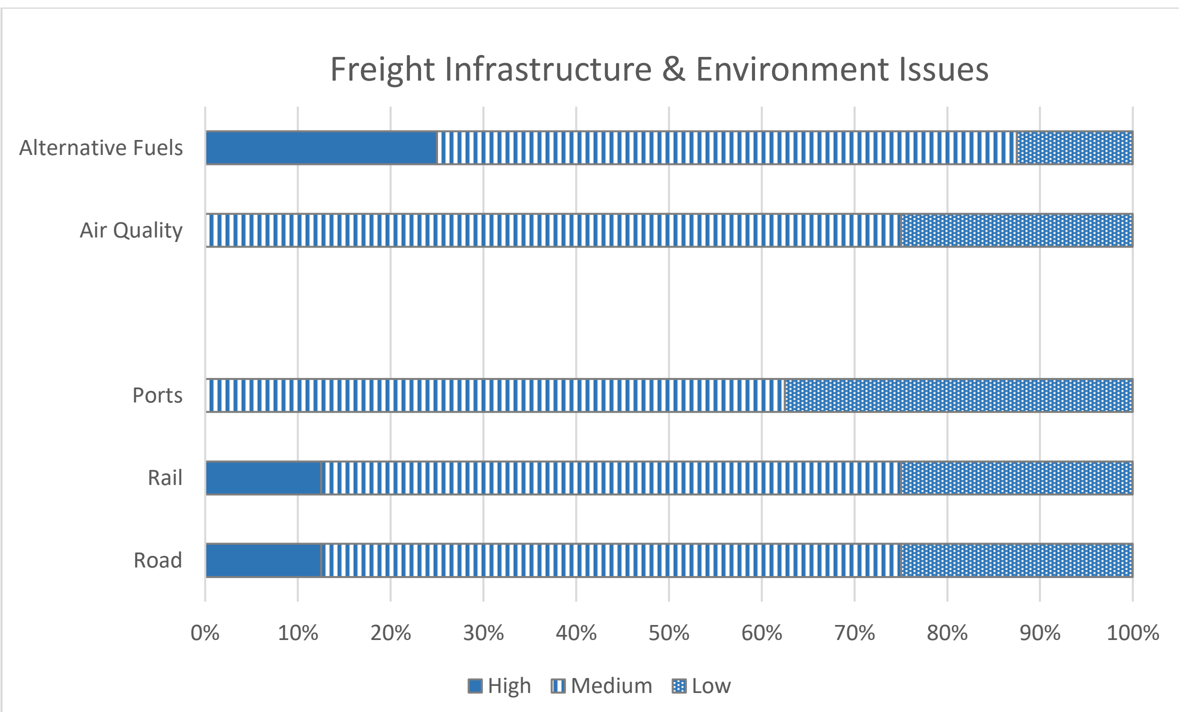

Figure 8-4 DOTs' rating towards infrastructure preservation and environmental issues

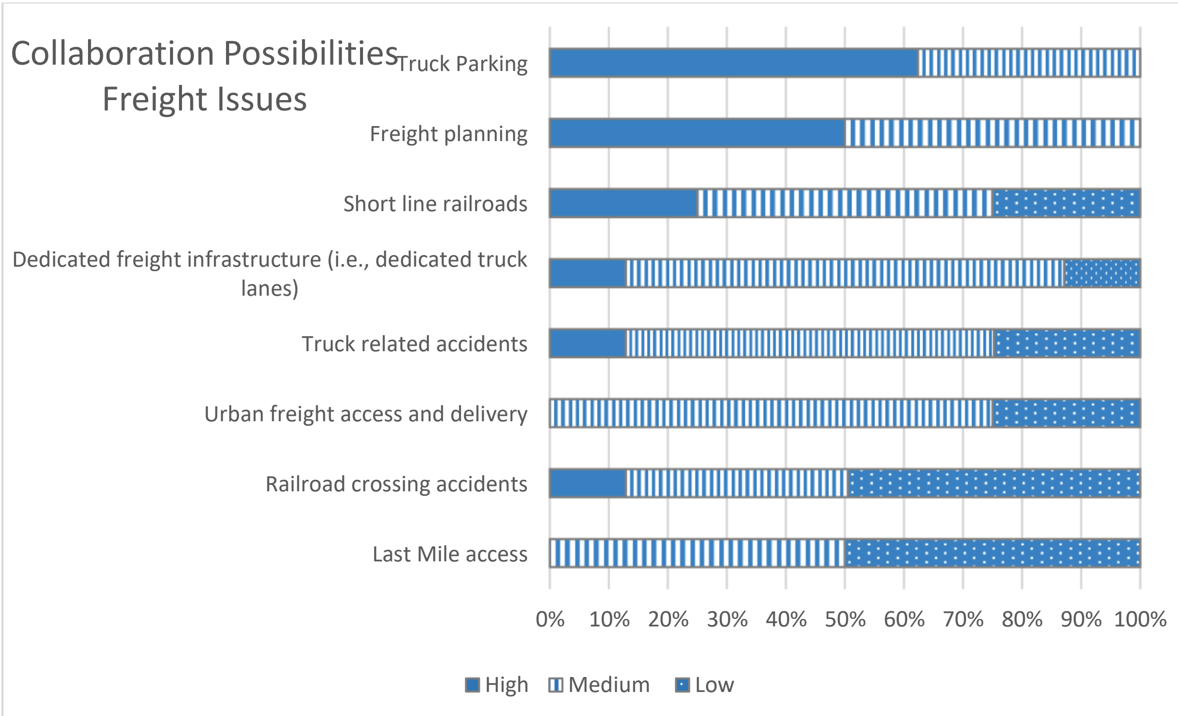

Figure 8-5 DOTs' rating towards possibility of States collaborating on freight related issues

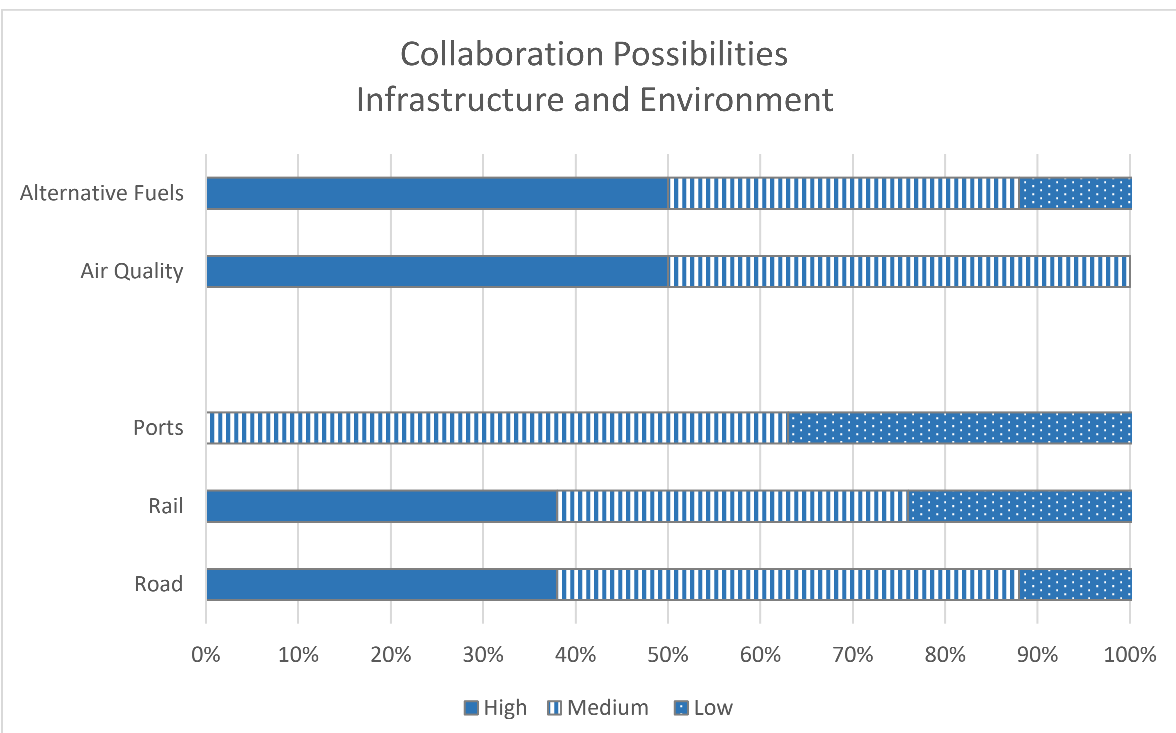

Figure 8-6 DOTs' rating towards possibility of States collaborating on infrastructure preservation and environmental issues

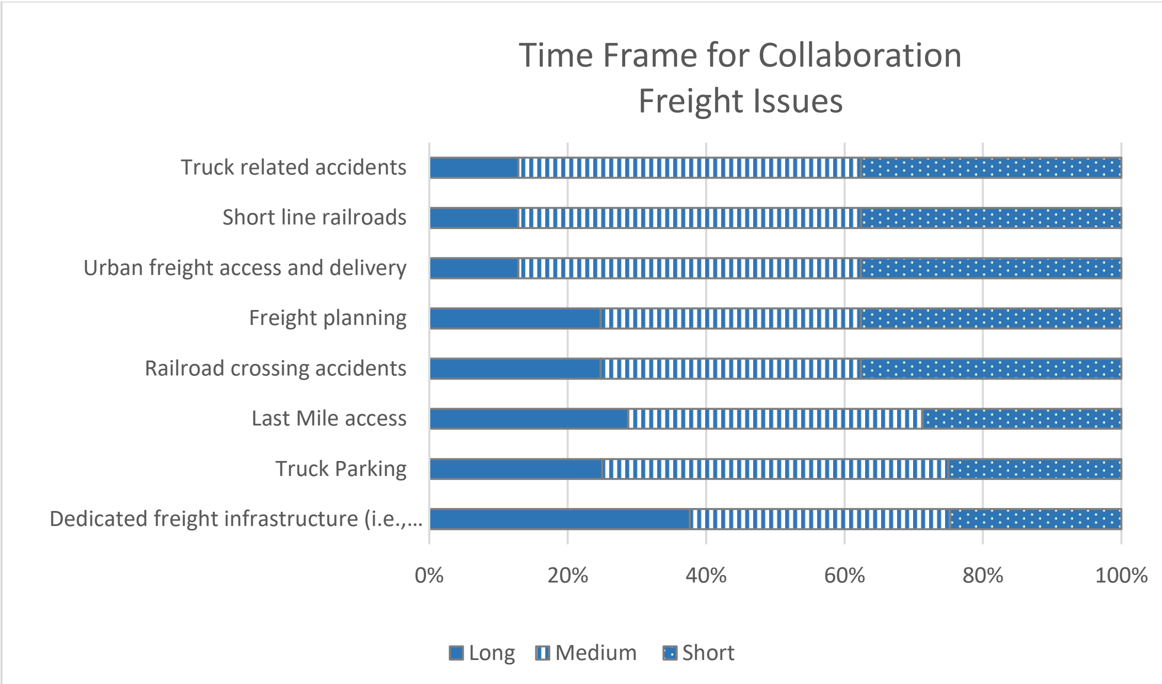

FIGURE 8-7 DOTS' RATING TOWARDS POSSIBLE TIME FRAME OF COLLABORATION AMONG STATES ON DIFFERENT FREIGHT RELATED ISSUES

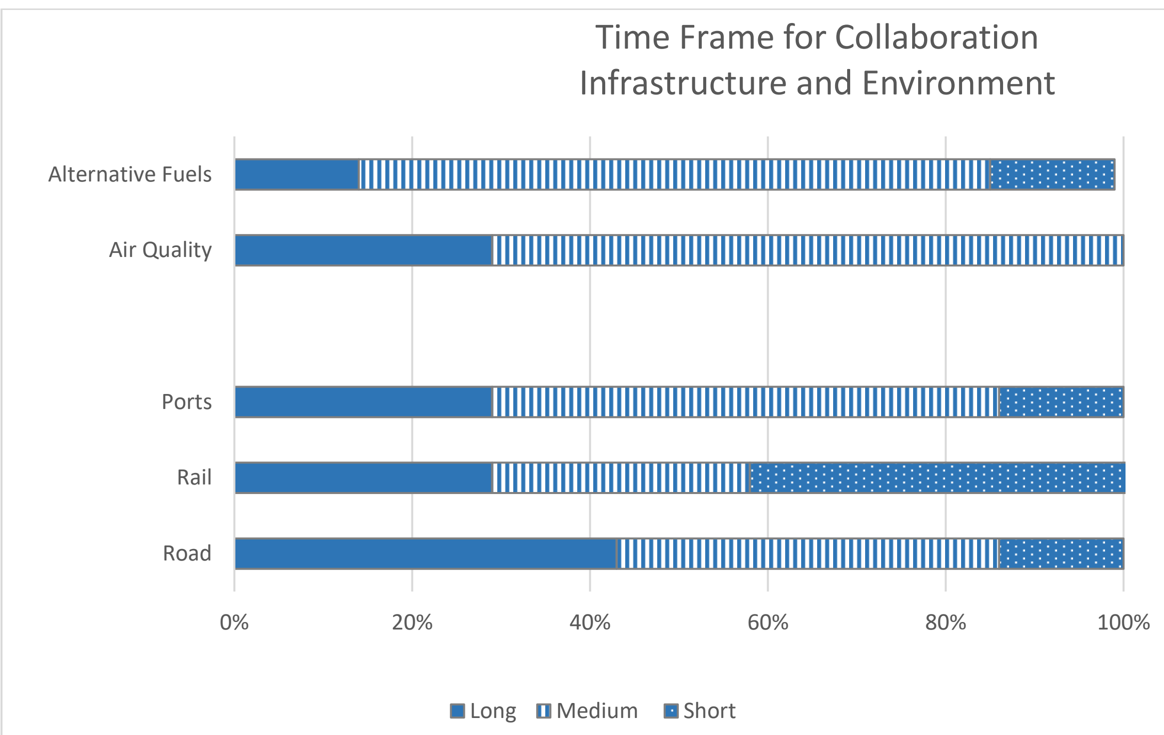

Figure 8-8 DOTs' rating towards possible time frame of collaboration among states on infrastructure preservation and environmental issues

CHAPTER 9 SUMMARY AND CONCLUSION

With the increasing growth in economic activity and population, freight flows and their impacts have increased. Accurate freight and truck movement identification has become critical for state DOTs and regional transportation agencies to develop transportation plans and policies. This research has implemented models and developed GIS tools to disaggregate the IHS Global Insight's TRANSEARCH commodity freight database to any jurisdictional level. Two disaggregation methods were integrated into GIS tools. The first method relied on the industry proportional weighting and economic indicator regression. The second was based on industry and economic indicator proportional weighting. Infogroup InfoUSA business and consumer contact database was used to obtain disaggregate-level zone economic indicator (employment, the value of sales, and sq. footage) values. BEA Input-Output Account Supply and Use tables were utilized to link industries that produce with industries that use the commodity and estimate their shares. The economic indicator regression was used to create a relationship between the aggregate zone economic indicators and freight flow productions and attractions. The economic indicator proportional weighting was employed to create a relationship between the disaggregate and aggregate zone freight flows using industry economic indicator shares. Three freight flow distribution methods were applied: the Gravity model, the Iterative Proportional Fitting, and Proportional Weighting. The developed ArcGIS tools were grouped into three sets: the preprocessing tools, the disaggregation tools, and the postprocessing tools. The preprocessing tools prepared the input data in disaggregation tools. The disaggregation tools were created for each of the disaggregate models. The postprocessing tools were created to provide the user with analytical and visualization capabilities. Analytical capabilities were achieved by giving users the ability to select the disaggregate flows by some condition or estimate disaggregate zone productions and attractions. The visualization was achieved by providing users with the ability to automate map creation to visualize either disaggregate OD flows or productions and attractions.
Findings

This research provided TDOT and local agencies (i.e., MPOs) with high-resolution commodity freight flow data that can be utilized to better understanding freight movement. These data can be used to plan and provide the adequate infrastructure to meet the growing needs of freight demand. These data can be used: i) in the existing (and future versions) of the statewide and local travel demand models for planning and forecasting, ii) maintain a database of intra- and inter-regional commodity flows, iii) obtain freight flows growth to enhance policy decision-making such as freight diversion, and iv) develop and analyze links between commodity flows, economic activity, and land use. This research Identified new and emerging data sets and how they can be used independently or in association with the existing data for freight demand modeling, and short- and long-term decision making to address freight challenges. This research also identified the effects of megatrends on supply chains' structure and operations, availability of data, and data needs by the public sector for efficient freight transportation planning. Finally, the workshop that was conducted identified and ranked opportunities for freight collaboration across states that belong to the Piedmont Atlantic (PAM), Northeast and Florida

Megaregion states regarding investment decision-making and planning for freight (and passenger) movements.

Recommendations

Several future research directions were identified during the completion of this project. The models developed as part of this project can be improved, first by better crosswalk tables between SCTG commodities and NAICS industries. The disaggregate commodity-level was currently limited to SCTG 2-digit level, while the TRANSEARCH data used by the research team was represented in the SCTG 3-digit code. Second, the accuracy can be further improved by purchasing the proprietary regional IMPLAN Input-Output tables that provide information on economic inputs and outputs at the state-level instead of the national-level BEA Input-Output Account tables. Third, use of up-to-date proprietary datasets, that were used in this research, could enhance the accuracy of the results produced by the developed models. Finally, validation of the results can be performed if local information about commodity production and attractions becomes available.

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