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Final Project Report

Measuring the Last-Mile: A Comprehensive Evaluation of Synthesis Approaches to Address Data Gaps for Local Freight Decision-Making (Phase 1)

BY

Alison Conway, Ph.D.
Email: aconway@ccny.cuny.edu

Michael Grossberg, Ph.D.
Email:

Shradha Godse, M.S.
Email: sgodse@ccny.cuny.edu

Fateme Rezapour Fardin, M.S.
Email: frezapourfardin@ccny.cuny.edu

The City College of New York
160 Convent Ave, Steinman Hall Room T-119
New York, NY 10031

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7. Author(s)
Alison Conway, https://orcid.org/0000-0002-2538-4501
Michael Grossberg, https://orcid.org/0000-0003-4841-773X
Shradha Balasaheb Godse, https://orcid.org/0009-0009-6079-730X
Fateme Rezapour Fardin, https://orcid.org/0009-0001-8235-0770

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The City College of New York
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16. Abstract
The purpose of this study is to comprehensively review the current landscape of freight data available for local agency decision-making, to identify existing data gaps and limitations that inhibit data-driven decision-making, and to identify relevant machine learning, mathematical modeling, and generative AI approaches to address these gaps. Specific project tasks included: a comprehensive review of both academic and practical freight data literature to identify commonly used freight data sources, common applications of freight data for agency decision-making, and specific performance metrics needed for different decision types; 2) a detailed case study of the New York City Department of Transportation – including a stakeholder workshop and a systematic review of seven agency and commercial data sources; 3) mapping of performance metrics vs. specific local agency data needs and vs. available data sources; 4) identification of critical data gaps and limitations; and 5) comprehensive review of applications of machine learning, mathematical modeling, and advanced generative modeling techniques to identify promising approaches to address persistent data gaps. Key outputs from this analysis include a comprehensive summary of freight data sources and their potential applications; evaluation matrices mapping detailed performance metrics to specific local freight-related decisions and mapping detailed performance metrics obtainable from existing data sources; and recommended approaches for freight data synthesis to address remaining gaps.

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EXECUTIVE SUMMARY

The goals of this study are to comprehensively review the current landscape of freight data available for specific types of local public-sector decision-making, to identify remaining gaps for data-driven decision-making, and to identify machine learning and generative AI (Artificial Intelligence) approaches to address these gaps. To accomplish these goals, we completed a multi-phase study.

Reviews of Academic and Practical Literature

First, we comprehensively reviewed both academic literature and 84 practical freight-related reports to identify (1) commonly used freight data sources, (2) common applications of freight data for decision-making, and (3) where identified, specific performance metrics used for different decision types. The practical reports were comprehensively queried using Google Notebook, with all individual findings verified through manual inspection of the original reports. Our analysis identified 10 common agency applications of freight data; these include: identifying the locations of freight activity, freight demand estimation, freight traffic performance measurement, freight route identification, infrastructure planning and design, safety management, parking and loading management, land use planning and site permitting, and policy and program evaluation.

Our academic and practical reviews identified a number of key findings, including:

- Agencies most commonly use data sources available to them at no costs, such as the Freight Analysis Framework (FAF) (for commodity flow estimation), National Performance Management Research Data Set (NPMRDS) (for traffic performance measurement), and publicly-available national, state, and local employment and land use datasets.
- Freight surveys remain important for understanding logistics stakeholder behaviors, and for informing behavior-based modeling approaches, but they also suffer from a number of critical limitations including limited coverage, time lags, knowledge gaps of individual stakeholders, and – in the case of local surveys - lack of standardization across jurisdictions.
- Agencies are also increasingly reliant on commercial data products, including a number of probe- and telematics-based datasets. These datasets offer promising potential solutions to address historic freight data granularity gaps. Probe data have already been widely applied for a number of applications, including traffic performance measurement, travel demand estimation, and characterizing trip and parking behaviors. Telematics additionally add new opportunities for capturing granular vehicle performance information, such a fuel consumption, speed profiles, and hard braking events. These data are now being used by states, Metropolitan Planning Organizations (MPOs), and cities for a wide variety of practical applications, including traffic performance-measurement, understanding truck flows and parking behaviors, measuring route usage, and as an input to state and regional demand models. They also provide value-added information to supplement other public data sources for a number of applications including route identification and planning, infrastructure management, and parking management.
- Vehicle-based data sources can also present unique challenges; they are heterogeneous and sometimes highly dimensional, may represent only a very small and non-representative sample of vehicles, may be fragmented due to technology performance, and are typically produced by the private sector, resulting in both technical (e.g. storage, standardization) and administrative (e.g. privacy laws and concerns) barriers to use.
- Commercial data providers who aggregate and anonymize data from these sources have helped to overcome privacy barriers and move these data sources into practical application, but it is difficult to assess the representativeness of these products for some applications. Researchers have fused these datasets with more traditional freight data sources or with infrastructure-based sensors for validation and enhancement. Researchers have also demonstrated the potential to spatially overlay probe data with other sources, such as land-use or economic/employment data, to link vehicle activities to specific industries.

- Infrastructure-based sensors (e.g. Weigh-in-Motion (WIM), Light Detection and Ranging (LIDAR), video) are useful for continuous monitoring, and as a source of validation data for both traditional models and for probe- and telematics-based datasets enhanced with weighting or expansion factors. A number of recent studies have demonstrated the value of infrastructure sensors for fine-grained vehicle classification. However, these have typically been employed in highway settings, so there is limited information about performance on local roads.
- Cities are exploring a wide variety of freight-related interventions – including area-based policies, curb management approaches, traffic control strategies, consolidation approaches, and alternative vehicles - to manage externalities such as air pollution and collision risks. The existing literature provides very little information about data sources to assess these proposed solutions at a population scale. The aggregation of both public and commercial datasets likely limits their direct applicability for these uses.

New York City Department of Transportation Case Study

Next, to investigate the daily freight data needs of a large local transportation agency, a case study was conducted with the New York City (NYC) Department of Transportation (DOT). NYC DOT is the city agency responsible for planning, design, construction, maintenance, and management of the city's surface transportation infrastructure, including roads, bridges, sidewalks and other pedestrian infrastructure, bus lanes and stops, bike lanes, curbs, and traffic signals and signs, among other street elements. On May 30, 2024, the research team conducted a workshop with representatives from various divisions across NYC DOT to develop a better understanding of the agency's specific freight data needs. The meeting was attended by 17 representatives from various NYC DOT divisions and programs, and the aims of this workshop were to: (1) identify ongoing and anticipated freight planning applications and operational decisions; (2) identify current freight data needs, and gaps; (3) identify current data sources; and (4) identify existing collaborations between public sector agencies and between these agencies and private sector partners to obtain local freight data. The workshop began with a semi-structured roundtable discussion of the agency's strategic goals and performance metrics and freight-related tasks and data needs. Mentimeter was then employed to collect real-time inputs from attendees. Following the workshop, the research team conducted a comprehensive analysis of the agency's available freight datasets to evaluate their utility for specific local freight-related decision. The analysis investigated four commercial proprietary datasets, three of NYC DOT's own datasets, and two additional open datasets from other city agencies. For each data source, we conducted a systematic review to (1) identify available data attributes and (2) catalogue specific metrics of interest obtainable from each data source. Using findings from the literature and practical reviews (see section 3.1), we then filtered the available data attributes to identify a final set of metrics of interest relevant to urban logistics decisions. We produced two evaluation matrices; the first mapped detailed performance metrics to each type of urban logistics decisions, and the identified which if these detailed performance metrics could be obtained from each NYC DOT data source.

The following are the key takeaways from the NYC Case Study:

- Critical data gaps identified by agency stakeholders as important, but difficult to measure, include: all vehicle characteristics, including vehicle types, classifications, weights, dimensions, load factors, and engine types; vehicle-related emissions; last-mile modes shares; carrier tour characteristics; and trip origins and destinations beyond NYC.
- Data granularity needs, in both time and space, vary considerably depending on the specific agency application of the data.
- Commercial datasets provide reasonably detailed information about many metrics. While these metrics are independently useful, they are typically provided to the agency user as area- or segment-based aggregated estimates, limiting the ability to study linkages across metrics.

- Most common agency freight data applications could benefit from more detailed vehicle characteristics in addition to traffic and behavior metrics. Currently available datasets provide very limited vehicle-specific information.
- Raw probe or telematics data can provide very rich information about a vehicle, its ownership, and its stopping and starting behaviors, potential enabling granular analysis of travel and parking behaviors and associated externalities; however, this data is typically not available at a population scale or even as a representative sample.

Review of Machine Learning and Advanced Generative AI Approaches

Finally, after identifying key data gaps and limitations through the reviews and case study analysis, we conducted a comprehensive review of previous applications of machine learning, statistical modeling, mathematical modeling, and advanced generative modeling techniques to identify potential methods to address persistent data gaps. We explored frameworks potentially useful for freight transportation simulation, including previous applications in transportation as well as applications in related domains. This review focused on data structures and how each approach was useful for analysis, estimation, and data fusion. We also identified previous applications of data synthesis approaches and explored the utility of synthetic data for scenario analysis. Our results identified several approaches that are promising for freight data synthesis:

- Generative AI approaches enable the creation of synthetic datasets and synthetic trajectories that are statistically similar to real-world freight data while protecting sensitive operational information and the fine-grained analytical requirements of local freight planning.
- Planners can simulate freight management scenarios using synthetic trip trajectories to verify behavioral outcomes before implementation, reducing uncertainty and supporting evidence-based decision-making
- Synthetic datasets can also be informed by the fusion of disparate sources.
- Synthetic data can address data privacy concerns, data scarcity concerns, and high costs for data.
- Synthetic data generation also enables the creation of rare event scenarios that are poorly represented in historical records but critical for robust policy evaluation.
- Potentially useful methods for implementation in Phase 2 of this project include:
    - Generative adversarial networks (GANs) and variational autoencoders (VAEs) for feature-specific refinement;
    - Diffusion models for improved spatiotemporal fidelity;
    - Kernel density estimation (KDE) for probabilistic realism; and
    - Petri nets for logical verification of multi-stop tour constraints.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ACRONYMNS

Acronym	Definition
AADT	Annual Average Daily Traffic
AADTT	Average Annual Daily Truck Traffic
AI	Artificial Intelligence
AIES	Annual Integrated Economic Survey
AIS	Automatic Identification System
ALDOT	Alabama Department of Transportation
ANPR	Automated Number Plate Recognition
ARC	Atlanta Regional Commission
ARDOT	Arkansas Department of Transportation
ARIMA	Autoregressive Integrated Moving Average
ATR	Automatic Traffic Recorder
ATRI	American Transportation Research Institute
AVC	Automatic Vehicle Classification
AVI	Automated Vehicle Identification
AVL	Automated Vehicle Location
AZDOT	Arizona Department of Transportation
BEA	Bureau of Economic Analysis
BLS	Bureau of Labor Statistics
BOT	Bureau of Transportation
BTS	Bureau of Transportation Statistics
CalTrans	California Department of Transportation
CBP	County Business Patterns
CEQR	City Environmental Quality Review (NYC)
CNN	Convolutional Neural Network
CODOT	Colorado Department of Transportation
CFS	Commodity Flow Survey
CMAP	Chicago Metropolitan Agency for Planning
CRTPO	Charlotte Regional Transportation Planning Organization
CTDOT	Connecticut Department of Transportation
DBSCAN	Density-Based Spatial Clustering of Applications with Noise
DDOT	District of Columbia Department of Transportation
DelDOT	Delaware Department of Transportation
DOE	Department of Energy
DOF	Department of Finance
DOT	Department of Transportation
DOT&PF	Department of Transportation & Public Facilities
DRCOG	Denver Regional Council of Governments
DVRPC	Delaware Valley Regional Planning Commission
EDC	Economic Development Corporation (NYC)
EIA	Energy Information Administration
EMFAC	Emission Factor
EPA	Environmental Protection Agency
EWGCOG	East-West Gateway Council of Governments
FAF	Freight Analysis Framework
FAST Act	Fixing America's Surface Transportation Act
FDOT	Florida Department of Transportation
FGTS	Freight and Goods Transportation System
FHWA	Federal Highway Administration
FMCSA	Federal Motor Carrier Safety Administration
FRA	Federal Railroad Administration

GAN	Generative Adversarial Network
GCN	Graph Convolutional Network
GDOT	Georgia Department of Transportation
GIS	Geographic Information System
GPS	Global Positioning System
GVW	Gross Vehicle Weight
GVWR	Gross Vehicle Weight Rating
H-GAC	Houston-Galveston Area Council
HIDOT	Hawaii Department of Transportation
HPMS	Highway Performance Monitoring System
IDOT	Illinois Department of Transportation
IPF	Iterative Proportional Fitting
INDOT	Indiana Department of Transportation
ITD	Idaho Transportation Department
ITE	Institute of Transportation Engineers
ITS	Intelligent Transportation System
KDE	Kernel Density Estimation
KDOT	Kansas Department of Transportation
KTC	Kentucky Transportation Cabinet
LA Metro	Los Angeles County Metropolitan Transportation Authority
LaDOTD	Louisiana Department of Transportation and Development
LEHD	Longitudinal Employer-Household Dynamics
LIDAR	Light Detection and Ranging
LODES	LEHD Origin-Destination Employment Statistics
LPM	License Plate Matching
LPMS	Lock-Performance Monitoring System
LSTM	Long Short-Term Memory
MAG	Maricopa Association of Governments
MAP-21	Moving Ahead for Progress in the 21st Century Act
MassDOT	Massachusetts Department of Transportation
MDOT	Mississippi Department of Transportation
MDT	Montana Department of Transportation
ML	Machine Learning
MNDOT	Minnesota Department of Transportation
MODOT	Missouri Department of Transportation
MPO	Metropolitan Planning Organization
MWCOG	Metropolitan Washington Council of Governments
NAICS	North American Industry Classification System
NASEM	National Academies of Sciences, Engineering, and Medicine
NBI	National Bridge Inventory
NCDOT	North Carolina Department of Transportation
NCHRP	National Cooperative Highway Research Program
NCFRP	National Cooperative Freight Research Program
NCTCOG	North Central Texas Council of Governments
NDC	Navigation Data Center (U.S. Army Corps of Engineers)
NDDOT	North Dakota Department of Transportation
NDOT	Nebraska Department of Transportation
NHDOT	New Hampshire Department of Transportation
NHPN	National Highway Planning Network
NHTS	National Household Travel Survey
NJDOT	New Jersey Department of Transportation
NJTPA	New Jersey Transportation Planning Authority
NMDOT	New Mexico Department of Transportation

NPMRDS	National Performance Management Research Dataset
NOAA	National Oceanic and Atmospheric Administration
NRC	National Research Council
NVDOT	Nevada Department of Transportation
NYC	New York City
NYSDOT	New York State Department of Transportation
NYMTC	New York Metropolitan Transportation Council
NYPD	New York (City) Police Department
OD	Origin-Destination
ODOT	Oregon Department of Transportation
OKDOT	Oklahoma Department of Transportation
PennDOT	Pennsylvania Department of Transportation
PHFS	Primary Highway Freight System
PSRC	Puget Sound Regional Council
QCEW	Quarterly Census of Employment and Wages
RFID	Radio Frequency Identification
RIDOT	Rhode Island Department of Transportation
RNN	Recurrent Neural Network
SANDAG	San Diego Association of Governments
SAS	Service Annual Survey
SCAG	Southern California Association of Governments
SCAQMD	South Coast Air Quality Management District
SCDOT	South Carolina Department of Transportation
SCTG	Standard Classification of Transported Goods
SDDOT	South Dakota Department of Transportation
SEMCOG	Southeast Michigan Council of Governments
SHRP	Strategic Highway Research Program
SSA	Singular Spectrum Analysis
STB	Surface Transportation Board
SVM	Support Vector Machine
TAZ	Traffic Analysis Zone
TDOT	Tennessee Department of Transportation
TIMS	Transportation Information Management System
TPO	Transportation Planning Organization
TRB	Transportation Research Board
TRID	Transportation Research Information Services Database
TTTR	Truck Travel Time Reliability
TXDOT	Texas Department of Transportation
UDOT	Utah Department of Transportation
USACE	U.S. Army Corps of Engineers
USGS	U.S. Geological Survey
VAE	Variational Autoencoder
VIN	Vehicle Identification Number
VDOT	Virginia Department of Transportation
VIUS	Vehicle Inventory and Use Survey
VMT	Vehicle Miles Traveled
Vtrans	Vermont Agency of Transportation
WAIRE	Warehouse Actions and Investments to Reduce Emissions
WashDOT	Washington State Department of Transportation
WGAN	Wasserstein Generative Adversarial Network
WIM	Weigh-in-Motion
WisDOT	Wisconsin Department of Transportation
WVDOT	West Virginia Department of Transportation
WYDOT	Wyoming Department of Transportation

1. INTRODUCTION

The freight transportation system forms the backbone of urban and regional supply chains, playing a critical role in sustaining quality of life and economic activity and ensuring service efficiency. The landscape of freight logistics is shaped by complex interactions among carriers, shippers, warehouses, cross-docking facilities, and infrastructure, all operating within increasingly congested and space-constrained environments. The rising demand for on-demand delivery, driven by global e-commerce expansion and rapid urbanization, has further heightened the operational complexity and urgency of optimizing freight flows (Chang et al., 2025; Li et al., 2025). The efficiency of the freight transportation system is heavily dependent on reliable data to inform a range of decisions at all levels of government and in the private sector about economic and infrastructure investments and policy issues (TRB, 2003; National Academies of Sciences, Engineering, and Medicine (NASEM), 2013c; Dablanc & Adoue, 2025). Data on goods movements are needed for a wide variety of policy decisions, and these decisions rely on diverse range of data sources, which vary in their spatial and temporal dimensions and level of detail (NASEM, 2013c).

Despite the growing need for data-driven planning, freight data available to the public sector often remains fragmented, incomplete, or inaccessible. Granular data, such as establishment-based vehicle counts or detailed information on truck movements, is often lacking (Sánchez-Díaz, 2017; Momtaz et al., 2020; Akter and Hernandez 2022). Since disaggregate data can reveal sensitive business operations (Gülmez et al., 2025; Yang et al., 2025), many data sources are highly spatially aggregated at the national level, making them difficult to use for state, regional, and local planning without further disaggregation (NASEM, 2011d; NASEM, 2017c; Momtaz et al., 2020; Akter and Hernandez 2022; Nie et al., 2025; Chang et al., 2025). Private-sector data are often proprietary and challenging to obtain due to confidentiality concerns (NASEM, 2007; Nie et al., 2025; Li et al., 2025). Due to data limitations, a comprehensive approach combining multiple data sources is often necessary to fully describe the freight system and support effective decision-making (Laranjeiro et al., 2019; Dablanc and Adoue, 2025). This often involves "data fusion," integrating information from various sources developed independently with different definitions and collection techniques (NASEM, 2011d; NASEM, 2013c). However, this integration is often challenging due to freight data heterogeneity, with inconsistent classifications and formats used across various sensors and proprietary systems (Guo et al., 2025; Li et al., 2025). Together, these limitations restrict the ability of researchers and public agencies to conduct high-resolution analysis needed for local infrastructure planning, design, and operations management. Emerging machine learning and generative artificial intelligence (AI) approaches may offer potential solutions to address these persistent local freight data gaps. In this study, we aim to comprehensively review the current landscape of data available for local public-sector decision-making, to identify remaining gaps for data-driven decision-making, and to evaluate the potential applicability of machine learning and generative AI approaches to address these gaps.

The methods employed in this study are detailed in Chapter 2. First, we comprehensively review currently available freight data sources, to evaluate the utility of these data sources for local decision-making, and to evaluate remaining gaps that need to be addressed to meet agency data needs. In Chapter 3, we define common sources of freight data used in public-sector applications. In Chapter 4, we describe the existing academic literature focused on freight data collection approaches, technologies, applications, and governance. In Chapter 5, we describe results from a practical review of public sector freight data applications and needs by states, metropolitan planning organizations (MPOs), and municipal governments. In Chapter 6, we detail findings from a case study analysis of freight data use at the New York City Department of Transportation (NYC DOT). Together, these reviews allow us to identify key freight data needs and gaps for local decision-making, summarized in Chapter 7. Finally, in Chapter 8, we review recent machine learning, generative artificial intelligence (AI), and mathematical modeling approaches applied in transportation and related fields to assess their potential applicability for addressing freight-specific data challenges. Our final conclusions are briefly summarized in Chapter 9.

2. METHODS

Figure 2.1 provides an overview of the methods employed in this project.

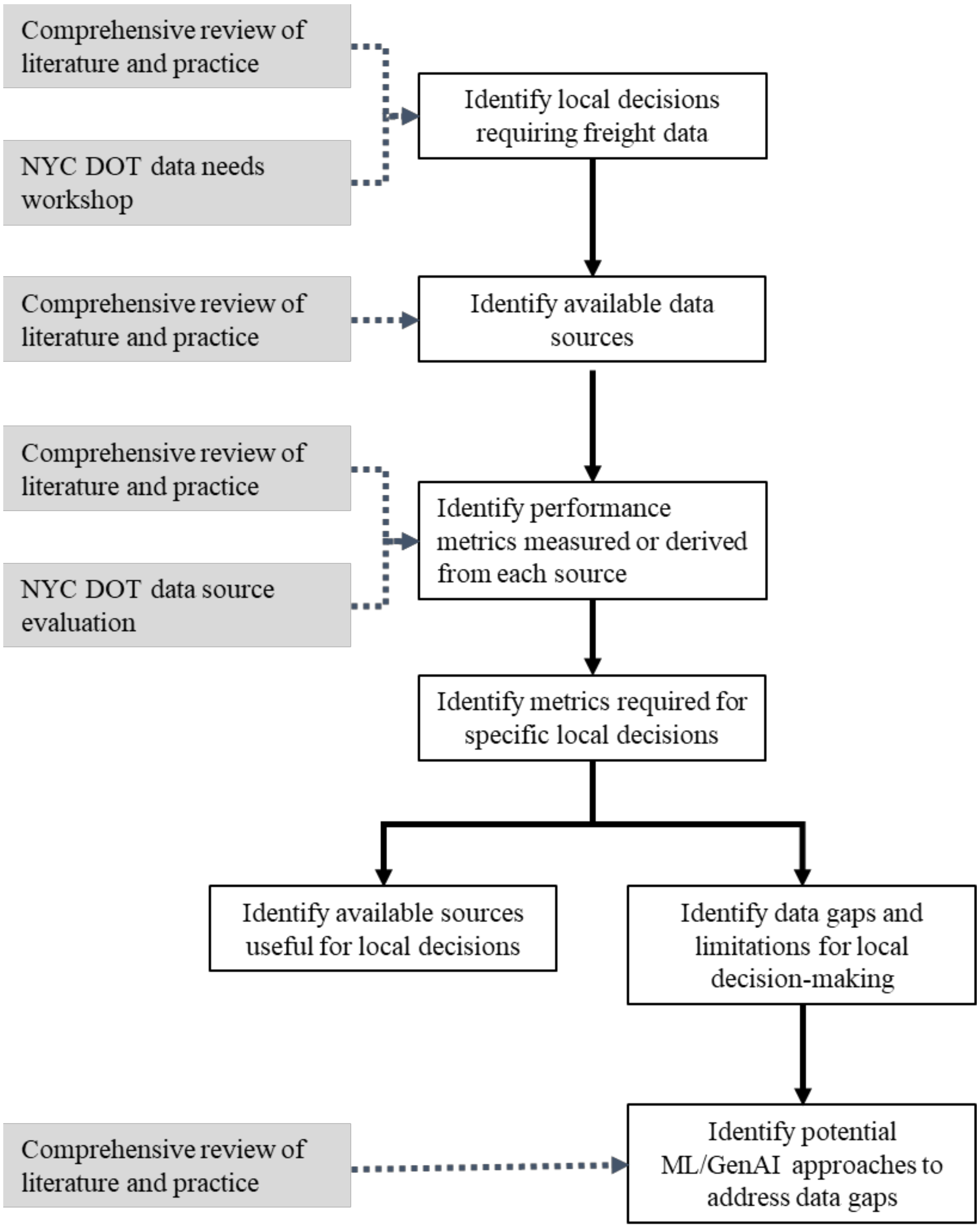

Figure 2-1. Project Methodology

2.1 Review of Literature and Practice: Local Freight Data Sources and Applications

The first task completed in this project was to comprehensively review both practical and academic literature to identify (1) commonly used freight data sources, (2) common applications of freight data for decision-making, and (3) where identified, specific performance metrics used for different decision types. To identify prior research related to freight data sources, data collection mechanisms, and freight data applications, a literature search was conducted using several journal databases and academic search engines, including Google Scholar, the Transportation Research Board's (TRB's) Transportation Research Information Services Database (TRID); ScienceDirect, and Sage Journals. Since practical applications of freight data often are not published as academic journal papers, we also scanned a number of practical sources to identify freight data sources and applications. The practical documents reviewed include: the most recent state freight plans for all 50 states and the District of Columbia; as well as 34 recent freight plans and freight-related reports published by 22 MPOs and 6 cities. In addition, reviews were conducted of the six published circulars from Transportation Research Board (TRB) workshops focused on freight data and freight data applications in the last decade. These documents were comprehensively queried using Google Notebook, with all individual findings verified through manual inspection of the original reports. The reports reviewed are listed in the bibliography and summarized in a table in Appendix A. Findings from these reviews are detailed in Chapters 3, 4, and 5.

2.2 New York City Department of Transportation Case Study

To investigate the daily freight data needs of a large local transportation agency, a case study was conducted with the New York City (NYC) Department of Transportation (DOT). NYC DOT is the city agency responsible for planning, design, construction, maintenance, and management of the city's surface transportation infrastructure, including roads, bridges, sidewalks and other pedestrian infrastructure, bus lanes and stops, bike lanes, curbs, and traffic signals and signs, among other street elements.

A number of documents published by NYC DOT since 2019 identify the agency's recent priorities for freight planning and operations. One of 10 priorities identified in NYC DOT's 2019 *Streets Plan* (since updated in 2012 and 2023) was "increasing the safety and efficiency of freight movement and delivery events while reducing traffic impact on the environment and needs of other users." The agency's 2021 *Delivering New York* plan identified four goals, to: "improve the safety of truck travel through and within the city"; "improve the efficiency of freight movement to, from, and within the city"; "foster the sustainable and responsible movement of goods"; and "expand partnerships within the public and private sectors to increase awareness and understanding of freight activity" (NYC DOT, 2021). In its 2021 *Delivering Green* plan published in collaboration with the NYC Economic Development Corporation, the agency identified four key priorities, to: "make the last mile efficient"; "green the last mile"; "create a culture of compliance"; and "increase mode shifting for goods movement from road to water, and to rail" (NYC DOT and NYC Economic Development Corporation (EDC), 2021).

2.2.1 Data Needs Workshop

On May 30, 2024, the research team conducted a workshop with representatives from various divisions across NYC DOT to develop a better understanding of the agency's specific freight data needs. The meeting was attended by 17 representatives from NYC DOT divisions and programs, including individuals working in Freight Mobility, the Office of the Commissioner, Regional and Strategic Planning, Engineering Review, Policy, and Alternative Fuels. The aims of this workshop were to: (1) identify ongoing and anticipated freight planning applications and operational decisions; (2) identify current freight data needs, and gaps; (3) identify current data sources; and (4) identify existing collaborations between public sector agencies and between these agencies and private sector partners to obtain local freight data. The workshop began with a semi-structured roundtable discussion of the agency's strategic goals and performance metrics and freight-related tasks and data needs. Mentimeter was then employed to collect real-time inputs from attendees. First, attendees were asked to rank on a scale of 0 to 3 the importance (0 = not important 1 = some interest, 2 = important, and 3 = critical) and the difficulty (0 = easy to measure, 1 = somewhat measurable, 2 = difficult to measure, 3 = not measurable) of measuring the specific performance metrics detailed in Table 3.1. Attendees were also asked to identify any current data sources that they use to estimate these metrics.

Table 2-1. Performance Metrics for Evaluation

Metric Category	Performance Metrics
Trip and Commodity Flow Metrics	Trip origins and destinations within NYC
	Trip origins and destinations beyond NYC
	Commodity origins and destinations (by weight or volume)
	Commodity origins and destinations (by weight or volume)
	Commodity origins and destinations (by value)
	Regional mode shares
	Last-mile mode shares
	Carrier tour characteristics
Freight Network Performance Metrics	Vehicle speed
	Travel time reliability
	Travel time reliability
	Collision frequency
	Collision severity
	CO_2 emissions
	Air pollutant emissions
Parking and Loading Metrics	Trip generation
	Parking/loading frequency
	Parking/loading duration
	Parking revenue
	Parking violation frequency
Vehicle Metrics	Vehicle type (e.g. truck vs. van);
	Vehicle classification (e.g. FHWA Class 9)
	Vehicle engine type (e.g. diesel vs. electric)
	Vehicle load factor (e.g. % of weight or volume capacity used)
	Vehicle load factor (e.g. % of weight or volume capacity used)
	Vehicle size dimensions (e.g. length, width, height)
	Vehicle weights (e.g. axle loads, gross vehicle weight (GVW))
	Vehicle safety equipment (e.g. mirrors, side guards)

Attendees were then asked to rank in order from one to six the *temporal* scales for which they need to measure freight activity from the following choices: 15-minute increments, hourly, weekday vs. weekend, day, month, and year. They were also asked to rank in order from one to six the *geographic* scales for which they need to measure freight activity from the following choices: 15-minute increments, hourly, weekday vs. weekend, day, month, and year.

2.2.2 Comprehensive Evaluation of Existing Data Sources

Following the workshop, the research team conducted a comprehensive analysis of the agency's available freight datasets to evaluate their utility for specific local decision-making. The analysis investigated four commercial proprietary datasets, including:

- A custom data purchase for March, May, August, and December (2015, 2016 and 2017) from the American Transportation Research Institute (ATRI);
- The Streetlight InSight platform (Jacobs, 2026);
- The Inrix Roadway Analytics platform (INRIX, 2026b); and
- The Altitude by Geotab platform (Geotab, 2026).

It is important to note that the datasets evaluated were the specific products purchased by NYC DOT at the time of the analysis, with associated temporal, geographical, and scope limitations. The datasets evaluated do not necessarily represent the full range of current data available from the providers, nor are the datasets directly comparable to each other given their varying temporal coverages. This evaluation should NOT be interpreted as a commercial product review, but rather as an assessment of which metrics the agency could obtain from their available data sources at the time of the analysis.

The study also explored three of NYC DOT's own datasets, including:

- A sample of the agency's automated vehicle location (AVL) data collected from the New York City Clean Trucks program;
- The agency's Transportation Information Management System (TIMS) database – which compiles all types of traffic counts of all surface modes conducted by the agency, including Automatic Traffic Recorder (ATR) counts, vehicle classification counts, and turning movement counts among others (NYC DOT, n.d.); and
- Weigh-in-motion (WIM) data collected from the automated weight enforcement system on the Brooklyn-Queens Expressway (NYC DOT, 2026).

Finally, the study explored open datasets from other city agencies with relevance to freight activity:

- The New York Police Department's (NYPD) publicly available collision records (NYPD, 2024); and
- The New York City Department of Finance's (NYC DOF) Parking Violation Records (NYC DOF, 2024).

For each data source, we conducted a systematic review to (1) identify available data attributes and (2) catalogue specific metrics of interest obtainable from each data source.

2.3 Mapping of Performance Metrics

Using findings from the literature and practical reviews (see section 3.1), we then filtered the available data attributes to identify a final set of metrics of interest relevant to urban logistics decisions. We sorted these metrics within three primary dimensions:

1. **Vehicle Characteristics**: Attributes defining the physical fleet (e.g., class, weight, engine type, etc).
2. **Network/Infrastructure Performance**: Indicators of system efficiency (e.g., Vehicle Miles Traveled (VMT), congestion, travel time reliability, parking occupancy, etc).
3. **Travel Behavior Characteristics**: Granular operational patterns (e.g., tour characteristics, parking durations, dwell times, etc).

We first mapped the performance metrics against specific local freight applications. This mapping ensures that each performance metric directly informs local planning or operational tasks, including: identifying the locations of freight activity, freight demand estimations, freight traffic performance measurement, freight route identification, infrastructure planning and design, safety management, parking and loading management, land use planning and site permitting, and policy and program evaluation. We then explored the dimensions, activity metrics, and limitations of each source. The key output is an evaluation matrix detailing these results for each dataset. This structured characterization allowed us to clearly identify available sources useful for local decisions, and conversely, to identify data gaps and limitations for local decision-making. The resulting table is also useful for identifying opportunities to enhance the value of individual datasets value through data fusion.

2.4 Review of Literature and Practice: Machine Learning Approaches

Finally, after identifying key data gaps and limitations through the reviews and case study analysis, we conducted a comprehensive review of previous applications of machine learning, mathematical modeling, and advanced generative modeling techniques to identify potential methods to address persistent data gaps. We explored generative artificial intelligence (AI) methods and other statistical and mathematical frameworks potentially useful for freight transportation simulation, including previous applications in transportation as well as applications in related domains. This review focused on data structures and how each approach was useful for analysis, estimation, and data fusion. We also identified previous applications of data synthesis approaches and explored the utility of synthetic data for scenario analysis. From the results, we identified a number of potentially useful methods for implementation in Phase 2 of this project, as well as the key benefits provided by these approaches.

3. COMMON SOURCES OF FREIGHT DATA FOR AGENCY DECISION-MAKING

Freight-related decision-making relies on a number of types of data. This section provides a summary of the key data sources used in freight-related applications. Notably, many of the applications identified are at a statewide or regional scale, rather than for local applications.

3.1 Freight Surveys

Historically, surveys have been a primary source of data for freight decision-making. Surveys may be implemented via a variety of methods including by phone, by mail, by internet, through personal interviews, or through focus groups (NASEM, 2011c). Depending on the purpose, surveys can be completed at different geographic scales. Based on findings from **National Cooperative Highway Research Program (NCHRP) Synthesis 410 (**NASEM, 2011c) and **Allen, Browne, and Cherrett** (2012), the common types of surveys conducted to evaluate freight activity include the following:

- **Commercial vehicle trip diaries** capture the detailed activities of a single vehicle, usually over one or a few days, including exact locations served, routes, arrival/departure times, and goods transported. Commercial vehicle trip diaries are typically completed by the vehicle driver.
- **Commodity flow surveys** are used to collect information about the types and quantities of good flowing to or from a specific establishment. Commodity flow surveys can be completed by a shipper or receiver.
- **Establishment surveys** measure the number of vehicle trips to or from an establishment during specific time periods (e.g., hour, day, month). Establishment surveys may also collect information about the type of goods shipped or delivered. Establishment surveys can be completed by a shipper or receiver.
- **Freight operator surveys** capture freight operator's vehicle (or fleet) activity patterns in an area. Freight operator surveys are often completed by a fleet or operations manager.
- **Roadside/intercept surveys** are often conducted at locations such as rest stops or weigh stations where truck typically stop, and they capture the characteristics of the ongoing trip at the time of the survey. Roadside intercept surveys are completed by the vehicle driver.
- **Vehicle observation surveys** monitor freight activities. Monitoring is either carried out in person by trained surveyors or recorded on video for post-analysis.

3.2 National Surveys

Several large national surveys serve as a primary data source for state and regional freight planning activities. Notably, data granularity constraints limit direct applicability of these sources for local applications.

- The ***Commodity Flow Survey (CFS)*** conducted in partnership by the U.S. Census Bureau and the U.S. DOT Bureau of Transportation Statistics is a primary national data source used to inform a variety of state and regional freight planning and modeling applications. The CFS is a survey of shippers from the following industries: mining, manufacturing, wholesale trade, auxiliaries, and some retail and service trade industries (BTS and the U.S. Census Bureau, 2026). The survey captures information by industry sector on the commodities, weights, values, origins and destinations, and modes of shipments from surveyed establishments. The CFS is one of the primary inputs to the Freight Analysis Framework (FAF) (see Section 4.4) and has also informed other key freight models such as the freight trip generation models developed in NCHRP Report 739/NCFRP Report 19 (NASEM, 2012a). Although it is one of the most important sources of freight data in the U.S., the CFS does have limitations that limit its direct applicability for local decision-making. The survey is conducted on a 5-year cycle, most recently in 2022. The survey does not cover all industries; it covers domestic shipments only, and it provides limited geographic detail in publicly available datasets.

- The purpose of the ***Vehicle Inventory and Use Survey (VIUS)*** is to identify the characteristics of the US vehicle fleet and to understand vehicle use. The survey captures information about vehicle characteristics and technologies, such as vehicle age, fuel type, safety equipment, trailer configurations, vehicle use, fuel economy, and maintenance costs. This data is useful to characterize on-road fleets and track trends, to inform freight demand and emissions modeling, and to inform energy and environmental impact analysis. VIUS was conducted in 2021 for Bureau of Transportation Statistics (BTS) by the U.S. Census Bureau, with support from the Federal Highway Administration (FHWA) and the Department of Energy (DOE). Like the CFS, the VIUS provides limited geographic detail, and the most recent survey was conducted only after a 20-year hiatus.
- The ***Service Annual Survey (SAS)*** provides estimates of revenue and other measures for most traditional service industries. These include all for-hire (truckload and less-than-truckload), heavy and tractor-trailer, and light or delivery services identified by North American Industry Classification System (NAICS) code, excluding private carriage (NASEM, 2014b). Data collected include motor carrier revenue by commodity classes, end-of-year fleet size by type, fuel expenditures, payroll, and purchased freight transportation. Starting in 2024, the SAS has been integrated into the Annual Integrated Economic Survey (AIES) (U.S. Census Bureau, 2025). Like all of the other national surveys, it is limited in its data granularity.
- The ***National Household Travel Survey (NHTS)*** is conducted by FHWA every five to seven years, and is the primary source of national data to analyze trends in personal and household travel (FHWA, 2023). Data is collected on daily trips taken by households and individuals in those households, over a 24-hour period. These details are collected for all trips, modes, purposes, trip lengths, and all areas of the country, urban, and rural. In the most recent (2022) NHTS, household delivery-related metrics include number of online purchase deliveries, number of times food delivered, number of times goods delivered, and number of times groceries delivered in past 30 days. The Federal Highway Administration launched the NextGen NHTS in November 2024 that focuses on providing national travel behavior data on a more frequent basis than prior NHTS efforts. This effort includes moving to a biennial household travel survey and adding annual passive original destination (OD) truck and passenger data products at the national level (NHTS, 2024a). Information on travel patterns of special populations and emerging transportation modes is documented in the 2022 NHTS summary report (FHWA, 2023).

3.3 State, Regional, and Local Surveys

Other surveys are more typically implemented by state, regional, or local governments to inform specific agency activities; the following are examples of surveys implemented at the state or regional level.

- The Maricopa Association of Governments implemented an **establishment survey** to quantify trip attraction characteristics across various sectors and to provide essential data for updating activity-based models concerning destinations, timing, and transport modes (Maricopa Association of Governments (MAG) Establishment Survey Report, 2017).
- The Southeast Michigan Council of Governments (SEMCOG's) Commercial Vehicle Study included both an **establishment survey** and a **commercial vehicle trip diary**. To better understand commercial vehicle travel and traffic patterns, the study collected data on total trips, vehicle types, origins/destinations, and stops made over a 24-hour period (Southeast Michigan Council of Governments, 2017).
- The Puget Sound Regional Council (PSRC) Household Travel Survey, and NYC DOT Citywide Mobility Survey are comprehensive **household surveys** that collect information about household-based travel activities, including deliveries of specific types of goods (PSRC, 2019; NYC DOT, 2022).
- In collaboration with the New York State Trucking Association, the New York State Department of Transportation (NYSDOT) is currently conducting a **Truck Intercept Survey** (New York State Department of Transportation, 2024). The goals of this survey are to: (1) identify the needs of

different segments of the trucking community; (2) assess the adequacy of parking and facilities; and (3) identify locations for and needed services and amenities at truck stops and other rest areas.

3.4 Commodity Flow Data

Commodity flow estimates are used to inform a number of strategic freight planning decisions. There are two primary sources of commodity flow data commonly used by state DOTs and MPOs.

- The ***Freight Analysis Framework (FAF)***, a data product produced by a partnership between BTS and FHWA, is the commodity data source most commonly used by state DOTs and MPOs for strategic freight planning. The FAF integrates data from the Commodity Flow Survey and other national data sources, including "Census Foreign Trade Statistics, Economic Census data, Department of Agriculture's Census of Agriculture, Vehicle Inventory and Use Survey (VIUS), National Highway Planning Network (NHPN), Highway Performance Monitoring System (HPMS), Energy Information Administration (EIA), and other industrial data." (BTS, 2025a). The FAF provides tonnage, value, and ton-mile estimates for imports, exports, and domestic shipments moving to/from origins and destinations (states and FAF regions) in the United States. The current version, FAF5, provides forecasts for future freight demand scenarios under three economic growth scenarios through 2025 (FHWA & BTS, 2024). Data products include tabular Origin-Destination (O-D) estimates, as well as assigned network flows for baseline and forecast years. The Federal Highway Administration also provides visualization tools for FAF data (FHWA & BTS, 2023). While an important national data source, the FAF also has some limitations. As it relies on careful integration of multiple data sources, including the CFS which is conducted only once every five-years, there is a notable time lag in data availability. Due to commercial privacy concerns, FAF estimates are also available only at aggregate geographic scales. The most granular data available is for FAF zones that typically represent an aggregation of multiple counties (that are not always geographically contiguous), necessitating disaggregation using other data sources (see section *4.8)* and limiting the FAF's applicability for local decision-making. BTS has recently produced county-specific FAF estimates as an experimental data product (BTS, 2025b). Also, it is used for commodity tonnage and value projections (LA Metro, 2021; ITD, 2023)

- S&P Global's ***Transearch Database*** is a commercial commodity flow dataset also used by a number of state DOTs and MPOs for strategic freight planning and travel demand forecasting. TRANSEARCH provides annual, nationwide estimates of freight traffic flows in tons, value, and units by origin/destination, mode, and detailed Standard Classification of Transported Goods (SCTG)-level commodity classes (GDOT, 2023; H-GAC, 2023). Specific state applications of Transearch data include analyzing freight flows (MAG, 2017), identifying key freight corridors (SCDOT, 2022; Southeast Michigan Council of Governments, 2012), and developing truck trip tables for statewide and regional models (MAG, 2017; INDOT, 2023).

Other mode-specific sources have also been used to characterize or disaggregate commodity flows. Examples include the ***Surface Transportation Board (STB) Carload Waybill Sample***, a stratified sample of carload waybills for all U.S. rail traffic (NYMTC, 2017; CTDOT, 2022; Vtrans, 2022; VDOT, 2022; IDOT, 2023; MNDOT, 2024), ***U.S. Army Corps of Engineers (USACE) Navigation Data Center (NDC)*** data, which provides waterborne tonnage and commodity movement data used to understand port-level import/export flows (NJTPA, 2020), and ***municipal solid waste flows*** (NJTPA, 2020). Submission of carload waybills to the STB is required from all rail carriers terminating 4,500 or more revenue carloads annually (Surface Transportation Board, 2024). According to a study by the Mid-America Freight Coalition, this data is typically used in state rail plans to determine a state's freight rail demand in terms of carloads, tonnage, and value (Srivastava et al., 2020). ***U.S. Bureau of Economic Analysis (BEA) Make-Use Tables***, which link industries to commodities produced/consumed, have also been utilized for commodity-based economic modeling.

3.5 Employment Data

State and local agencies utilize a number of employment-based data sources to locate and characterize freight activities. Publicly-available employment-related data sources that have also been used in freight-related studies include:

- The Bureau of Labor Statistics (BLS) ***Quarterly Census of Employment and Wages (QCEW)***, which contains employment and wage information used for socioeconomic and demographic forecasting. The dataset provides quarterly and annual estimates of establishments, employment, and wages by industry. Industries are classified according to the North American Industry Classification System (NAICS). The New York Metropolitan Transportation Council (NYMTC) utilized QCEW in the freight component of its 2017 plan (NYMTC, 2017).
- The U.S. Census Bureau's ***County Business Patterns (CBP)*** dataset, which provides annual NAICS-based counts of employment & establishments. CBP data has been used to map freight-related businesses, industry distribution, and job concentrations at county or zip-code levels (Lawson, 2019a; Hancock, 2021; CalTrans, 2023; H-GAC, 2023; NJDOT, 2023).
- ***Longitudinal Employer–Household Dynamics (LEHD)*** data, produced as a partnership between the Census Bureau and U.S. states, includes a number of tables useful for mapping freight-related employment activities. The modeled ***LEHD Origin-Destination Employment Statistics (LODES)*** dataset includes origin-destination estimates, residence areas characteristics, and workplace area characteristics for industry-specific employees at a census block group scale. Residence and work area characteristics classify industries by two-digit NAICS code, while O-D estimates are provided for aggregated sectors. The Alabama DOT used LEHD data to map the density of freight-dependent businesses (ALDOT, 2022), and MNDOT used it as a data input to a comprehensive freight mapping tool (Hancock, 2021).

A number of agency freight-related studies have also relied on commercially available real estate, business establishment, and transaction datasets. Examples include:

- ***CoStar Commercial Real Estate Data,*** which is a source of commercial real estate information. Specifically, it provides estimates of Gross Floor Area (GFA), which is the independent variable used by Atlanta Regional Commission (ARC) to apply ITE trip generation rates for comparative analysis (ARC, 2024).
- ***Dun & Bradstreet Employment Data***, which includes information like estimated employee counts predicted for businesses lacking official figures. This dataset has been used to estimate which industry sectors account for freight trips in New York City and to identify high-activity ZIP codes (NYC DOT, 2021).
- ***Data Axle (formerly InfoUSA) Business Establishment Data***, which offers metrics such as firms, employment, and revenue. This dataset has been used by a number of agencies to identify the locations of freight-related industries (NJTPA, 2020; SCAG, 2022; H-GAC, 2023; NDDOT, 2023; Ohio DOT, 2023; and MNDOT, 2024).
- ***Nielsen IQ, formerly Rakuten Intelligence*****,** which provides e-commerce shipment volumes and carrier shares for modeling parcel demand and delivery patterns (Nielsen IQ, n.d.). It was used by NJTPA for estimation of granular ecommerce demand (NJTPA, 2020).

3.6 On-board Sensor Data

On-board sensor data is data collected from technologies integrated to or carried on-board freight vehicles. Two general types of sensor data have been used in freight planning - probe data and telematics data – with the former having been rapidly integrated into agency applications over the last decade.

3.6.1 Probe Data

Probe data are data that monitor the movements of individual vehicles over time. Probe data typically include location, time, speed, heading, and may include additional data about a vehicle's current status (e.g. engine status) (Inrix, 2026a). In freight applications, probe data are typically collected from Global Positioning System (GPS) units on-board commercial vehicles. While many of the research studies discussed in section 5.5.1 below utilize raw GPS datasets obtained from carriers, in practice, public agencies typically rely on commercial datasets that aggregate probe data from operator fleets, removing operator-specific information. Commonly used data sources include:

- The ***National Performance Management Research Dataset (NPMRDS)*** is a probe-based dataset made available by FHWA to state DOTs and MPOs to estimate required traffic and truck performance metrics, such as truck travel time reliability (TTTR). NPMRDS data is limited to the National Network, and includes speed and travel time data aggregated by road segment in 5-minute, 15-minute, and 60-minute bins.
- Several agencies alternatively use data from ***Inrix****,* a commercial provider, to estimate traffic performance metrics.
- Data from other commercial probe-based data providers – particularly the ***American Transportation Research Institute (ATRI)*** and ***Streetlight*** - have been used in a variety of freight planning applications, including identification of bottleneck locations, estimation and validation of trip origins and destinations, estimation of segment and route utilization, and analysis of truck parking demand and utilization (Hancock, 2017; Hancock, 2021; CalTrans, 2023; Gick, 2023).

3.6.2 Telematics Data

Telematics are an emerging source of freight data that provide granular details about a vehicle's operations. Telematics companies collect data from a variety of on-board sensors; in addition to the same types of location information typically collected from probes, telematics data can also include information about engine status and performance and vehicle acceleration and deceleration, among other metrics, enabling micro-scale analysis of variables such as fuel consumption and hard braking events. Telematics data has been used for environmental impact analysis (Boriboonsomsin, Sheckler, and Barth, 2012; Bousonville, Dirichs, and Kruger, 2019; Hu et al., 2022; Farzaneh et al., 2020; Xiao and Jaller, 2025), safety analysis and hard-braking events (Kamla, 2016; Zhang et al., 2022; Gick, 2023), supply chain mapping (Hernandez, 2019), electric truck infrastructure planning (Gick, 2023); and estimation of resilience metrics (Hernandez, Li, and Jiang, 2023). Most U.S. freight planning research (see section 4.2.6) and practice has relied on two providers of telematics data:

- ***Geotab*** aggregates data from more than 4 million commercial vehicles equipped with its vehicle tracking technologies. The company provides access to its processed data for agencies and researchers through its Altitude platform (Geotab, 2026).
- ***EROAD*** is a regulatory telematics company that specializes in fleet solutions and has 226,000 vehicles worldwide, with approximately 90,000 in the U.S. EROAD collects granular information (every 250 meters) from electronic logging devices (Gick, 2023). EROAD does not currently offer a commercial platform, but data has been shared directly with researchers for a number of studies (Hernandez, 2019; Gick, 2023; Hernandez, Li, and Jiang, 2023).

3.7 Infrastructure-Based Sensors

Infrastructure-based sensors have historically been used by state DOT's and local agencies to collect periodic or continuous data for estimating traffic performance metrics such vehicle classification counts or average annual daily truck traffic (AADTT). Previously, traffic counts have relied on manual observation or relatively simple technologies such as pneumatic tubes, inductive loops, and magnetometers (FHWA, 2014). Agencies frequently access these types of information through the ***Highway Performance Monitoring System (HPMS)***, which is a national-level highway information system that includes data on the extent, condition, performance, use, and operating characteristics of the nation's highways. The HPMS includes road segment data for interstates and arterials, sample attributes for collector systems, and summary data for the local roads. In more recent years, a number of more advanced sensing technologies have been developed and implemented or piloted for freight planning applications.

- **Weigh-in-Motion (WIM) systems**: WIM systems rely on a number of technologies, including piezoelectric sensors, load cells, and bending plates (NASEM, 2020) to measure vehicle and load characteristics - such as axle weights, gross vehicle weight, speed, and vehicle classification - as vehicles move at normal traffic speeds. They are used widely in practice for vehicle size and weight enforcement and to collect data useful for freight and infrastructure planning applications (NASEM, 2020).
- **Inductive loop sensors:** Inductive loop sensors are intrusive detection technologies installed directly beneath the surface of roadways that detect vehicles based on changes in magnetic fields or electrical inductance (National Academy of Sciences, 2019). These unique magnetic signatures provide detailed data that can be used to count axles, determine vehicle lengths, classify specific commercial truck body types, and track or re-identify individual vehicles as they move across a network of detectors (Hernandez, Tok, and Ritchie, 2016; National Academy of Sciences, 2019).
- **LIDAR:** Light Detection and Ranging (LIDAR) systems are non-intrusive sensors that operate on similar principles to radar but use light waves, typically emitted from lasers, to measure the distance, speed, and direction of objects (National Academy of Sciences, 2019). these systems capture detailed physical characteristics (such as vehicle height and trailer configuration), making them highly effective for advanced speed estimation and detailed truck classification without requiring in-pavement installation (Li et al., 2021), National Academy of Sciences, 2019).
- **Camera based systems (e.g. photo and video for vehicle identification and classification):** Camera-based systems utilize still photography or continuous video feeds combined with advanced computer vision algorithms to automatically monitor and analyze traffic. In practice, they are used to classify a wide range of road users (from specific truck types to bicyclists), track turning movements, and identify safety behaviors such as "near misses" (National Academy of Sciences, 2019)).

3.8 Infrastructure Inventory Data

Infrastructure inventories are an important data source in freight planning for a number of purposes, including project prioritization, route identification and classification, and resiliency planning. Types of infrastructure data useful for freight related decisions include:

- **Roadway functional classifications,** which are useful for identifying expected freight types and volumes using a roadway segment (ARDOT, 2022; Maryland DOT, 2022; SC DOT, 2022; ALDOT, 2023, MWCOG, 2023; FDOT, 2024; NYSDOT, 2024);
- **Truck route designations,** which are also useful for identifying expected freight vehicle types using a facility and may also identify key freight routes (City of Seattle, 2016; City of Minneapolis, 2020; City of Dallas, 2021; NYC DOT, 2021);
- **State and national bridge inventories,** which can be used to identify current bridge conditions and vehicle load capacities and restrictions (IDOT, 2023; H-GAC, 2023; HIDOT, 2023);
- **Bridge regulatory restrictions** are also useful to identify weight and height constraints (DelDOT, 2022)**;** identification of these constraints informs freight route designations (NCTCOG, 2022; WisDOT, 2023)**,** enables prioritization of freight-critical infrastructure projects **(**CODOT, 2024; H-GAC, 2023; NCDOT, 2023**;** Oregon DOT, 2023; LaDOTD, 2024), informs truck permitting (DelDOT, 2022; Maryland DOT, 2022), and enables resiliency planning (AZDOT, 2022; NDDOT, 2023) and design and control updates for route alternatives (WYDOT, 2022).
- **Pavement condition and management system data** are useful to identify freight-critical locations in need of repair (ARDOT, 2022; CTDOT, 2022; RIDOT, 2022; NCDOT, 2023; TXDOT, 2023; MNDOT, 2024), and can inform life-cycle analyses of proposed treatments (WYDOT, 2022; VDOT, 2022; SDDOT, 2022).

- **Hazmat routing data**, such that accessible from FMCSA, the ***National Hazardous Materials Route Registry by State*** (IDOT, 2023), can also be used to identify critical freight routes for safety analysis and resiliency planning.
- **Parking supply inventories** are used in assessment of long-haul truck availability and can inform prioritization of truck parking infrastructure projects. States are required to under *Jason's Law* to develop truck parking inventories (FHWA, 2015).

3.9 Safety Incident Data

Most freight-related safety analyses have historically relied on retrospective **collision or incident records,** such as those obtained from Federal Motor Carrier Safety Administration (FMCSA), Federal Railroad Administration (FRA), or from state or local police or transportation agency databases. In recent years, telematics data has emerged as a potential new data source for proactive safety management, as it enables identification of hard braking events (Kamla, 2016; Zhang et al., 2022; Gick, 2023). A key challenge of safety incident data for commercial vehicles is inconsistency in field vehicle classification that may lead to undercounting of incidents (Cheung and Braver, 2015).

3.10 Other Administrative Records

A wide variety of regulatory/administrative datasets, when accessible, can also provide data useful for freight-related decision-making. For example:

- **Spatial land use data** is useful to identify the existing and expected locations of specific types of freight activity. For example, NJDOT (2023) identifies three types of freight-related facilities: freight generating, freight handling, and freight receiving. Land use data is also useful to identify freight clusters to guide future development; examples include ARC's (2024) identification and tracking of freight clusters to promote context-sensitive uses and H-GAC's (2023) use of its Regional Land Use Information System to identify areas for future industrial development. Land use data also informs analysis and management of potential conflicts between freight and other uses; examples include CalTrans' (2023) development of environmentally conscious land use policies, DelDOT's (2022) Protect-Manage-Accommodate framework to ensure adequate access for freight with appropriate levels of prioritization based on land use context, and NCTCOG's (2022) "Freight Land Use Policy Toolkit" which aims to help cities manage externalities from planned industrial districts.
- **Vehicle registration data** can be used to analyze the age, vehicle class, and engine/fuel type of registered trucks (MNDOT, 2024), although statewide fleets may not necessarily be representative of local or interstate operations.
- **Oversize and overweight permit data** can be used to identify key freight routes for typical operations and resiliency planning and to identify potential locations for infrastructure maintenance and retrofit (Conway, 2021; Hancock, 2021; ARDOT, 2022; RIDOT, 2022; GDOT, 2023, KDOT, 2023; NJDOT, 2023; WisDOT, 2023).
- **Curb management data** – including space inventories and sensor-based (e.g. camera) demand estimates - can enable evaluation of available loading space (SCAG, 2022).

4. FREIGHT DATA RESEARCH

This section summarizes prior research that has been conducted on freight data uses and specific freight data applications.

4.1 Data for Statewide and Regional Freight Planning

A number of prior researchers have conducted comprehensive reviews of available freight data sources. Mani and Prozzi (2004) conducted a state-of-the practice review of available freight datasets, identifying 31 public and private sector sources, including trade statistics, commodity flows, transaction/shipment records, and mode-specific sources. These datasets primarily inform national and regional movements, with limited applicability in the last-mile context. Victoria and Walton (2004) evaluated freight data needs for Metropolitan Planning Organizations (MPOs) and assessed the potential for archived intelligent transportation system (ITS) data to address agency needs. Their study identified five categories of data needed for metropolitan planning: cargo, road transportation, major freight generators and corridors, non-road transportation modes, and economic, land-use, and socio-economic data. NCHRP Synthesis 410 (NASEM, 2011c) provided a state of the practice review on how agencies (46 state DOTs, 8 MPOs, and 2 Port Authorities) were collecting data for freight planning – including specific survey collection methods, and what specific data sources they were reliant on. Their study identified a lack of vehicle-trip specific information as the most critical data gap for practitioners. Other issues identified included a need for "regular" data collection, and needs for training in survey methods and ITS-based data sources. NCHRP Report 29 (NASEM, 2014b) evaluated innovative strategies for obtaining truck activity data: the study recommended implementation of a new Vehicle Inventory and Use Survey (VIUS) and development of a national freight GPS framework that would use app-based data collection to overcome privacy barriers. The study also identified agent-based modeling as a promising strategy, but one likely requiring long-term development for implementation outside of academic settings.

4.2 Data for Urban Freight Planning

Allen, Browne, and Cherrett (2012) reviewed 162 urban freight studies from 18 countries to identify their data collection mechanisms. Their study identified six common survey types (establishment surveys, freight operator surveys, vehicle observation surveys, driver surveys, roadside interview surveys, and vehicle trip diaries) as well as other less frequently used mechanisms, including commodity flow surveys, parking surveys, GPS tracking, and supplier and service provider surveys. As part of the European BEST Urban Freight Solutions (BESTUFS) project, Allen et al. (2014) reviewed the data collected for understanding urban goods movements across 11 European countries. Their review identified twenty types of relevant data: commodity flow, site/land use/establishment, shipper, receiver, goods vehicle activity, vehicle operating, and distribution industry surveys; vehicle licensing data; loading/unloading/parking infrastructure data; collision records; and theft records. They found that although data was collected by a wide variety of government and private sector stakeholders, these efforts are not well-coordinated, resulting in a "patchy and unreliable" picture of urban freight. They also found that even in countries with the best available data sources, more aggregate data typically had to be disaggregated for application at an urban scale. Their study concluded that the quality and quantity of available urban freight data was far less than both national freight data and urban passenger data. NCHRP Project 49 reviewed urban and metropolitan applications of emerging freight data sources including GPS, cellular, inductive loops, radar, lidar, wireless address matching, and computer vision (National Academy of Sciences, 2019).

4.3 Freight Surveys

Traditionally, infrastructure operators have relied on surveys to collect information about freight supply chains and related goods flow. In 2003, the Transportation Research Board published ***A Concept for a National Freight Data Program***, a proposed framework for improving U.S. national freight data for decision-making (TRB, 2003). The report proposed a development of an integrated national data collection that incorporated inputs from carrier surveys, distributor surveys, shipper surveys, receiver surveys, and freight informatics, including intelligent transportation systems and traffic monitoring data. Notably, this report predated the widespread availability of location-based probe data sources. Freight supply chains involve a number of private sector stakeholders, including shippers, carriers, receivers, and freight forwarders. As noted above, Allen, Browne, and Cherrett (2012) identified six common survey types: establishment surveys, freight operator surveys, vehicle observation surveys, driver surveys, roadside interview surveys, and vehicle trip diaries. Although less commonly used in urban applications, additional survey types they identified included including commodity flow surveys, parking surveys, GPS tracking, and supplier and service provider surveys. Their study determined that establishment and vehicle observation surveys were most useful to provide insights on a variety of urban freight issues. Depending on the relationship between them, freight stakeholders may have visibility of only a limited portion of a supply chain, or even an individual goods movement. NCHRP Synthesis 410 (NASEM, 2011c) provided a state of the practice review on how agencies (46 state DOTs, 8 MPOs, and 2 Port Authorities) were collecting data for freight planning – including specific survey collection methods, and what specific data sources they were reliant on. Holguin-Veras and Jaller (2014) provide a comprehensive review of five stakeholders - shippers/producers, carriers, distribution centers/warehouses, receivers, and transportation agencies – and their expected knowledge of specific data elements, including: amount of cargo, number of loaded vehicle-trips, number of empty vehicle-trips, number or frequency of deliveries, commodity type, shipment size, cargo value, and land use patterns. Their study notes some specific visibility gaps among these stakeholders, including shippers having a limited view of empty vehicle trips, carriers potentially lacking knowledge of commodities and shipment values, and receivers having limited awareness of vehicle activities. Toilier et al. (2016) describe the process for designing and implementing the Paris Urban Goods Movement survey, one of the most comprehensive urban freight surveys conducted globally.

4.4 Data for Freight Modeling

A few researchers have comprehensively reviewed freight data needs for freight modeling. Tavasszy and de Jong (2014) reviewed data sources for modeling freight transportation, primarily in the European context. Their study identified 11 primary categories of data used in freight modeling applications: international trade statistics, national accounts (e.g. input-output tables, make-use tables), mode-specific transportation statistics, shipper surveys, specific project-based interview data, consignment bills and radio frequency identification (RFID) tags, traffic count data, safety inspection data, network data, cost functions, and terminal data. Holguin-Veras and Jaller (2014) comprehensively summarized the data needs for specific freight modeling approaches – examples include commodity and trip generation models, distribution models, freight mode choice models, and microsimulations models among others. They developed a recommended framework for comprehensive data collection in mid- and large-sized cities. Their review identified the following categories of data that are needed for specific applications: information/insight into logistical patterns of flows; freight generation data; freight trip generation data; delivery tours; economic characteristics and spatial distribution/location of agents; network characteristics; special choice processes (e.g. mode, delivery time); and other economic data (e.g. production functions, input-output models).

Researchers have also discussed data needs for specific freight modeling applications. Tavasszy (2008) detailed recent advances and international experience in freight modeling, focusing on three primary areas: logistics modeling, behavioral modeling, and freight network modeling (particularly mode and route choice). His work detailed data needs to inform model improvements, specifically the need for technologies that would provide continuous monitoring of freight flows. Samimi et al (2014) developed a nationwide agent-based freight mode choice micro-simulation model that relies on publicly available data sources including U.S. Census Bureau County Business Patterns, the FAF, U.S. Bureau of Economic Analysis Input-Output tables. Their study synthesized firm-to-firm mode choices. Relying on a local establishment survey, Sanchez-Diaz (2017) employed regression analysis and discrete choice modeling to develop estimates of freight trips and freight volumes generated by common urban business types in Gothenburg, Sweden. Davis et al. (2024) developed a method for synthesizing urban truck tours using publicly available data sources.

Shoman et al. (2023) comprehensively investigated the potential for and existing challenges to the use of "big data" for road freight transportation modeling. They found that while "big data" has the potential to improve freight traffic, demand, and energy modeling, there are also major barriers to implementation including organization, technical, legal, and political challenges. Examples include data availability, ownership, quality control, and storage challenges; high data dimensionality; data heterogeneity; representativeness concerns; lack of standardization; and data privacy concerns.

Transportation Research Board (TRB) has published syntheses on metropolitan (NASEM, 2008a) and statewide and megaregional (NASEM, 2017c) freight forecasting, as well as a number of comprehensive guides for specific freight modeling applications including statewide freight forecasting (NASEM, 2008b); freight trip generation (NASEM, 2012a); freight, freight trip, and service trip generation (NASEM, 2016b); and identification and evaluation of freight demand factors (NASEM, 2012d). TRB also published two reports focused on improving freight demand modeling developed under the second Strategic Highway Research Program (SHRP 2) (NASEM 2013c; NASEM, 2014a) as well as proceedings from a conference focused on the use of freight demand modeling tools for public sector decision-making (NASEM, 2008c).

4.5 Applications of On-Board Sensor Data

4.5.1 Probe Data

Over the last decade, with the rapid implementation of cellular devices and GPS-based navigation systems, probe data have quickly become widely utilized for freight planning and operations management applications. A number of research studies have investigated methodologies for use of probe data for specific planning, performance measurement, and urban logistics applications. NCHRP Synthesis 611 (NASEM, 2023c) details the current practices of state DOTs for these uses.

4.5.1.1 Truck Flows

A number of studies have investigated broad applications of GPS data for freight planning, particularly in statewide applications. Flaskou et al. (2015) developed methods to process raw GPS data to estimate a number of factors - including truck movement direction, stops, trip ends, and travel speeds and reliability – while addressing outlier data. Thakur et al. (2015) also developed methods for converting a large volume of truck GPS data from ATRI into a truck trip database for the state of Florida. Zanjani et al. (2015) describes the process of estimating an O-D matrix for trips within, into, and out of Florida by combining GPS-derived truck activity with observed truck traffic volumes. Kamali et al. (2016) developed a map-matching algorithm to derive truck routes from GPS data. Their study additionally developed a "shared link length ratio" metric for quantifying the extent of overlap of specific routes between O-D pairs. Camargo, Hong, and Livshits (2017) developed an open-source methodology to convert GPS traces into truck trajectories for select link and select O-D analysis, time of day analysis, and advanced visualization such as heat-maps and trajectory playback. Hernandez et al. (2019) developed a comprehensive framework for processing truck GPS data for statewide freight planning, performance measurement, and flow analysis applications. Their report details methods for stop identification, map matching, and quantifying trip characteristics, as well as assesses the representativeness and coverage of the dataset employed in the study. Karam et al. (2020) sought to identify the specific metrics that could be derived from truck GPS data to inform public-sector decision-making in Denmark. Their study found that three metrics of particular importance to public authorities included O-D matrices, driving patterns, and parking patterns. Their study also found that GPS and shipment data are useful for deriving these metrics, while loop detector data and rest area observations are useful for validation. Demissie and Kattan (2022) developed heuristic-based methods to estimate truck origin-destination flows and destination choice models from truck GPS data in Alberta, Canada.

4.5.1.2 Truck Travel Behavior

Other studies have focused on using GPS data to understand truck travel behaviors. Pluvinet et al. (2012)

investigated the use of GPS data to characterize urban logistics activity. Their study demonstrated the value of using GPS to identify route characteristics for individual vehicles, such as route length, number of stops, fuel consumption, and CO_2 emissions, but also recognized an ongoing need for survey-based data for a detailed understanding of urban logistics behavior and its relationship to specific land uses. You and Ritchie (2018) developed an eight-step methodology to characterize the daily operations of clean drayage trucks at California's San Pedro Bay Port, including characterizing daily activity cycles and trip chaining behavior. Laranjeiro et al. (2019) employed GPS data to examine urban logistics activity in Sao Paolo, Brazil, estimating vehicle speed profiles and characterizing stopping behaviors within specific neighborhoods. Asborno, Hernandez, and Yves (2021) developed a method for identify the catchment area of multi-modal freight facilities using truck GPS and maritime AIS (Automatic Identification System) data. He et al. (2024) also utilized heavy truck GPS data to develop a model to describe the flow of goods from port facilities in the Guangdong-Hong Kong-Macau Greater Bay Area to inland facilities as a function of trip distance. Choudhry and Qian (2023) developed a comprehensive framework for inferring truck activities from GPS data, including development of a device-matching algorithm to link fragmented data. Collins et al. (2025) proposed a methodology for analyzing the travel patterns of medium- and heavy-duty trucks in California's Inland Empire using the Streetlight data platform.

4.5.1.3 Traffic Performance Measurement

Significant research attention has also focused on the development of freight traffic performance measures from GPS data. Ma, McCormack, and Wang (2011) conducted one of the first studies examining the use of truck GPS data for traffic statewide performance measurement. Their study for the Washington Department of Transportation developed methods for cleaning and processing a large volume of GPS data to estimate truck travel times between traffic analysis zones (TAZs) and evaluate system reliability. Sun and Ban (2013) developed a method for classifying vehicles as passenger cars or trucks based on vehicle accelerations or decelerations derived from truck GPS data. In a study conducted for the Minnesota Department of Transportation, Liao (2014) demonstrated the utility of using GPS data to estimate truck traffic performance measures (e.g. speed, travel time reliability), using WIM, loop detectors, and automated traffic recorder data for validation. Wang, Goodchild, and McCormack (2015) developed a method for quantifying truck travel time reliability using the coefficient of variation of speed distributions, overcoming the sample size and data accuracy challenges from solely spot-speed based approaches. Habtemichael, Paleti, and Cetin (2015) compared traffic performance metrics for passenger and freight vehicles from several prob data providers (INRIX, HERE, and ATRI), noting that in some conditions, passenger metrics such as speed, travel time, and travel time reliability can be significantly different from those of freight vehicles. Pérez-González et al. (2023) developed a neural networks-based approach for predicting truck travel times and estimating truck travel time reliability and fluidity metrics from GPS data. TRB has published three relevant comprehensive guides on freight performance measures (NASEM, 2011d), estimating truck travel time reliability (NASEM, 2016a), and identifying, classifying, evaluating, and mitigating freight bottlenecks (NASEM, 2017b).

4.5.1.4 Truck Stopping and Parking

Another focus area of research has been on the estimation of truck trip ends and characterization of truck parking activity. Aziz et al. (2016) developed a method to identify highway truck stops from GPS data. Gingerich, Maoh, and Anderson (2016) proposed an entropy-based method for classifying "primary" stops for good transfer and "secondary" stops for other driver or vehicle needs from truck GPS data. Their study found that higher entropy values are an indicator of secondary stops. Hughes et al. (2019) tested a variety of machine learning techniques and ensemble models to predict stop delivery times and to determine is a stop duration is expected to exceed a defined threshold. Kinjarapu et al. (2022) also developed a method to classify truck stops as primary or secondary based on dwell times and entropy. Patel et al. (2022) developed a two-step machine learning approach for identifying and classifying truck steps. Their approach employed a Density-Based Spatial Clustering of Applications with Noise (DBSCAN) clustering technique for identifying stops and a random forest classifier for determining stop types. Yang et al. (2022) developed a two-step method for identifying heavy truck trips ends from GPS data. They identify truck stops by evaluating trajectory characteristics and then classify stops based on statistically-determined time thresholds combined with network and point-of-interest data. Haque et al. (2017) evaluated specific forms of econometric models to predict truck parking utilization from GPS data. Their study found that a generalized ordered-response probit model was the best performing structure for this task. In a study completed for the Arkansas Department of Transportation Diaz-Corro, Akter, and Hernandez (2019) evaluated two methods for development of expansion factors to leverage commercial GPS data to estimate population-level truck parking activity.

4.5.2 Telematics Data

More recently emergent as a freight data source, telematics data has been recently investigated for implementation in a number of freight-related applications. Boriboonsomsin, Sheckler, and Barth (2012) used telematics data to derive improved heavy vehicle inputs, including VMT estimates, time-of-day and day of week distributions, speed distributions, and trip start patterns, for emissions modeling. Bousonville, Dirichs, and Kruger (2019) used telematics data to estimate machine learning models to predict truck fuel consumption under varying weather conditions. Hu et al. (2022) used telematics data to evaluate the environmental impacts, including fuel efficiency and NOx emissions impacts, of the London Lorry Control Scheme. Farzaneh et al. (2020) compared the use of GPS and portable activity monitors (which collect data such as engine status, engine and vehicle temperatures, and vehicle speed and distance information) to measure idling activity for drayage trucks operating in the Port of Houston. Xiao and Jaller (2025) utilized Geotab data to estimate the impacts of truck idling and parking search activity on vulnerable communities. Kamla (2016) evaluated the use of hard-breaking events identified from telematics data as a predictor of accident risk, controlling for traffic and geometric factors. Zhang et al. (2022) investigated whether data from onboard driver safety warning systems could improve the performance of risk assessment models for implementation in the insurance industry. Hernandez (2019) combined telematics data with other spatial data sources to characterize trip activities within specific commodity supply chains. Hernandez, Li, and Jiang (2023) explored the use of telematics data to measure freight system resilience following major disruptive events, demonstrating its utility in bottleneck identification and in detecting changing traffic patterns and route adaptations.

4.6 Infrastructure-Based Sensor Data Applications

There are a variety of infrastructure-based sensors used in freight applications, particularly for vehicle classification, traffic monitoring, and estimation of load distributions. Victoria and Walton (2004) identified automated vehicle classification (AVC), automated vehicle identification (AVI), and license plate matching (LPM) as infrastructure-based technologies useful for collection urban freight data. Other key technologies with recent advances include weigh-in-motion systems, inductive loop sensors, and LIDAR. TRB published a comprehensive report detailing the use of WIM data for various applications, including freight logistics planning (NASEM, 2020). This study found that many states do not use WIM data in freight planning or logistics; those that do use it for evaluating freight movements (mostly of heavy or overweight vehicles). A few used WIM data for corridor planning or facility design, and one to inform truck seize and weight policy development. A number of recent studies have explored WIM and sensor use for fine-grained vehicle classification. Hyun et al. (2015) developed a modified decision tree model for detailed truck body configuration using WIM data. Anderson et al. (2020) examined the potential use of Oregon Department of Transportation WIM data for estimating freight and commodity flows. Studies by Gajda and Stencel (2014) and Tok et al. (2017) detail the use of inductive loop sensors for vehicle classification, and Li, Tok, and Ritchie (2019) examine the use of single inductive loops for truck speed estimation. Studies by Asborno et al. (2019), Li et al. (2021), and Li et al. (2021) detail innovative methods for classifying vehicles using LIDAR data. Hernandez, Tok, and Ritchie (2016) tested an integrated system for detailed vehicle classification using inductive loop sensors and WIM. Dablanc and Adoue (2025) discuss the potential to use automated number plate recognition (ANPR) data collected through low-emission zone enforcement systems for freight planning applications.

4.7 Freight Data Fusion

A number of studies have demonstrated that the value of individual data sources can be enhanced with data fusion or integration. TRB has published several comprehensive guides aimed at improving integration across data sources, including reports focused on developing (NASEM, 2010a) and implementing (NASEM, 2015a) a freight data architecture. A number of researchers have successfully integrated data from multiple sources for freight planning applications. Pinjari et al. (2014) conducted one of the first studies investigating use of truck GPS data for freight planning applications. Their study had multiple objectives to evaluate use of ATRI data for various state freight planning applications. Their study demonstrated the utility of the data for a number of applications, including speed estimation and bottleneck identification, deriving and characterizing truck trips, and evaluating trip characteristics such as duration, length, and time-of-day profiles. They also determined that due to the non-randomness of the sample that the GPS data needed to be supplemented with local truck count data for deriving robust O-D tables. Roider et al. (2015) proposed a method to improve the quality of freight vehicle estimates – particularly to address undercounting of freight vehicles - in Austria through integration of four data sources: national statistics, roadside interviews, and toll gantry and counting station counts. Ben-Akiva et al. (2016) integrated GPS data and information collected from web-based surveys to produce a comprehensive dataset for understanding truck routing behavior. Eluru at al. (2018), also conducting a project for the Florida Department of Transportation, evaluated a number of freight data sources for potential fusion applications, including the FAF, TRANSEARCH, ATRI, WIM, vehicle classification data, and parcel level land use data. As additionally detailed in Momtaz et al. (2020), they developed econometric methods for fusing FAF network flow estimates and TRANSEARCH production-consumption commodity flows to obtain county-level commodity flows. They also fused truck O-D flows derived from ATRI data with TRANSEARCH commodity flows to estimate commodity specific O-D flows (Eluru et al., 2018).

4.8 Freight Data Disaggregation

Due to the lack of granularity of commonly used freight data sources, considerable research attention has been given to the development of freight data disaggregation methods. A number of researchers have developed methods for disaggregating U.S. national level commodity flow datasets to more disaggregate scales. Vishwanathan et al. (2008); Opie, Rowinski, and Spasovic (2009); Dixit, Venigalla, and Bronzini (2011); Bujanda, Villa, and Williams (2012); and Chin, Hwang, and Oliveira (2013) have all developed methods for disaggregating FAF data to more locae scales using economic or employment data. Horowitz (2010) developed a method for disaggregating the FAF using observed traffic data. Smith and Wall (2023) disaggregated FAF commodity flows to counties in New York State and to specific US-Canadian border crossings in New York and Vermont using county-level employment shares and BTS Transborder Freight Data. National Cooperative Freight Research Program (NCFRP) Report 26 (NASEM, 2013e) summarized methods for obtaining sub-national commodity flows using disaggregation methods, demand estimation based on local economic activity, and through implementation of establishment or roadside truck intercept surveys.

A number of researchers have also developed disaggregation methods for state applications. Sorratini and Smith (2000) developed a four-step model approach for freight demand forecasting in Wisconsin using trip rates from the Commodity Flow Survey, supplemented by TRANSEARCH data, and an economic input-output model, IMPLAN. Ambite et al. (2002) proposed an automated method for disaggregating commodity flows to a metropolitan scale using relevant publicly available data sources, including employment estimates. In a project completed for the Southern California Association of Governments (SCAG), Fischer, Ang-Olson, and La (2000) developed a method to estimate external urban truck trips by disaggregating TRANSEARCH commodity flows to commodity-specific truck trips that could be assigned to the roadway network. Their method used employment, land-use, and commercial facility data to disaggregate commodities to a TAZ scale, input-output models to determine the share of good destined for consumers and industries, and the Truck Inventory and Use Survey (a precursor to the Vehicle Inventory and Use Survey) to allocate commodities to truck trips. Giuliano et al. (2007) developed a method for estimating intra-metropolitan freight flows in the Los Angeles region using secondary data sources such as local employment and import/export data. Ranaiefar et al. (2013) developed a structural commodity generation model to estimate commodity flows to freight analysis zones in California using FAF and county business pattern data. Camargo, Tok, and Ritchie (2016) tested a "pseudo-stepwise" method to disaggregate the California State Freight Forecasting Model to the more granular scale of the California Statewide Travel Demand Model (which models passenger vehicle demand). Their model relied on employment data for several economic sectors.

4.9 Freight Data Sharing

Several studies have addressed the issue of freight data sharing, particularly between the private and public sectors. NCFRP Report 25 (NASEM 2013d) provides guidance for freight data sharing between the public and private sectors, and identifies both common barriers and potential "motivators" for data sharing. Barriers identified include legal, resource, competition, institutional, and coordination factors. Motivators include stakeholder engagement, articulating the benefits of sharing, funding and cost-sharing, technology innovation, non-disclosure agreements, scrubbing data, and legislative changes. Seedah et al. (2013) conducted a study for the Texas Department of Transportation (TXDOT) to explore the feasibility of private sector data-sharing and integration of public and private sector data sources to meet data needs for freight planning. Their study included workshops with potential freight data users from the state DOT, MPOs, and local governments in five Texas cities. Their findings emphasize that emerging technologies such as GPS present a new opportunity for cooperation between the public and private sectors on a statewide scale, and recommend engagement of a trusted third part such as a research institution or consultant to facilitate an integrated freight data system. Illemann, Karam, and Reinau (2021) developed a framework for identifying how shared private sector freight data can be used for public sector planning. Their study identified six primary uses: identifying freight movement patterns, identifying freight parking patterns, estimating greenhouse gas emissions, traffic planning, traffic safety analysis, and informing research efforts.

4.10 General Freight Applications

Although not specifically focused on data, TRB has published a number of guides relevant to specific local, urban, and metropolitan freight decisions. Several studies have developed guidance on freight planning practice, including: policy, planning, and programming in small- and medium-sized communities (NASEM, 2007); freight facility location selection (NASEM 2011b); implementing effective metropolitan freight strategies (NASEM, 2018), planning freight-efficient land uses (NASEM, 2022), and integrating freight into community planning and design (NASEM, 2023b). Others have focused specifically on urban freight, producing guidance on understanding urban goods movement (NASEM, 2012b) and urban freight and city logistics research (NASEM 2013b; NASEM 2013g). A number of guides have been developed to inform project decisions, including: funding and project selection (NASEM, 2009; NASEM, 2013f); protecting freight infrastructure and routes (NASEM, 2012E); and integrating freight and active transportation into project development (NASEM, 2023a). Finally, several studies have produced guidance relevant to freight performance and impacts, including: understanding the impacts of public policies on freight transportation (NASEM, 2011a); improving metropolitan freight system performance (NASEM, 2015b); estimating the environmental impacts of freight (NASEM, 2010b; NASEM, 2012c; and NASEM, 2013a); and deploying clean trucks (NASEM, 2017a).

4.11 Key Findings from the Review of Academic Literature

Freight planning, modeling, and operational decision-making rely on a wide variety of data sources which contribute different value.

- Freight surveys remain important for understanding logistics stakeholder behaviors, and for informing behavior-based modeling approaches. However, they also suffer from a number of critical limitations including limited coverage, time lags, knowledge gaps of individual stakeholders, and – in the case of local surveys - lack of standardization across jurisdictions.
- "Big data" – particularly probe and telematics-based datasets - offer promising potential solutions to address historic freight data granularity gaps. Probe data have already been widely applied for a number of applications, including traffic performance measurement, travel demand estimation, and characterizing trip and parking behaviors. Telematics additionally add new opportunities for capturing granular vehicle performance information, such a fuel consumption, speed profiles, and hard braking events.
- Vehicle-based data sources can also present unique challenges; they are heterogeneous and sometimes highly dimensional, may represent only a very small and non-representative sample of vehicles, may be fragmented due to technology performance, and are typically produced by the private sector, resulting in both technical (e.g. storage, standardization) and administrative (e.g. privacy laws and concerns) barriers to use.
- Commercial data providers who aggregate and anonymize data from these sources have helped to overcome privacy barriers and move these data sources into practical application, but it is difficult to assess the representativeness of these products for some applications. Researchers have fused these datasets with more traditional freight data sources or with infrastructure-based sensors for validation and enhancement. Researchers have also demonstrated the potential to spatially overlay probe data with other sources, such as land-use or economic/employment data, to link vehicle activities to specific industries.
- Infrastructure-based sensors (e.g. WIM, LIDAR, video) are useful for continuous monitoring, and as a source of validation data for both traditional models and for probe- and telematics-based datasets enhanced with weighting or expansion factors. A number of recent studies have demonstrated the value of infrastructure sensors for fine-grained vehicle classification. However, these have typically been employed in highway settings, so there is limited information about performance on local roads.

5. AGENCY APPLICATIONS OF FREIGHT DATA

Recognizing that not all freight data applications appear in published research studies, the following section summarizes findings from a comprehensive review of published freight plans and recent freight-specific national workshops to identify practical freight data needs and recent agency data applications.

5.1 Commodity Flow Forecasting

Freight forecasting models are used in most states to inform policy decisions, to inform project prioritization and investment, and to predict project social and economic impacts (NASEM, 2017c). Both states and MPOs rely on either the ***FAF*** or ***S&P Global Transearch data***, or both, for estimating future commodity flows (**FAF:** CRTPO, 2014; PSRC, 2018; NJTPA, 2020; Alaska DOT&PF, 2022; CTDOT, 2022; NVDOT, 2022; SCDOT, 2022; Vtrans, 2022; WYDOT, 2022; ALDOT, 2023; CalTrans, 2023; H-GAC, 2023; ITD, 2023; MWCOG, 2023; NCDOT, 2023; OKDOT, 2023; ODOT, 2023; UDOT, 2023; MNDOT, 2024; **Transearch:** EWG COG, 2013; MAG, 2017; NJTPA, 2020; Michigan DOT, 2021; MODOT, 2022; SCDOT , 2022; GDOT, 2023; IDOT, 2023; INDOT, 2023; TXDOT, 2023; H-GAC, 2023; NMDOT, 2023, New York State Freight Plan, 2024; San Francisco Bay Area Goods Movement Plan, 2016). For rail-specific estimates, several states and MPOs supplement these data with the STB Carload Waybill Sample (NYMTC, 2017; CTDOT, 2022; Vtrans, 2022; VDOT, 2022; IDOT, 2023; MNDOT, 2024). Commodity flow forecasting is not a common use of freight data by local agencies, likely in part due to the limited granularity of the available data. Forecasts can also be integrated with other data sources to predict associated externalities. For example, conducting case studies in Michigan and Rhode Island, S&P Global employed the U.S. Environmental Protection Agency (EPA) MOVES model and Geotab vehicle idling time data to estimate emissions from truck flows forecast using Transearch data (Gick, 2023).

5.2 Identifying the Locations of Freight Activity

Agencies rely on a wide variety of public and commercial datasets to identify the locations of freight-related business establishments. States and MPOs have used a number of publicly-available employment-related datasets for this purpose, including the ***QCEW*** (NYMTC, 2017), ***CBP*** (Lawson, 2019a; Hancock, 2021; CalTrans, 2023; H-GAC, 2023; NJDOT, 2023; MNDOT, 2024); **LEHD** (ALDOT, 2023)*;* and state level employment dataset*s* (NJDOT, 2023). Some state, regional, and local agencies have also used commercial business and real-estate datasets such as ***Data Axle*** (formerly InfoGroup) (NJTPA, 2020; Hancock, 2021; SCAG, 2022; H-GAC, 2023; NDDOT, 2023; Ohio DOT, 2023; and MNDOT, 2024), ***Dun and Bradstreet*** (NYC DOT, 2021), and ***CoStar*** (ARC, 2024) to identify freight-related business establishments. Other agencies have relied on **local parcel and zoning records** to identify current and expected freight-related land uses (EWGCOG, 2013; MAG, 2017; Lawson, 2019a; NJTPA, 2020; Maryland DOT, 2022; MODOT, 2022; CalTrans, 2023; City of Portland, 2023; IDOT, 2023). For example, NJDOT (2023) identifies three types of freight-related facilities: freight generating, freight handling, and freight receiving. Chicago Metropolitan Agency for Planning (CMAP) combined land use data with **INRIX GPS trajectory data** to understand how freight activities have shifted over time (Hancock, 2021).

5.3 Estimating Truck Trip Demands

State, regional, and local agencies use a variety of data types to estimate truck trip demands for applications at multiple scales, ranging from statewide or regional model development and validation to project-specific traffic impact analysis. Commercial business and real-estate datasets such as ***Data Axle*** (formerly InfoGroup) (H-GAC, 2023*)* and ***Dun and Bradstreet*** (NYC DOT, 2021) have been used as inputs to truck trip generation models. For specifically modeling ecommerce demand, NJTPA utilized ***Rakuten Intelligence*** (now Neilsen IQ) e-commerce data to estimate package volumes, carrier shares, and O-D patterns. Agencies have also utilized **commercial location-based datasets** to estimate truck origin-destination pairs and validate travel demand models. Florida DOT combined ***ATRI*** and ***FAF*** data to calibrate and validate its supply-chain freight model and adjust truck trip distribution (Hancock, 2017). GDOT utilized **probe data** to validate its trip generation and travel demand models. MAG fused a wide variety of data sources – including national establishment time series data (NETS), ATRI and StreetLight truck GPS data, and Transearch, and FAF commodity flow data to develop a multi-layer megaregional, multimodal, agent-based behavioral freight model (Hancock, 2017). The Idaho Statewide Freight Data and Commodity Supply Chain Analysis Study combined ***EROAD* telematics data**, publicly available economic data, and shipper and establishment surveys to identify origin–destination pairs by industry for trips destined to the state (Gick, 2023).

In addition to the FAF disaggregation methods discussed in section 5.8 to translate FAF estimates into local truck activity, a number of agencies have used other data sources to understand port-related activities. NJTPA has utilized ***USACE Navigation and Civil Works Decision Support (NDC)*** data to estimate port-level waterborne tonnage by commodity (NJTPA, 2020). With researchers from the University of Arkansas, USACE utilized ***AIS, Lock-Performance Monitoring System (LPMS) and truck GPS*** data to estimate disaggregated commodity flows at the port level (Hancock, 2021). The Hampton Roads Transportation Planning Organization (TPO) utilized several commercial probe datasets to measure the volume of port-related truck traffic on the surrounding highway network (Lawson, 2019a).

5.4 Traffic Performance Measurement and Management

As mandated under Moving Ahead for Progress in the 21st Century Act (MAP-21), in 2017, FHWA implemented requirements for states and MPOs to develop performance targets for freight performance on the National Highway Network. These agencies are required to estimate a specific performance metric – truck travel time reliability – during five specified time periods: weekday morning peak (6 am - 10 am), weekday midday (10 am – 4 pm), weekday afternoon peak (4 pm - 8 pm), weekends (6 am - 8 pm); and overnights for all days (8 pm - 6 am) (FHWA, 2024b). FHWA provides access to the ***NPMRDS*** for this purpose, but agencies are also permitted to utilize an equivalent dataset. Many agencies do rely on the NPMRDS to estimate truck traffic performance measures, as well as to identify and prioritize truck bottleneck locations (Lawson, 2019a, ARDOT, 2022; CMAP, 2022; CTDOT, 2022; MDOT, 2022; RIDOT, 2022; WYDOT, 2022; ITD, 2023; KDOT, 2023; NJDOT, 2023; WVDOT, 2023; Miami-Dade TPO, 2024; Maine DOT, 2023; ODOT, 2023; UDOT, 2023). Several other agencies utilize ***INRIX*** data for the same applications (RIDOT, 2022; VDOT, 2022; Iowa DOT, 2023; H-GAC, 2023). NHDOT applies truck AADT as a mobility metric and to compute truck delay (NHDOT, 2019). Traffic performance measures including volume to capacity ratio truck percentage were used to guide delay-reduction strategies in Alabama's Mid-Period Freight Bottleneck report (ALDOT, 2023) and to identify locations in need of geometric improvement (CalTrans, 2023). The Texas A&M Transportation Institute examined the utility of using telematics data to estimate speed profiles in work zones (Gick, 2023). A study completed for Oregon DOT utilized telematics data to analyze truck activity at roundabouts (Gick, 2023).

5.5 Truck Route Identification/Designation

A common state, regional, and local application of freight data is identification and classify key freight routes and corridors. Route identification is completed for a variety of purposes. Critical freight routes are defined at both the national and state levels to inform project prioritization and funding eligibility. Under the FAST Act (Fixing America's Surface Transportation Act), states (and some MPOs) are required to designate components of the National Highway Freight Network, including (1) the primary highway freight system (PHFS), which includes "highways identified as the most critical highway portions of the U.S. freight transportation system determined by measurable and objective national data"; (2) other interstates not designated as part of the PHFS; (3) critical rural and urban freight corridors, which are public roads that "provide access and connection to the PHFS and the Interstate with other important ports, public transportation facilities, or other intermodal freight facilities" (FHWA, 2025). The most basic method to identify primary freight corridors is to assign them based on highway functional classifications (ARDOT, 2022; Maryland DOT, 2022; SCDOT, 2022; ALDOT, 2023, MWCOG, 2023; TDOT, 2023; FDOT, 2024; NYSDOT, 2024). Traffic counts, such as vehicle classification counts or average annual daily truck traffic

(AADTT), obtained from the HPMS or from state-level roadway traffic inventories are also commonly utilized to identify key freight routes and corridors (MetroPlan Orlando, 2013; NHDOT, 2019; NVDOT, 2022; SCDOT, 2022; ALDOT, 2023; H-GAC, 2023; INDOT, 2023; MWCOG, 2023; WisDOT, 2023; FDOT, 2024; Central Florida Regional Freight Mobility Study, 2013). In Washington State, the DOT designates its Freight and Goods Transportation System (FGTS), which classifies truck, rail, and water corridors into five categories based on freight tonnage moved (WashDOT, 2022; WashDOT, 2023). DRCOG used traffic metrics including AADTT and percent of peak traffic by trucks, as well as proximity to key intermodal facilities and stakeholder inputs, to identify priority freight corridors (DRCOG, 2024). In Wisconsin, WisDOT developed a Freight Factor Scoring system that integrates truck volumes, oversize/overweight vehicle activity, and commodity metrics to identify its primary and secondary freight corridors (WisDOT, 2023). North Carolina DOT similarly integrated traffic counts, waybill data, and WIM data to develop a project score quantifying freight impacts for prioritizing state transportation improvement plan projects (Hancock, 2017). More recently, agencies such as Northern Alameda County and MNDOT have used commercial location-based data sources to identify commonly used routes to inform route designation and truck access management decisions (Hancock, 2021). A number of cities have also recently designated or updated their dedicated truck routes (City of Seattle, 2016; City of Minneapolis, 2020; City of Dallas, 2021; NYC DOT, 2021) and revised their of route classifications (City of Seattle, 2016; City of Portland Bureau of Transportation, 2022).

Route information is also required for the purpose of oversize and overweight vehicle permitting (DelDOT, 2022; NJDOT, 2023; KDOT, 2023; NCDOT, 2023). Many agencies also use freight data in resiliency planning – specifically to understand responses to system disruptions and to identify routing challenges in advance of an event. These applications require integration of additional data types. Oak Ridge National Lab (Hancock, 2021) and Pennsylvania Department of Transportation (PennDOT) (Gick, 2023) have used probe-based data sources to study the traffic impacts of truck involved incidents and to monitor truck responses to infrastructure failures. In Colorado, oversize/overweight permit heatmaps have been overlayed with route information to inform potential route restrictions in advance of extreme events such as wildfires (Conway, 2021). Hydrological data has also been used to assess how stormwater may affect freight infrastructure. In South Carolina, stream gauge data from the U.S. Geological Survey (USGS) was used to develop bridge and crossing hydraulic equations (SCDOT, 2022). Wisconsin uses rainfall depth data from the National Oceanic and Atmospheric Administration (NOAA) to perform flood risk assessments to reduce severity of impacts of extreme weather and natural disasters (WisDOT, 2023).

5.6 Infrastructure Design and Management

Freight data can also inform infrastructure design and management decisions. While infrastructure inventories such as the National Bridge Inventory (NBI) and state-level bridge and highway inventories provide information about bridge ratings and current bridge and pavement conditions (IDOT, 2023; H-GAC, 2023; HIDOT, 2023, WVDOT, 2023), agencies may also use vehicle classification (City of Portland BOT, 2023; DDOT, 2023; FDOT, 2024), WIM load data (DDOT, 2023; NJDOT, 2023; KDOT, 2023; and NCDOT, 2023), and oversize/overweight permit data (Hancock, 2021) to support pavement design and update pavement construction and reconstruction standards (City of Portland BOT, 2023), to analyze the impacts of freight on pavement management requirements (DelDOT, 2022), to guide targeted repairs along truck route networks (NYC DOT, 2021), and to identify deficient road segments (Hancock, 2021).

Geometric design relies on identification of a design vehicle, typically defined as the largest vehicle that is a frequent user of a roadway. Depending on the context, the design vehicle can vary, but it is usually a large transit, freight, or emergency vehicle. If local data is unavailable, a design vehicle may be determined by reviewing traffic counts, conducting interviews with adjacent businesses, or observing physical evidence such as tire tracks on curbs or damage to infrastructure (City of Portland Office of Transportation, 2008). The city of Portland has defined freight design vehicles by roadway class or by specific roadway function.

For example, their guide identifies the WB-67 interstate semi-trailer as the design vehicle for a Regional Truckway and an SU-30 single-unit truck for Local Service Truck Streets (City of Portland Office of Transportation, 2008). Other design-related applications potentially relying on vehicle classification data include the identification of locations requiring geometric improvements such as left-turn lanes, turning radius adjustments, and recessed stop lines (City of Seattle, 2016; City of Portland Bureau of Transportation, 2023), and the development of standards for truck routes and shared streets (City of Dallas, 2021). As noted above, traffic performance data can be useful to identify locations in need of geometric improvement (CalTrans, 2023). Additional design-related areas identified as freight data needs include incorporation of freight-related metrics in Complete Streets checklists (City of Minneapolis, 2020) and evaluating locations for combined bus and truck prioritization (NYC DOT, 2023).

Freight data has also been used in planning and scoping studies for locating energy infrastructure. Agencies have used detailed trip data to analyze the recharging needs of medium- and heavy-duty trucks by examining the origins, destinations, routes, and operational characteristics of truck trips (RIDOT, 2022; Gick, 2023). Although they have not identified specific data sources, several other agencies have expressed a need for planning for electric vehicle charging infrastructure (City of Minneapolis, 2020; NYC DOT, 2021; NYC EDC, 2021).

5.7 Safety Management

Historic state or local agency crash records are commonly used to inform safety-related improvements. These records are used to calculate truck crash rates, to identify safety-critical locations for intervention (SCAG, 2013; Lawson, 2019a; Lawson, 2019b; City of Minneapolis, 2020; KTC, 2022; H-GAC, 2023; ITD, 2023; NJDOT, 2023; DRCOG, 2024) and to inform targeted safety strategies (CTDOT, 2022; Maryland DOT, 2022; NCTCOG, 2022; MWCOG, 2023; WisDOT, 2023; NYSDOT, 2024). In addition to general locations of truck- or rail-involved incidents, specific events of concern have included crashes involving parked trucks - identified from FMCSA and in some state databases (Hancock, 2021, WVDOT, 2023) - and bridge strike locations, which have been used to guide updated signage (NYC DOT, 2021). Recently, telematics data has been used to identify harsh braking events, providing a potential opportunity for proactive safety intervention (Gick, 2023).

5.8 Parking and Loading Management

Freight parking and loading studies often rely on a combination of public and private data sources. Particularly following the passage of Jason's Law (FHWA, 2015), state-level parking studies have been conducted to assess capacities for long-haul or overnight truck parking. Agencies such as the Connecticut DOT (2022) and Montana DOT (2022) have forecast truck parking demand, inventoried parking supply, and monitored utilization. Both NJTPA (2020) and Delaware Valley Regional Planning Commission (DVRPC 2022) have developed publicly available GIS maps of truck parking locations. Other states have leveraged commercial probe datasets, including Streetlight and ATRI, to identify truck parking locations (AZDOT, 2019; WVDOT, 2023; MNDOT, 2024; Hancock, 2021; NYSDOT, 2024) and assess their use (WVDOT, 2023). Private-sector data from trucker apps, such as the Trucker's Friend database (FHWA, 2015) and TruckerPath (AZDOT, 2019), provide real-time information on location, services, and parking availability. FDOT (2024) has integrated its inventory information with sensor network to provide real-time truck availabilities to drivers.

In cities, parking- and loading-related concerns are mostly focused on first- and last-mile loading and unloading activities. Local freight plans identify a wide variety of potential data applications, including documenting locations of private loading docks and spaces (City of Minneapolis, 2020), evaluation of parking and loading locations, supply and demand, and utilization (City of Minneapolis, 2020; City of Dallas, 2021; City of Portland Bureau of Transportation, 2023), and implementing and evaluating curb management policies such as commercial parking permits (City of Portland Bureau of Transportation, 2022), green loading zones (City of Portland Bureau of Transportation, 2023), and reservation systems (City of Portland Bureau of Transportation, 2023). Several states and cities have also identified an interest in implementing micro-hubs or consolidation facilities for transloading of goods from larger vehicles to smaller vehicles for end delivery (NYC DOT, 2021; DDOT, 2023; Metropolitan Council, 2023) and evaluating the repurposing of underutilized spaces for these uses (MassDOT, 2023; MNDOT, 2024). However, little information is provided about the specific data sources available or needed to evaluate these approaches. Among the studies reviewed, only Seattle identified an ongoing Commercial Vehicle Load Zone data collection and monitoring program to maintain updated inventories (City of Seattle, 2016). LA Metro noted a need for a curbside asset inventory (LA Metro, 2021).

5.9 Land Use Planning and Site Permitting

While land-use data informs freight planning decisions (see sections 5.2, 5.3, and 5.4), freight data can also inform land-use decisions, including zoning updates and project and site permitting. Land use data is useful to identify freight clusters to guide future development; examples include ARC's (2024) identification and tracking of freight clusters to promote context-sensitive uses and H-GAC's (2023) use of its Regional Land Use Information System to identify areas for future industrial development. Land use data also informs analysis and management of potential conflicts between freight and other uses; examples include Caltrans' (2023) development of environmentally conscious land use policies, DelDOT's (2022) Protect-Manage-Accommodate framework to ensure adequate access for freight with appropriate levels of prioritization based on land use context, and NCTCOG's (2022) "Freight Land Use Policy Toolkit" which aims to help cities manage externalities from planned industrial districts. The City of Minneapolis (2020) has recognized a need to update zoning regulations to include requirements for on-site loading facilities; these requirements could be informed by observed trip rates and expected parking times.

While local land use policies and ordinances alone are useful to identify land use incompatibilities and institutional barriers to preserving freight land (NCTCOG, 2022), freight transportation-related data may also be necessary for well-informed land-use decision-making. Project permitting typically requires traffic impact analysis (see section 5.3). States, municipalities, and other agencies have also recently begun to implement or explore indirect source rules, a type of environmental permitting requiring freight-generating facilities to mitigate their environmental footprints. In Southern California, the South Coast Air Quality Management District's Warehouse Actions and Investments to Reduce Emissions (WAIRE) program requires warehouses to collect truck trip counts using telematics, in-road/driveway sensors, video, manually, or through transaction record for impact estimation and annual reporting (SCAQMD, 2021). Also in Southern California, SCAG has employed trip generation estimates derived from business establishment data and the California Air Resources Board's Emission Factors (EMFAC) Model to estimate facility-specific emissions (Hancock, 2021).

5.10 Policy and Program Evaluation

Many cities and regions are currently exploring a wide variety of freight interventions with aim to improve freight efficiency, or at least maintain freight access, while mitigating externalities including traffic congestion, safety risk, air pollution, and CO_2 emissions. Some locations are exploring access management strategies such as off-hour deliveries (NYC DOT, 2021; City of Portland Bureau of Transportation, 2023), time-restricted truck-free zones (City of Minneapolis, 2020), and low-emission zones (City of Minneapolis, 2020; City of Portland, 2023; SANDAG, 2024). Others are interested in implementing new control and vehicle technologies such as truck signal priority (City of Seattle, 2016; City of Portland Bureau of Transportation, 2023); commercial cargo bikes (NYC DOT, 2021; City of Portland Bureau of Transportation, 2023; SANDAG, 2024); short-sea shipping (blue highways) (NYC DOT, 2021); autonomous vehicles (City of Dallas, 2021); and clean or zero emissions trucks (City of Minneapolis, 2020; LA Metro, 2021; NYC DOT, 2021; City of Portland Bureau of Transportation, 2023; SANDAG, 2024). Cities are also looking to update truck-related regulations such as truck size and weight regulations (NYC

DOT, 2021) and idling policies (City of Minneapolis, 2020; City of Portland Bureau of Transportation, 2022). Several cities have identified an interest in developing new project evaluation metrics or prioritization frameworks that consider a wide range of impacts, including safety, environmental sustainability, and economic vitality, among others (City of Chicago, 2021; City of Dallas, 2021; City of Portland Bureau of Transportation, 2023). However, there is little information provided about what specific data or analysis approaches to measure the broad impacts from these interventions.

5.11 Key Findings from Review of Practical Applications

The following are key takeaways from this review of practical freight data applications:

- Agencies most commonly use data sources available to them at no costs, such as the FAF (for commodity flow estimation), NPMRDS (for traffic performance measurement), and publicly-available national, state, and local employment and land use datasets.
- Agencies are also increasingly reliant on commercial data products, including Transearch data, which provides more granular commodity flow estimates, and a number of probe- and telematics-based datasets such as those provided by ATRI, Inrix, Streetlight, and Geotab.
- Commercial probe- and telematics-based sources are now being used by states, MPOs, and cities for a wide variety of practical applications, including traffic performance-measurement, understanding truck flows and parking behaviors, measuring route usage, and as an input to state and regional demand models. They also provide value-added information to supplement other public data sources for a number of applications including route identification and planning, infrastructure management, and parking management.
- Cities are exploring a wide variety of freight-related interventions to manage externalities such as air pollution and collision risks. Interventions of interest include but are not limited to area-wide policy changes (e.g. truck size and weight regulations, idling regulations, access restrictions), curb management strategies (e.g. loading zone permits, loading space reservation systems), traffic controls (e.g. dedicated lanes, signal prioritization), consolidation approaches (e.g. consolidation centers, micro-hubs), mode shifts (e.g. short-sea shipping), and alternative vehicles (e.g. cargo bikes, electric vehicles, autonomous vehicles). Evaluating the impacts of proposed or piloted changes – both for freight operators and for surrounding communities - requires an understanding of local vehicles and their engines, operator behaviors, and supply chain behaviors. The existing literature provides very little information about data sources to assess these proposed solutions at a population scale. The aggregation of both public and commercial datasets likely limits their direct applicability for these uses.

6. CASE STUDY: FREIGHT DATA SOURCES AT THE NYC DOT

Building on findings from the literature and practical review, the research team conducted a detailed case study with the NYC DOT to explore in-depth freight data use within a large local agency. This case study included a freight data workshop with agency stakeholders and systematic review of NYC DOT's available freight data sources.

6.1 Performance Metric Evaluation

As discussed in section (3.2.1), NYC DOT workshop attendees were asked to identify both the difficulty and the importance of obtaining specific freight performance metrics of interest. This section details findings from this exercise.

6.1.1 Trip and Commodity Flow Metrics

NYC DOT respondents identified the FAF and CFS as primary commodity flow data sources used by the agency. They also identified several trip-related data sources, including commercial probe-based datasets (ATRI, Streetlight, and Inrix), automated vehicle location (AVL) data collected from participants in the NYC Clean Trucks Program, and other operational data collected from pilot program participants as sources of origin-destination information. Other datasets used for identifying trip origins and destinations include the New York Metropolitan Transportation Commission's (NYMTC's) Best Practices Model, NYC DOT's Citywide Mobility Survey (which measures home delivery frequencies), and trip generation rates obtained from the Institute of Transportation Engineers (ITE) Trip Generation Manual and the City Environmental Quality Review (CEQR) Manual.

Figure 6-1 displays the importance and difficulty ratings for collecting trip and commodity flow metrics. Scores indicate that the NYC DOT freight data users consider all of the metrics to be important to measure, except for understanding commodity origins and destinations by value. Results indicate that commodity origins and destinations by weight and volume, regional mode shares, and trips origins and destinations within the city are important and relatively easy to measure. Last-mile modes shares, carrier tour characteristics, and trips origins and destination beyond NYC are also considered important, but are more difficult to measure.

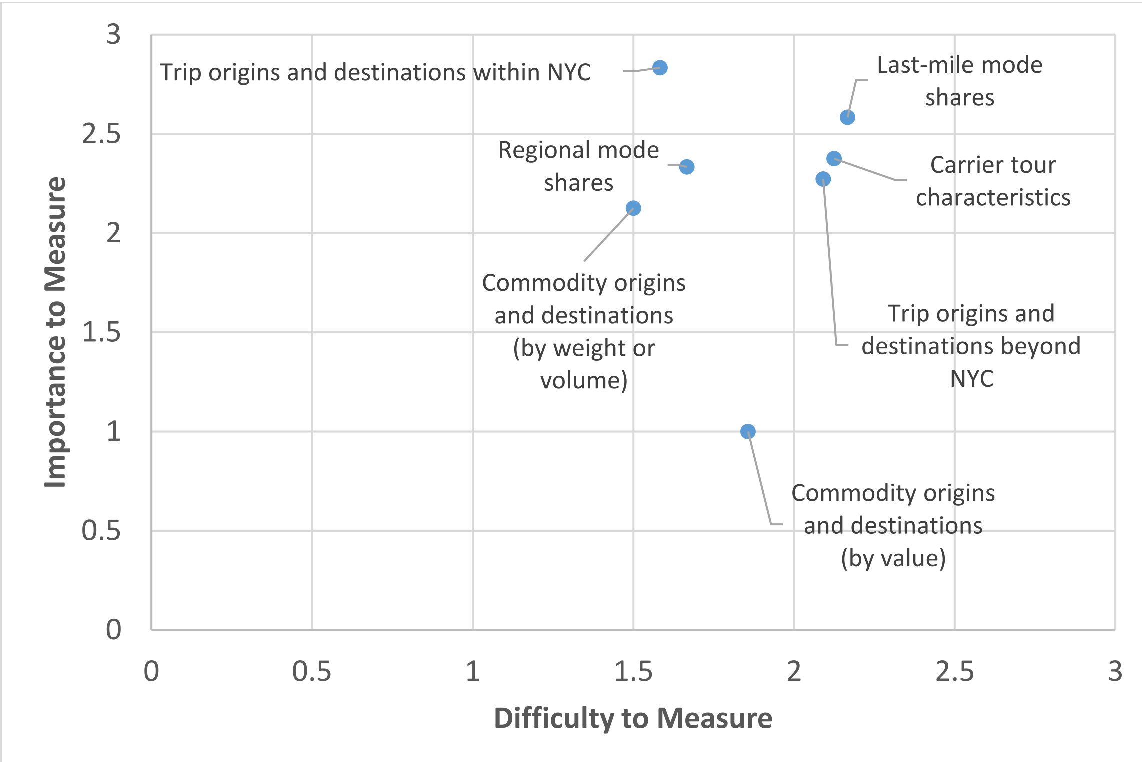

Figure 6-1. Trip and Commodity Flow Metric Ratings

6.1.2 Freight Network Performance Metrics

NYC DOT respondents also used probe-based datasets (Inrix, Streetlight, AVL) as well as telematics data (Geotab) to estimate freight network performance metrics. NYPD collision data are used to estimate crash rates. Corridor traffic analysis is conducted to estimate some traffic-related measures. Argonne National Lab's AFLEET tool is used to assess emissions and energy use.

Figure 6-2 displays the importance and difficulty ratings for collecting freight network performance metrics. Results indicate that all freight network performance metrics are important or critical to measure. Collision frequencies and severities are easy to measure with existing data sources, and vehicle speeds are relatively easy to obtain. Travel time reliability is slightly more difficult to measure. CO_2 and air pollutant emissions are not typically measurable from existing data sources.

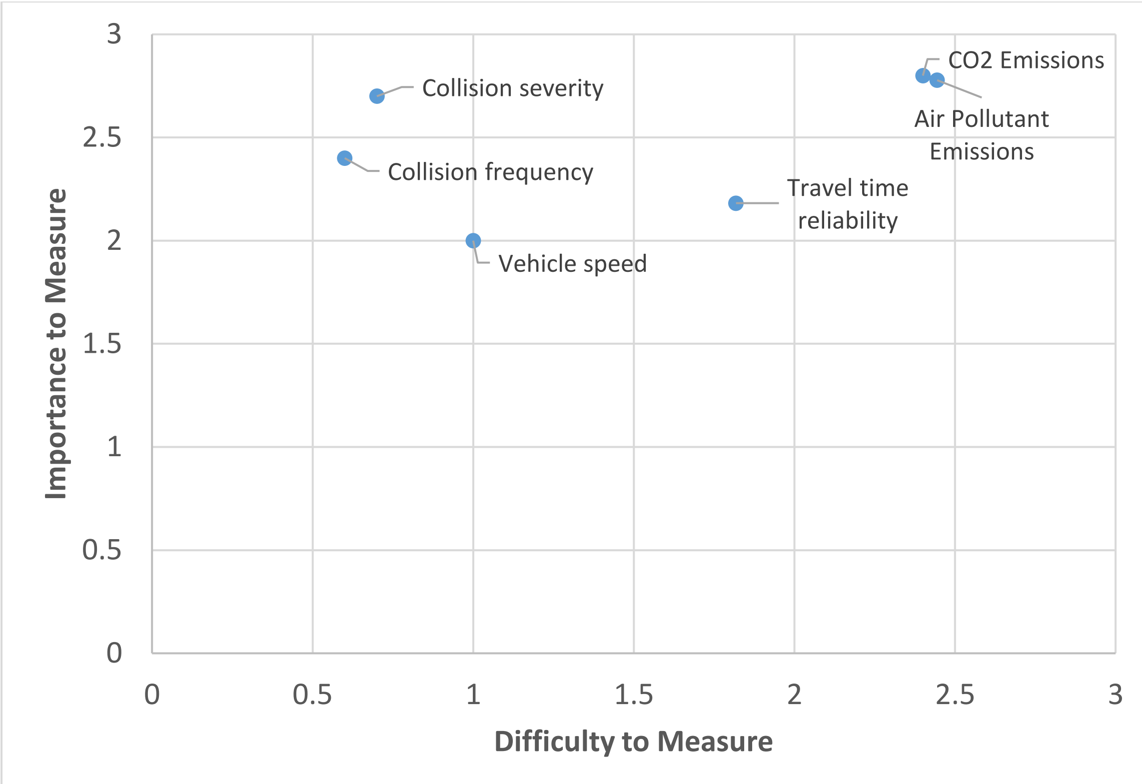

Figure 6-2. Freight Network Performance Metric Ratings

6.1.3 Parking and Loading Metrics

NYC DOT respondents identified a number of data types used for collection of parking and loading data. Several identified NYC DOT time lapse camera data and field surveys, including manual and video counts. Others identified parking meter-related data, including meter transactions and agency data on parking revenue by meter zone, as well as NYC Department of Finance Parking Violation records. One respondent identified GPS dwell time data, and another identified merchant surveys.

Figure 6-3 displays the importance and difficulty ratings for collecting parking and loading metrics. Overall, parking and loading related metrics were considered easier to measure relative to other metric types; however, notably, most of the data sources identified provided limited network coverage. Cameras, field surveys, and manual and video counts are typically implemented only in selected locations. GPS dwell time data only covers equipped vehicles which may not be representative. Respondents identified parking violations as relatively easy to obtain but of limited importance to measure, and parking revenue to be only slightly more difficult and important to measure. Notably, parking violations are only issued in locations where enforcement occurs, and meter transactions only exist in locations where curbs are priced. Trip generation, parking and loading duration, and parking and loading frequency were considered of critical importance and only somewhat measurable with existing data sources. While collisions are generally relatively easy to measure from collision records, attendees did note that inconsistency of vehicle classifications for trucks and commercial vehicles present a challenge when using these datasets.

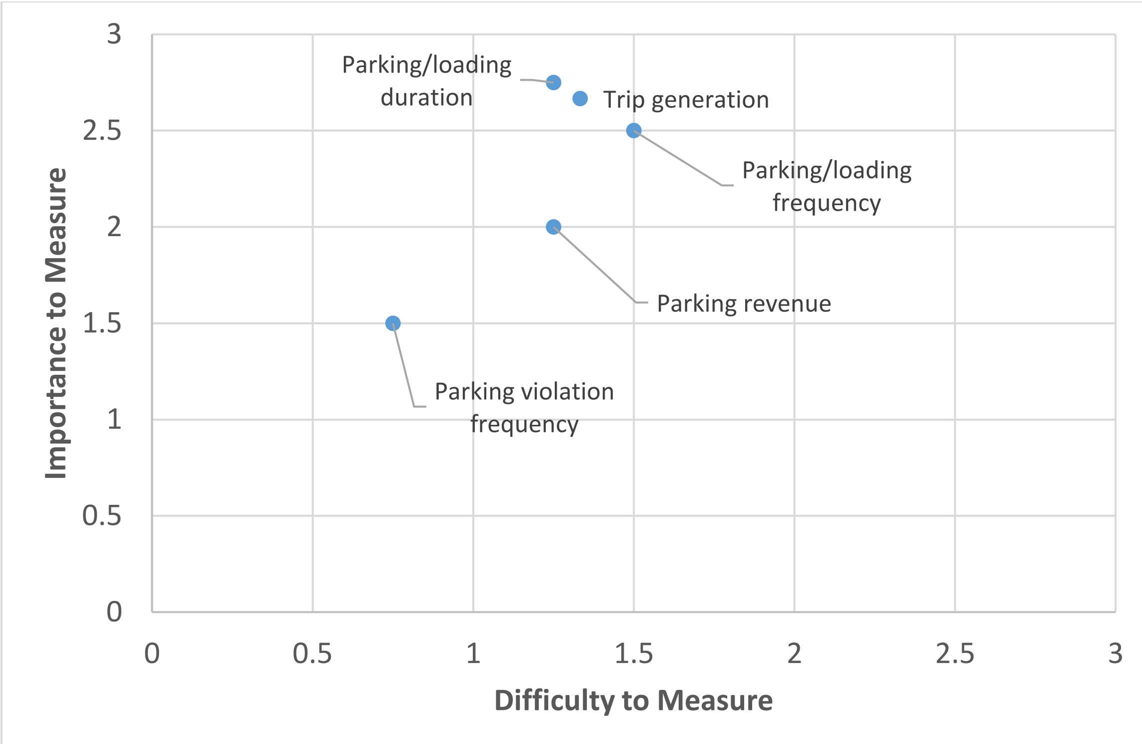

Figure 6-3. Parking and Loading Metric Ratings

6.1.4 Vehicle Metrics

NYC DOT respondents also identified a number of data types used for collection of vehicle data. Data sources identified included manual or video field surveys, vehicle classification, and turning movement counts obtained from NYC DOT's TIMs portal, the New York State (NYS) Traffic Data Viewer, and contractors. Other sources include basic vehicle classification information from Streetlight data, NYS Department of Motor Vehicles registration data, and original equipment manager (OEM) statistics.

Figure 6-4 displays the importance and difficulty ratings for vehicle metrics. Vehicle metrics are considered important but relatively difficult to measure using existing data sources. Only vehicle type, engine type, size, and safety equipment were ranked as between somewhat and difficult to measure, with all other metrics falling in the difficult to not measurable range.

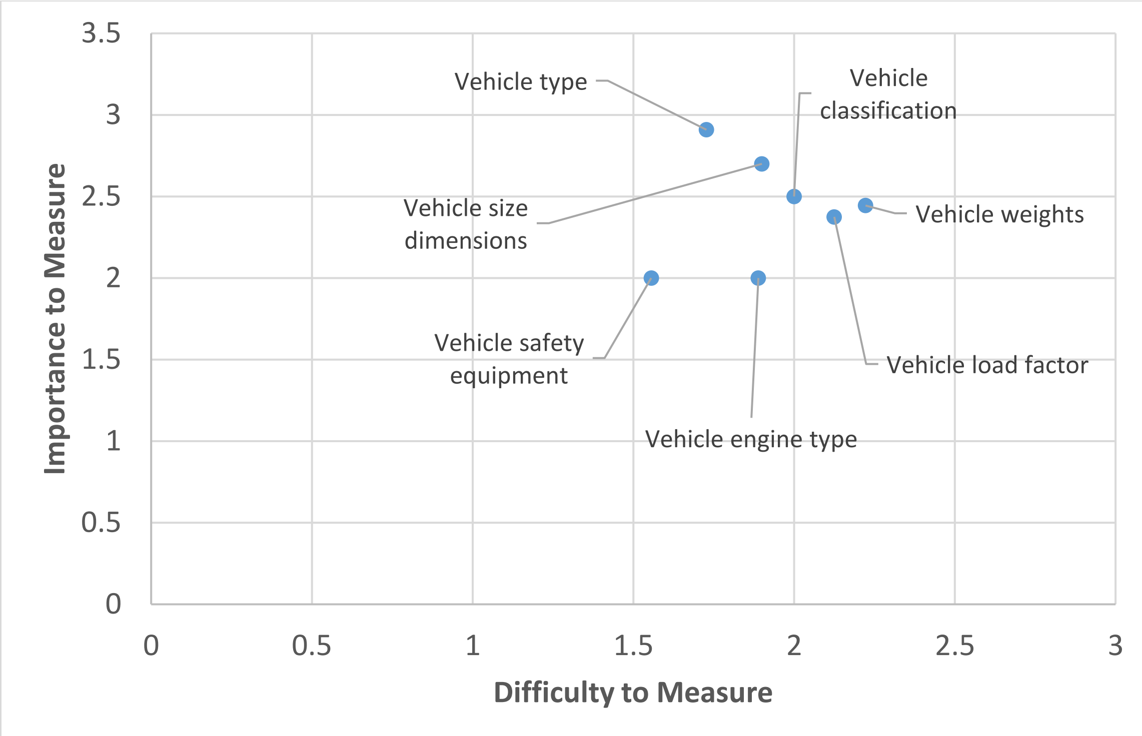

Figure 6-4. Vehicle Metric Ratings

6.1.5 Data Granularity

As detailed in Tables 6-1 and 6-2, the needed spatial and temporal granularity vary significantly by use, with some users requiring only data that is more aggregate in time and space, and others requiring significantly more granular data.

Table 6-1. Time Granularity Rankings

Time Granularity	**Percent Choosing Rank**						**Average Rank**
	1	**2**	**3**	**4**	**5**	**6**	
Hourly	37.5	50.0	12.5	0.0	0.0	0.0	**1.75**
Weekday vs weekend	0.0	33.3	50.0	16.7	0.0	0.0	**2.83**
Day	28.6	28.6	0.0	28.6	0.0	14.3	**2.86**
15 min	28.6	0.0	14.3	0.0	14.3	42.9	**4.00**
Year	16.7	0.0	16.7	33.3	0.0	33.3	**4.00**
Month	0.0	0.0	0.0	16.7	83.3	0.0	**4.83**

Table 6-2. Geographic Granularity Rankings

Geographic Granularity	**Percent Choosing Rank**							**Average Rank**
	1	**2**	**3**	**4**	**5**	**6**	**7**	
Corridor	20.0	30.0	20.0	20.0	10.0	0.0	0.0	**2.70**
Neighborhood	18.2	27.3	27.3	18.2	9.1	0.0	0.0	**2.73**
Roadway Segment	33.3	0.0	22.2	33.3	11.1	0.0	0.0	**2.89**
Block	12.5	25.0	12.5	0.0	12.5	37.5	0.0	**3.88**
Intersection	0.0	28.6	28.6	0.0	14.3	14.3	14.3	**4.00**
City	22.2	11.1	0.0	11.1	11.1	33.3	11.1	**4.22**
Region	11.1	0.0	0.0	11.1	22.2	0.0	55.6	**5.56**

6.2 Detailed Mapping of Existing Data Sources for Local Decisions

As detailed in *Section 3.2.2*, we evaluated each dataset available to NYC DOT to identify key performance metrics related to traffic demand, demand characteristics, network/infrastructure performance and vehicle characteristics, and then mapped these metrics to specific local decision-making applications.

6.2.1 Freight Applications vs. Performance Metrics

Based on findings from the reviews described in Chapters 4 and 5, the research team developed the following mapping of local freight-related decisions with potential performance metrics of interest (Table 6-3, next page). In the table, a check mark indicates that the performance metric listed in that row is relevant to the decision type at the top of the column. A p indicates that the performance metric is possibly applicable. As can be seen from the resulting matrix, there are a wide variety of performance metrics of interest for local freight-related decisions, and the metrics of interest vary considerably based on the specific application. While the most general planning applications (location identification and demand estimation) rely only on traffic performance or behavioral metrics, all other applications could benefit from information about vehicle characteristics, network performance, and travel behavior. Policy and program applications will vary considerably, but based on the interventions of interest detailed in section 6.10, also frequently require inputs from all three metric categories.

Table 6-3. Performance Metrics of Interest for Local Freight Application Areas

	Location ID	Demand Est.	Traffic Perf. Measurement	Route ID	Infrastructure Design	Safety Management	Parking & Loading Mgmt.	LU Planning & Permitting	Policy & Program Evaluation
Vehicle characteristics									
Vehicle type			✓	✓	✓	✓		✓	
Vehicle class			✓	✓	✓	✓	✓	✓	p
Vehicle weight capacity					✓		✓		p
Vehicle cube capacity							✓		p
Gross vehicle weight					✓				p
Axle loads					✓				p
Load factor (% volume capacity used)									p
Vehicle engine type				p	p			✓	p
Engine status								✓	p
Fuel/energy consumption				p				✓	p
Hard braking						✓			p
Other vehicle technologies (e.g. loading or safety equipment)						✓		✓	p
Network/infrastructure performance									
Vehicle miles traveled				✓	✓			✓	p
Congestion/delay			✓	✓	✓			✓	p
Travel time reliability			✓	✓					p
Collision frequency				✓	✓	✓			p
Collision severity				✓	✓	✓			p
Segment/route volumes	✓			✓	✓	✓		✓	p
Turning movement counts					✓	✓			
Trip origins and destinations	✓	✓		✓			✓	✓	p
Segment/route speeds			✓	✓		✓		✓	p
Segment/route reliability			✓	✓		✓			p
Parking facility occupancy							✓		p
Loading dock occupancy							✓		p
Curb occupancy							✓		p
Travel behavior characteristics									
Tour origins and destinations	✓	✓		✓			✓	✓	p
Tour characteristics							✓		p
Route choices				✓	✓		✓	✓	p
Vehicle domiciles	✓			✓			✓	✓	p
Building/site trip generation	✓	✓		✓	✓	✓	✓	✓	p
Time of parking/loading events							✓	✓	p
Duration of parking/loading events							✓	✓	p
Trip cost			✓				✓		p

6.2.2 NYC DOT Freight Data Sources vs. Performance Metrics

The Table 6-4 maps the same performance metrics vs. each available NYC DOT dataset. In this table, A check indicates that the metric is available in the dataset. An *s* indicates that some information relevant to the metric is available in the dataset. A *d* indicates that this metric could be derived from the raw data included in the dataset. An *a* indicates that while this metric is not measurable in the specific data available to NYC DOT, our literature review results indicate that this metric may be measurable in the full scope of the vendor's commercially available data.

Table 6-4. Performance Metrics Obtainable from NYC DOT Data Sources

Metrics of Interest	**Data Type**								
	Raw Probe	Commercial Probe			Commercial Telematics	Traffic Counts	WIM	Collision Records	Parking Violations
	Data Source								
	AVL	ATRI	Inrix	Streetlight	GeoTab	TIMs	DOT	NYPD	DOF
Vehicle Characteristics									
Vehicle type	✓			✓	✓	✓		✓	✓
General vehicle class	✓	✓	✓	✓	✓	✓			
FHWA vehicle class							✓		
Gross vehicle weight	s			s	s		✓		
Axle loads							✓		
Vehicle engine type	✓				✓				
Engine status	✓								
Hard braking					✓				
Network/Infrastructure Performance									
Vehicle miles traveled	d		✓	✓	✓				
Congestion/delay		a	✓	✓	✓				
Travel time reliability			✓	✓	✓				
Collision frequency								✓	
Collision severity								✓	
Segment/route volumes		✓		✓	✓				
Vehicle classification count						✓			
Turning movement count				✓		✓			
Segment/route speeds		✓	✓	✓	✓				
Segment/route reliability		a		✓	✓				
Parking facility occupancy		s			s				
Curb occupancy					s				
Travel Behavior Characteristics									
Trip origins and destinations	d	✓		✓	✓				
Tour origins and destinations	d	a		s	✓				
Tour characteristics	d			s	✓				
Route choices	d			s	s				
Vehicle domiciles	d	a			✓				
Building/site trip generation	s	s		s	s				
Time of parking/loading events	d	a			✓				s
Duration of parking/loading events	s	✓			✓				s

As can be seen from the table, both raw and commercial probe data and telematics data are useful for traffic performance measurement. General vehicle type shares, stopping behaviors, origins and destinations and repeated routes can all be obtained from commercial probe- and telematics-based datasets. However, it is difficult to assess their representativeness of the vehicle population as these datasets are derived from limited vehicle samples and rely on best-available scaling factors that are difficult to validate.

Limited vehicle-specific information is available in the existing data sources, aligning with findings from the stakeholder survey. Only limited engine type information is provided, limiting utility for differentiated emissions modeling. Only the WIM dataset provides detailed vehicle classification information and detail about vehicle loading (specifically axle loads and gross vehicle weight). Only the TIMs database provides location-specific turning movement and vehicle classification counts. Both of these datasets provide information only from selected, non-random locations. Limited safety information is available in the commercial datasets, with the exception of segments-specific counts of harsh braking events available in Geotab's Altitude platform.

Notably, a number of differences were observed in how performance metrics were captured across the available datasets:

- **General vehicle class:** In the Streetlight and Geotab datasets, and in turning movement counts provided in the TIMs database, general vehicle classes include light-duty, medium-duty, and heavy-duty trucks. Both commercial providers use the same general definitions for classification based on vehicle gross vehicle weight ratings (GVWR), which are obtainable from a vehicle's VIN number. The INRIX platform categorizes vehicles only into two broad groups – passenger vehicles and fleet vehicles.
- **FHWA vehicle class:** FHWA defines 13 detailed vehicle classes (FHWA, 2013). In the WIM dataset, FHWA vehicle class can be derived from the vehicle's measured axle counts, spacings, and loads using FHWA's 13-class Scheme F rules (or state-specific variants) applied by the WIM processing software.
- **Gross vehicle weight:** WIM systems directly capture axle loads, which are used to compute the GVW, so the WIM dataset directly provides a GVW estimate. In the commercial datasets (Streetlight and Geotab), the vehicle's GVW is not directly provided, but, as noted above, GVW ranges can be identified based on the GVWR. In the AVL data, this same value (GVWR) can be determined from the VIN number.
- **Vehicle miles traveled:** In the AVL dataset, VMT can be derived from the odometer reading at each ping. In the commercial datasets, VMT is provided as an aggregate estimate by segment or defined geographic area (e.g. census tract or TAZ). INRIX IQ provides only normalized vehicle miles traveled (VMT) at the country, state, and metropolitan (market) levels. Normalized VMT represents the total distance traveled by a specific vehicle type within a defined geographic area and time period, expressed relative to a baseline reference period.
- **Congestion/delay:** Streetlight provides a "Congestion Analysis" tool for all vehicles operating within a county, city or census tract, producing a detailed, interactive report of volume, congestion, and reliability metrics for the specified region and network – but it does not isolate freight traffic. Similarly, Inrix Signal Analytics offers visualizations showing weekly, monthly and daily (including different day parts) control delay (sec/vehicle) by intersection and average travel time, delay, and volume at corridor level capturing signal-induced congestion patterns for network optimization analysis, but without freight specific insights. Geotab Altitude provides traffic analysis data for congestion zones by time of day and general vehicle classes, which can help identify peak-hour bottlenecks and freight contributions to delays. Although not included in NYC DOT's specific data purchase, ATRI regularly produces a national report identifying key freight bottlenecks using its dataset (ATRI, 2026).
- **Parking facility occupancy:** NYC DOT's ATRI data includes counts of parked trucks within fixed geographies (in this case, traffic analysis zones (TAZs)) along with parking duration statistics (minimum, maximum, median, average). Geotab's stop analytics include stop counts and durations mapped to individual road segments, with aggregation available at broader geographical zones.
- **Curb occupancy:** While curb occupancy is not directly measured in any dataset, Geotab's road segment-level stop counts and durations capture curbside usage for last-mile delivery (short max-duration stops to exclude overnight parking), unauthorized roadside parking (min-duration

threshold to exclude stop-and-go traffic), and heavy duty truck parking dynamics, potentially informing occupancy analysis.

- **Trip/tour origins and destinations:** AVL breadcrumb data (2-minute intervals) can be used to identify trip origins and destinations using timestamps and ignition on/off status for each truck trip. Truck tour origins and destinations can also be derived by combining this with the odometer reading. The ATRI data includes the total number of trip counts from origin to destination across specified time periods (evening peak, mid-day, morning peak, off-peak, Saturday peak, and other) for weekdays/weekends in customized months and years. The Streetlight dataset provides origin-destination analysis to analyze traffic from one group of locations to another group of locations. It also offers origin-destination through middle filter analysis to look at trips that travel from one group of locations to another group of locations, but through a specific filter of locations. The Geotab dataset includes origins and destinations for single trips. It is also the only dataset that identifies chained consecutive trips including sub-journeys, with the ability to count destination stops on the way to the final destination. This function is useful to understand how vehicle tours are organized. Geotab also categorizes trips by vocation – door-to-door, hub-and-spoke, local, long distance, or regional; and gives journey counts by general vehicle class (light/medium/heavy) that comes from each vocation type along with the journey counts from each industry (based on NAICS primary industry code).
- **Route choices:** Streetlight provides "top routes" that go between the selected origins and destinations. In Geotab's platform, for any O/D pair that has a journey between them, route analysis can be performed by choosing common routes used/common roads visited.
- **Building/site trip generation:** Truck trips originating from or destined to user-defined areas like warehouses or distribution centers can be obtained from several of the datasets. In the AVL data, trip ends can be identified using ignition on/off patterns and the unchanged odometer readings within specific zones. The Streetlight and ATRI datasets aggregate OD pairs where either origin or destination falls in the user-defined zone, providing time-period specific generation rates. The Geotab platform extends this to chained trips and intermediate sub-journey stops, capturing vocation-specific activity (door to door, hub and spoke, local, long distance, regional) by vehicle class and NAICS industry.
- **Duration of parking/loading events:** Parking duration can be derived from the AVL data using the location and engine status, when a vehicle remains at the same location for a sustained period and an "off" ignition status distinguishes true stops from brief idling in traffic. The ATRI dataset provides counts of parked trucks within fixed geographies (here, TAZs) along with parking duration statistics (minimum, maximum, median, and average), derived from processed truck GPS stop data. These metrics can be used to understand how intensively selected zones are used for truck parking and to estimate parking demand and utilization over time. Geotab's stop analytics compute stop durations in individual road segments and within broader zones, which can be interpreted as the length of parking or loading events for trucks.

The following metrics were not measurable in any available dataset: vehicle cube capacity; load factor; fuel consumption; other vehicle technologies (e.g. loading or safety equipment); loading dock occupancy; and trip cost.

6.3 Key Takeaways from NYC Case Study Analysis

The following are key findings from analysis of the NYC DOT case study:

- Critical data gaps identified by agency stakeholders as important, but difficult to measure, include:
    - All vehicle characteristics, including vehicle types, classifications, weights, dimensions, load factors, and engine types;

  - Vehicle-related emissions;
  - Last-mile modes shares;
  - Carrier tour characteristics; and
  - Trip origins and destinations beyond NYC.
- Data granularity needs, in both time and space, vary considerably depending on the specific agency application of the data.
- Location identification and demand estimation applications rely primarily on behavioral and network performance metrics. All other applications (traffic performance measurement, route identification, infrastructure design, safety management, parking and loading management, land use planning and site permitting, and policy and program evaluation) could benefit from more detailed vehicle characteristics in addition to traffic and behavior metrics.
- Commercial datasets do provide reasonably detailed information about many metrics, such as general vehicle classes and GVWR; trip origins and destinations and route usage; parking frequencies and durations; and speed, congestion, and delays. Geotab's Altitude platform additionally provides aggregated estimates of trip industries and vocations, trip-chaining chaining behaviors, and engine types. While these metrics are independently useful, they are typically provided to the agency user as area- or segment-based aggregated estimates, limiting the ability to study linkages across metrics for individual vehicles.
- Currently available datasets provide very limited vehicle-specific information. WIM data provides detailed vehicle load information, but is available only for a single freeway location. TIMs provides some vehicle classification counts, but only in a few, non-random locations. In some commercial datasets, traffic performance metrics do not distinguish between passenger and freight vehicles. Operator costs are not captured in any of the available datasets.
- The raw AVL dataset provides very rich information about each vehicle, its ownership, and its stopping and starting behaviors, potential enabling granular analysis of travel and parking behaviors and associated externalities; however, this dataset represents only a small, non-representative sample of the city's freight vehicle population.

7. FREIGHT DATA FOR LOCAL DECISION-MAKING: SUMMARY OF FINDINGS

Based on the reviews of freight data applications in research and practice detailed in Chapters 4 and 5, and the NYC case study detailed in Chapter 6, this section provides a brief summary of the current state of freight data for local decision-making.

7.1 Data Utility for Local Applications

Local applications are often distinct from state or regional applications in that they typically require data that is more granular in time and space and require visibility of local streets. Commodity data is not generally used for local applications as it is not available at the required granularity. Area-wide surveys (e.g. establishment surveys, household surveys) are rarely conducted at the local level. While operator surveys and detailed activity records can provide granular information about vehicle tours and delivery activity, when made available to local agencies, this type of data is usually collected only from a small number of operators - for example participants in a program or pilot study. Land use and real estate data are useful to identify the locations likely to generate freight transportation activities and, as inputs to historic models, to estimate trip impacts, but these data provide limited information to characterize the resulting activities – for example to identify vehicle types, arrival times, or parking durations. Administrative records such as vehicle registration information or oversize and overweight permits can be useful to characterize vehicles and routes, but datasets may be challenging to align with local geographies; for example, statewide estimates of vehicle types may not be representative of the vehicles operating in any specific municipality in that state.

As detailed in the preceding chapters, probe- and telematics-based datasets offer a promising solution for a number of potential local applications. However, as demonstrated through a variety of research applications, GPS and telematics data provide the richest information for many applications when time and location information are available in "bread-crumb" format rather than pre-aggregated in time and space, and when the data include specific vehicle, engine, and operator-identifying information. In practice, available GPS datasets typically either represent a small sample from one or a few operators, or are obtained from commercial providers in pre-aggregated form, often limiting access to characteristics specific to individual vehicles.

Infrastructure-based sensors offer some potential to address probe-data gaps, as they can be used to capture information from all passing vehicles. With recent advances in AI, technologies including WIM, inductive loop sensors, and LIDAR can capture fine-grained vehicle classifications and, in the case of WIM, information about vehicle loads. However, due to installation expenses and maintenance needs, to date these technologies have rarely been applied in local settings; most applications have been on highways, where traffic operations are less complex and where images and sensors are less likely to be occluded by surrounding activity. Further research is needed to assess performance in urban settings.

7.2 Remaining Gaps and Limitations

Although sensor-based data sources offer significant potential to enhance data for local applications, a few persistent challenges still limit direct applicability of these existing data sources for many freight-related decisions.

7.2.1 Granularity

As demonstrated by the wide variety of desired granularities identified in the NYC case study (see *Section 6.1.5*), as well as in the research and practical applications, local freight data is most useful when it can be aggregated in time and space at different scales. However, data are rarely available at small granularities, but are more typically available in pre-aggregated formats from government or commercial data sources. The primary reason that data are typically aggregated is to protect the privacy of individual stakeholders, including shippers, operators, and receivers. Data may be aggregated in time, in space, or by vehicle, engine, or commodity type. Aggregation of data according to these variables can limit its usefulness for many applications.

7.2.2 Scarcity

Available data also are typically not representative of the full vehicle population. On-vehicle sensor data is often directly obtained from only one or a few individual operators, resulting in data scarcity. Commercially-available probe- and telematics-based datasets contain richer data from many operators, but the representativeness of even these vehicle samples remain difficult to assess and validate, and the data made available to customers is typically in an aggregated format. For some applications such as traffic performance measurement (e.g. speed, travel time reliability), representativeness of the sample may not be critical, but when data are applied for applications such as travel or parking demand estimation or estimating vehicle or engine characteristics, it is important that either (1) the sample is representative or that (2) the missing components of the population can be identified. Limited infrastructure-based sensors also provide rich data, but provide sparse network coverage.

7.2.3 Cost and Access

While the reviews conducted as part of this study did not directly explore the specific costs of available datasets, heavy reliance on publicly-available datasets such as the FAF and NPMRDS at the state and regional levels is notable. While NYC DOT, a very large agency that manages streets in the nation's largest city, had access to a variety of commercially available data sources at the time of this analysis, this level of access is not typical among smaller, less well-resourced agencies.

8. MACHINE LEARNING AND GENERATIVE AI APPROACHES TO ADDRESS DATA LIMITATIONS

The emergence of synthetic data generation offers a potential solution to persistent local freight data gaps. As discussed in the preceding chapters, real-world freight data is often restricted due to privacy concerns, limited in its representativeness (Nie et al., 2025; Chang et al., 2025), and expensive to acquire. Synthetic data, artificially generated through algorithms rather than traditional data collection, replicates the statistical properties of real-world datasets while addressing privacy, scarcity, and cost challenges (Nie et al., 2025; Li et al., 2025). Leveraging advanced algorithms, researchers can now replicate truck tours, delivery patterns, and vehicle behaviors with high fidelity (Guo et al., 2025; Fouladvand et al., 2024). Generative models, particularly those based on deep learning frameworks like Generative Adversarial Networks (GANs) can enable the simulation of freight operations under multiple policy scenarios even when real data is missing or restricted. These capabilities have been extensively reviewed in the context of urban mobility systems, where synthetic data generation is critical for privacy preservation, scalability, and robustness of machine learning applications (Fouladvand et al., 2024). This review explores methods of generating synthetic data, their specific applicability to freight transport, and ways in which they practically address freight data gaps.

8.1 Synthetic Data Generation: Methods and Frameworks

Synthetic data generation has been widely studied for enhancing decision-making across domains. In freight transportation and logistics, the evolution from traditional statistical methods to advanced machine learning and generative AI (ML/GenAI) approaches has improved the accuracy, scalability, and applicability of predictive modeling and synthetic data generation. Multiple studies demonstrate the use of ML techniques, such as ensemble learning, deep recurrent neural networks (RNNs), clustering, regression models, and diffusion models, to address challenges like predicting critical time intervals, generating synthetic mobility data, creating urban freight consolidation zones, predicting stop delivery times, and forecasting truck parking occupancy. The following sections detail these emerging frameworks and the advancements that they offer compared to traditional approaches.

8.1.1 Historic Frameworks Used in Freight

Historically, freight forecasting and data synthesis have relied on statistical and rule-based models. Gravity models and linear regression have been widely used to estimate freight flows and demand between regions, based on spatial and economic variables (Metaxatos, 2014). These models are interpretable and require less data, but they struggle to capture non-linear relationships and dynamic changes in freight patterns. Iterative Proportional Fitting (IPF) has been used to disaggregate aggregate data (e.g., census or survey) into synthetic OD matrices for simulation, but lacked the ability to reflect real-time or high-frequency variation (Metaxatos, 2014). Singular Spectrum Analysis (SSA) decomposes time series into trend, seasonal, and noise components and has been applied to rail freight forecasting. However, it is less effective in capturing complex, non-linear, or abrupt changes in freight traffic (Milenković et al., 2024**)**. Classical time series ARIMA (Autoregressive Integrated Moving Average) models have been regularly applied for forecasting freight volumes and travel times, providing good performance for stationary, linear time series but are limited in their ability to process and learn from the vast, high-dimensional, and often unstructured datasets now available (Milenković et al., 2024**)**. Furthermore, moving beyond these traditional constraints, for instance, to address the privacy risks associated with sensitive logistics movement data, Niu et al. (2024) proposed the Kernel Density Estimation (KDE) based framework to securely publish spatiotemporal trajectory data by integrating KDE with differential privacy. The framework generates synthetic datasets that preserve the original density distribution and trajectory diversity while preventing the deduction of private individual location patterns. This approach ensures that both trajectory paths and count values remain protected, providing a high-utility solution for analyzing complex movement patterns without exposing sensitive operational details.

8.1.2 Advanced Generative Models in Transportation

In recent years, several types of advanced generative models have been applied for transportation applications.

8.1.2.1 Generative Adversarial Networks

Generative Adversarial Networks (GANs) have been widely explored for synthetic data generation. GANs are generative models built from two neural networks that are trained together: a generator that tries to create realistic synthetic samples (for example, trips or trajectories) and a discriminator that learns to distinguish real data from generated data. Goodfellow et al. (2014) introduced GANs to address inherent difficulties of deep generative models associated with probabilistic computations in training. The training of GANs involves a dynamic process where the generator and discriminator improve through competition. Initially, the generator produces data that is easily distinguishable from the real dataset. However, as training progresses, the generator improves its ability to create data similar to the real ones, while the discriminator becomes better at telling real from fake. This process continues until the generator produces data indistinguishable from authentic data, at which point the Generative Adversarial Network GAN is considered to have converged. Arjovsky et al. (2017) introduced the Wasserstein GAN (WGAN), which addressed the limitations of traditional GANs by stabilizing the training process and improving the quality of generated data. Choi et al. (2021) proposed TrajGAIL, a novel generative modeling framework designed to produce realistic urban vehicle trajectories. The author utilizes the Generative Adversarial Network (GAN) architecture as a foundational framework by formulating vehicle movement as a partially observable Markov decision process. This approach effectively handles both data sparsity and driver privacy concerns inherent in urban vehicle trajectory datasets.

8.1.2.2 Diffusion Models

Diffusion Models have also been applied to transportation applications for their ability to match data distribution by learning to reverse a gradual, multi-step noising process. The process begins with a forward stage that adds Gaussian noise to data at each timestep until it becomes nearly unrecognizable noise. The model then employs a neural network to learn the reverse distribution, effectively cleaning up noisy signals into realistic trajectories. This enables the generation of rich, diverse scenarios for freight truck movements. Yang et al. (2023) conducted a comprehensive survey of diffusion models, identifying their capacity for high-fidelity data synthesis and their evolving application in temporal data modeling which focuses on time-series data imputation and forecasting methods, and the framework for generating synthetic freight trajectories while preserving stakeholder privacy. Nichol and Dhariwal (2021) improved denoising diffusion probabilistic models by learning the variances of the reverse process, which allows for high-quality data generation and offers new directions for the practical modeling of transportation systems. Albrecht et al. (2024) used Generative Adversarial Networks (GANs) and Variational Auto Encoders (VAEs) to generate synthetic carsharing trip data and then evaluated their usefulness with a Train-Synthetic-Test-Real (TSTR) setup, where a prediction model is trained only on synthetic trips and evaluated on real trips. Adding synthetic data improved trip prediction accuracy by about 4.63% compared with a model trained and tested on real data alone.

8.1.2.3 Petri Nets

Petri Nets have also been applied for transportation modeling. Petri nets also known as a place/transition net (PT net) are a graphical and mathematical language for modeling systems where events such as vehicle movements from one state (for example moving) to another (for example idle) occur at discrete points in time. They represent the system using places, transitions, and tokens that move through the network to capture state change, interactions, and control logic. Colored Petri nets extend this idea by attaching attributes to tokens, so that different vehicle types, routes, or control states can be represented within the same model. Fu and Chen (2018) proposed a macroscopic traffic modeling framework for heterogeneous road networks using colored Petri nets. This approach enables the representation and simulation of diverse vehicle types, road segments, and traffic dynamics within a unified mathematical model.

8.1.3 Advanced Generative Models in Other Domains

Advanced generative models have also been applied in other domains, demonstrating the potential for different applications in freight transportation. In finance, Ranja et al. (2023) employed Time-GAN and XGBoost models to predict ATM cash requirements, demonstrating the utility of synthetic data for time-series prediction. In telecommunications, Pandey et al. (2023) validated synthetic data to evaluate Mobile Edge Computing performance within 5G networks. The authors address the scarcity of real-world datasets by using a Generative Adversarial Network (GAN) enhanced with bidirectional Long Short-term Memory (LSTM) layers. In insurance, Rusdah and Murfi (2020) demonstrated the effectiveness of XGBoost in addressing missing values in life insurance risk prediction. Their approach highlights the robustness of gradient-boosted decision trees in handling incomplete datasets while maintaining predictive accuracy.

8.1.4 Predictions in Transportation Using Machine Learning Techniques

Machine learning approaches, including ensemble learning, deep neural networks, and hybrid models, are specifically designed to leverage large-scale data, extracting patterns and insights that were previously inaccessible (Li and Bai, 2016; Valatsos et al., 2022). Given that real freight transportation data often suffers from privacy concerns, sparsity, and proprietary restrictions, hindering high-resolution analysis **(**NASEM, 2011d; NASEM, 2013c**)**, synthetic data generation plays a crucial role in enabling these advanced ML techniques. It provides the necessary volume and diversity of data, allowing models to be robustly trained and validated even when access to real-world datasets is limited or sensitive (Gülmez et al., 2025; Yang et al., 2025). The following are some specific freight applications:

- **Route and Travel Time Prediction:** Valatsos et al. (2022) used ensemble learning (Random Forest, Gradient Boosting, XGBoost) to accurately predict critical time intervals for international freight shipments, outperforming traditional models by leveraging route-level and real-time data. Li and Bai (2016) demonstrated that Gradient Boosting Regression Trees (GBRT) provided high-accuracy travel time predictions for freight vehicles, outperforming conventional regression approaches, especially when using large trajectory datasets. The development and validation of such predictive models, especially when real-world trajectory datasets are sensitive or incomplete, can be significantly supported and enabled by high-fidelity synthetic mobility data (Yang et al., 2025; Gülmez et al., 2025), which allows for the comprehensive training and testing of these models across diverse scenarios without compromising privacy.
- **Urban Freight and Parking Management:** In urban contexts, synthetic data plays a critical role in enabling effective ML applications for freight management and parking systems, particularly by addressing privacy and data scarcity concerns. For instance, Berke et al. (2022) explicitly highlighted the use of privacy-preserving synthetic datasets generated by deep recurrent neural networks to overcome data access limitations, allowing for robust model training and validation in urban freight and parking management. Similarly, Ouadi et al. (2020) and Errousso et al. (2020) used machine learning for optimizing freight management and urban parking systems. Gutmann et al. (2021) combined XGBoost and LSTM to predict truck parking occupancy.

8.1.5 Integration and Policy Implications

For Pinjari et al. (2014), integration is characterized by the fusion of large streams of truck GPS data provided by ATRI with existing transportation datasets to create a comprehensive picture of freight movement. These efforts are integrated directly into the Florida Statewide Model (FLSWM) to validate and calibrate its freight components. The corresponding policy and planning implications are significant: the research revealed that car-centric tools like Google Maps systematically underestimate truck travel times, highlighting the need for accurate, truck-specific planning parameters for reliable forecasting. Additionally, the integrated data enables policymakers to rank highway bottlenecks using a "freight congestion index" to prioritize infrastructure funding, analyze truck re-routing patterns for disaster and incident management, and assess the need for future freight corridors based on actual routing patterns between major hubs. Wang and Yan (2023) highlight the integration of prescriptive analytics combining descriptive, predictive, and operations research to optimize freight transportation decisions, such as truck route planning and last-mile delivery, by leveraging machine learning to predict variables like travel time and driver behavior. This data-driven approach provides a foundation for policymaking by emphasizing the necessity for robust data collection, storage protocols, and the establishment of information-sharing platforms to enable joint optimizations across intermodal networks. Furthermore, the authors address a fundamental challenge where policy restrictions or confidentiality agreements often hide the actual costs of alternative decisions, arguing that overcoming this validation hurdle is crucial for encouraging stakeholders to adopt integrated models that enhance strategic competitiveness and network efficiency.

8.2 Applications of Synthetic Data in Freight Transportation

Synthetic data has been implemented in the freight domain for two primary purposes: model training and validation, scenario analysis, and data sharing. The following sections summarize experience for these applications.

8.2.1 Synthetic Data for Model Training and Validation

ML and synthetic data approaches have been employed for model training and validation, especially when real-world data is limited, incomplete, or privacy-sensitive. Berke et al. (2022) employed deep recurrent neural networks to generate privacy-preserving synthetic mobility data. These synthetic datasets enable robust model training and validation for transportation modeling, even when access to real data is restricted. Hughes et al. (2019) evaluated lasso regression, ridge regression, elastic net, naive Bayes, logistic regression, and neural networks for predicting stop delivery times from GPS data. Their work demonstrates how ML models, trained and validated on large operational datasets, can improve delivery efficiency and support dynamic scheduling. Li and Bai (2016) used Gradient Boosting Regression Trees (GBRT) to predict freight vehicle travel times, leveraging real trajectory data for both pre-start and post-start predictions. Ludowieg et al. (2023) developed ML models to predict freight vehicle demand for urban loading zones, using historical and contextual data to validate operational strategies for curbside management.

8.2.2 Synthetic Data for Scenario Analysis

Machine learning and synthetic data generation have also enabled advanced simulation and scenario testing in freight transportation, allowing practitioners to evaluate operational strategies and infrastructure planning. Examples of scenario analysis applications include:

- **City Logistic Planning:** Ouadi et al. (2020) proposed a hybrid ML framework combining clustering (k-means, k-medoids) with Support Vector Machines (SVM) and Decision Trees to create urban zones for freight consolidation. This approach allows simulation of different zoning policies and their impact on logistics efficiency, supporting scenario-based planning for city logistics. Nie et al. (2025) developed a transferable, graph-based spatiotemporal learning model (IMPEL) leveraging large language models (LLMs) for joint estimation and prediction of city-wide delivery demand. Their framework enables scenario testing across multiple cities, and is adaptable across urban contexts.
- **Truck Parking Occupancy:** Gutmann et al. (2021) used a fusion of XGBoost and LSTM to simulate truck parking occupancy under different demand scenarios, providing actionable insights for dynamic parking management and policy testing.
- **Vessel Flow Simulation:** Li et al. (2025) introduced the MPTNSR model, which fuses CNN-

BiLSTM and Graph Convolutional Network (GCN) architectures to simulate and predict vessel traffic flows. This enables port authorities to test various operational scenarios (e.g., congestion management, berth allocation) with high accuracy and computational efficiency.

8.3 Key Benefits of Synthetic Data

Synthetic data offers a potential mechanism to overcome some of the key challenges that restrict the use of freight data for local decision-making, including privacy, scarcity, and cost. The following sections detail the potential benefits of synthetic data to address these specific challenges.

8.3.1 Privacy

Private-sector data is often proprietary and challenging to obtain because of confidentiality concerns (NASEM, 2007). Since real freight data (truck fleet GPS data) often includes sensitive business intelligence such as client locations, routing strategies, vehicle identification numbers (VINS) and delivery schedules, synthetic alternatives offer a privacy-preserving method for analysis and model training without exposing proprietary operations (Pinjari et al. 2014). Much of the critical freight data is held by private companies and is not publicly available for municipal or regional planning (Guo et al., 2025).

Synthetic data offers a solution for the creation of realistic datasets that can be shared and analyzed without compromising sensitive information (Yang et al., 2025; Gülmez et al., 2025). This capability is especially important for enabling cross-agency collaboration, model benchmarking, and policy experimentation in environments where traditional data sharing is constrained. Privacy-preserving synthetic data generation ensures adherence to privacy laws when analyzing sensitive freight patterns. Techniques like latent space sampling and differential privacy allow agencies to share datasets with researchers or neighboring municipalities without exposing carrier-specific routes or customer locations. This is critical for regional initiatives where collaboration requires strict data anonymization (Berke et al., 2022; Yang et al., 2023). Berke et al. (2022) demonstrated that deep RNNs can generate synthetic mobility datasets that preserve the statistical properties of real data while protecting individual privacy. This allows organizations to share and analyze data without exposing sensitive information. Nie et al. (2025) highlighted the importance of transferable ML models that can generalize across cities and datasets, reducing the need for direct data sharing and enabling knowledge transfer without compromising privacy. Yang et al. (2023) reviewed diffusion models for generative data synthesis, noting their potential for creating high-fidelity synthetic datasets that can be shared and used for scenario testing, model development, and benchmarking without privacy risks.

8.3.2 Scarcity

The privacy concerns, proprietary limitations, and spatial aggregation issues that constrain the availability of granular freight data directly hinder efforts to build robust, localized models for urban delivery systems, route optimization, emissions forecasting, and infrastructure planning (Chang et al., 2025; Li et al., 2025; Nie et al., 2025). As agencies seek high-resolution data for real-time decision-making and policy evaluation, synthetic data offers an opportunity to overcome data scarcity challenges. Synthetic data can support model development and validation when real data is sparse or incomplete (Guo et al., 2025; Li et al., 2025).

Synthetic data generated via machine learning and generative models such as GANs, VAEs, and diffusion models not only replicates real-world freight behaviors with high fidelity but also facilitates the simulation of various policy interventions without compromising sensitive business operations (Guo et al., 2025; Gülmez et al., 2025). The ability to generate realistic synthetic freight data could enable evaluation of policy proposals such as those detailed in *Section 6.10*. For example, synthetic datasets can simulate truck routes under different scenarios, allowing cities to quantify impacts on vehicle miles traveled (VMT), air pollution, and curb management before implementing costly infrastructure changes (Valatsos et al., 2022; Ouadi et al., 2020; Nie et al., 2025) Generative AI allows testing novel logistics strategies in a risk-free environment.

Cities can experiment with cargo bike networks, off-hour delivery incentives, or AI-driven traffic management systems using synthetic data that mirrors real-world complexity. This can accelerate the adoption of alternative distribution strategies (Yang et al., 2023; Li et al., 2025; Gutmann et al., 2021).

8.3.3 Cost

Real-world datasets often represent only small, limited samples of data, which limits their utility (Berke et al., 2022). Synthetic data systems can take these limited statistics and generate mobility traces for a much larger synthetic population, effectively "upscaling" data without the expense of gathering more real-world records (Nie et al., 2025; Li et al., 2025). It can improve the cost effectiveness of freight and urban mobility analysis by reducing both data collection and data access expenses. Simulated data is often the only feasible option when real data is unavailable, too expensive, or time-consuming to collect (Yaiprasert and Hidayanto, 2024). Real-world freight data is frequently restricted due to high acquisition costs, making synthetic alternatives a more accessible solution for local planning and operational decision-making (Nie et al., 2025). Deep learning systems that produce synthetic mobility trajectories for realistic populations further support cost effectiveness by allowing agencies and researchers to share high-utility mobility datasets while protecting individual privacy, which reduces legal, organizational and technical costs associated with negotiating access to raw location traces and implementing complex anonymization pipelines (Berke et al., 2022).

8.3.4 Fusion

Beyond addressing privacy and scarcity, the core value of generative approaches lies in their ability to infer the underlying probability distributions of freight movements from the data sources having data gaps and sample realistic truck paths from those distributions. No single freight dataset, whether GPS traces, traffic counts, or establishment surveys is sufficient on its own to capture the full complexity of urban truck operations. Machine learning-based simulation provides a principled way to fuse these heterogeneous data sources: generative models learn the statistical regularities across available datasets and encode them into a flexible, probabilistic representation of freight activity. Synthetic truck paths can then be drawn from this learned distribution, conditioned on the available data, to produce an ensemble of plausible freight scenarios rather than a single deterministic outcome. This flexibility is critical for policy analysis. Because the simulation framework produces paths sampled from a conditional distribution rather than fixed replays of observed data, it enables the estimation of performance measures such as total vehicle-miles traveled, parking demand, idling time, start/stop event frequency, and expected emissions exposure within a particular zone (e.g., a TAZ) that no individual dataset could support alone. Analysts can modify the conditioning inputs (e.g., restricting access to certain zones or shifting activity to a micro-hub) and re-sample paths to quantify how freight patterns and their associated impacts shift under alternative policy scenarios (Davis et al., 2024; de Bok et al., 2024). Here, the generative model is not only useful for data synthesis, but also as a tool for scenario analysis. It proposes solution paths conditioned on policy assumptions, from which decision-relevant metrics can be derived and compared.

8.4 Remaining Challenges

While emerging frameworks offer significant benefits in terms of scalability, privacy, and predictive accuracy, ongoing challenges remain in ensuring data realism, transferability, and validation, particularly as applications expand to more complex scenarios. The continued development and refinement of these frameworks will be essential for supporting data-driven decision-making. Ensuring that synthetic datasets accurately reflect the complexity and diversity of real-world freight operations is a persistent challenge. Current limitations include ensuring the realism and transferability of synthetic data. Nie et al., (2025) highlighted the difficulty of generalizing predictive models across different cities and operational contexts, as even advanced graph-based spatiotemporal learning models can struggle with transferability when local conditions change. Ouadi et al. (2020) show that clustering and hybrid ML frameworks are useful for reorganizing logistics in a local context, but capturing the full diversity of behaviors and spatial patterns in synthetic data remains a challenge, particularly for cities with heterogeneous land use and delivery patterns. As Valatsos et al. (2022) note, increasing model complexity can hinder stakeholder trust and operational adoption, raising the need for explainable AI in logistics. Milenković et al. (2024) found that even hybrid ARIMA-LSTM models underpredict freight volumes during rare events (e.g., Black Friday surges), with errors of 15–20%. This underscores the difficulty of capturing rare, high-impact events in synthetic datasets. Ouadi et al. (2020) and Li et al. (2025) have noted that with the rapid evolution of logistics trends and intervention over time, there will be a need to integrate behavioral, policy, and technological changes into synthetic data frameworks in order to capture and simulate the impacts of these.

9. CONCLUSION

As demonstrated by needs detailed in Chapters 6 and 7 and the applications detailed in Chapter 8, the integration of synthetic data generation and machine learning offers transformative potential for local freight transportation planning and policy evaluation. Deep neural networks have revolutionized urban transportation modeling by enabling high-resolution prediction, real-time decision-making, and behavioral analysis across transportation applications. Generative Adversarial Networks (GANs), Variational Autoencoders (VAEs), and Diffusion Models have become standard for synthesizing urban mobility data (Guo et al., 2025; Gülmez et al., 2025. Yang et al., 2023). These modeling techniques are effective for creating synthetic trip trajectories and for generating high-fidelity spatiotemporal datasets. Beyond probabilistic machine learning, Petri nets provide a mathematically rigorous framework for simulating and verifying complex transportation logic (Fu and Chen, 2018). Specifically, they enforce strict state-based rules; for example, a 'Transition' (such as a truck starting to load) cannot occur unless a specific 'Place' (the loading zone) is marked as available.

While numerous studies have employed these advanced approaches for general traffic and public transportation modeling, few have investigated potential freight-specific applications. Current freight modeling often relies on traditional methods or static clustering (Ouadi et al., 2020) rather than dynamic generative synthesis. Milenković et al. (2024) noted that even hybrid models (ARIMA-LSTM) struggle to capture the volatility of freight demand (e.g., rare events), and Guo et al. (2025) emphasized the need for generative frameworks capable of replicating complex truck tours and delivery patterns.

Our analysis identifies machine learning and generative AI techniques as viable solutions to address persistent freight data limitations of privacy, scarcity, and cost. Generative AI approaches enable the creation of synthetic datasets and synthetic trajectories that are statistically similar to real-world freight data while protecting sensitive operational information. These approaches can enable the fine-grained analytical requirements of local freight planning. Future research should evaluate different generative AI approaches for various specific applications, including:

- Generative adversarial networks (GANs) and variational autoencoders (VAEs) for feature-specific refinement (Guo et al., 2025; Gülmez et al., 2025);
- Diffusion models for improved spatiotemporal fidelity (Yang et al., 2023);
- Kernel density estimation (KDE) for probabilistic realism (Niu et al., 2024); and
- Petri nets for logical verification of multi-stop tour constraints (Fu and Chen, 2018).

Synthetic datasets can also be informed by the fusion of disparate sources, resulting in variable-rich data, such as comprehensive trip trajectories, useful for complex scenario analysis. Synthetic data generation also enables the creation of rare event scenarios that are poorly represented in historical records but critical for robust policy evaluation. Planners can simulate freight management scenarios using synthetic trip trajectories to verify behavioral outcomes before implementation, reducing uncertainty and supporting evidence-based decision-making

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APPENDIX A. PRACTICAL REPORTS REVIEWED

Agency	Year	Title
State Freight Plans		
Arizona Department of Transportation	2019	Arizona Truck Parking Study
Arkansas Department of Transportation	2022	Arkansas State Freight Plan
California Department of Transportation	2023	California Freight Mobility Plan 2023
Colorado Department of Transportation	2024	Colorado Freight Plan 2024
Connecticut Department of Transportation	2022	Connecticut Statewide Freight Plan Update
Delaware Department of Transportation	2022	Delaware State Freight Plan
Florida Department of Transportation	2024	Florida Freight Mobility and Trade Plan
Georgia Department of Transportation	2023	Georgia Freight Plan
Hawaii Department of Transportation	2023	Hawaii Statewide Freight Plan
Idaho Transportation Department	2023	2023 Strategic Freight Plan
Illinois Department of Transportation	2023	Illinois 2023 State Freight Plan
Indiana Department of Transportation	2023	Indiana Multimodal Freight and Mobility Plan
Iowa Department of Transportation	2023	Iowa State Freight Plan
Kansas Department of Transportation	2023	Kansas State Freight Plan
Kentucky Transportation Cabinet	2022	Kentucky Freight Plan
Louisiana Department of Transportation and Development	2024	Louisiana State Freight Plan
Maine Department of Transportation	2023	Maine Integrated Freight Strategy
Maryland Department of Transportation	2022	Maryland State Freight Plan
Massachusetts Department of Transportation	2023	Massachusetts Freight Plan
Michigan Department of Transportation	2021	Michigan Mobility 2045
Minnesota Department of Transportation	2024	Minnesota State Freight Plan
Mississippi Department of Transportation	2022	Mississippi Statewide Freight Plan
Missouri Department of Transportation	2022	Missouri State Freight and Rail Plan
Montana Department of Transportation	2022	Montana State Freight Plan
Nebraska Department of Transportation	2023	2023 Nebraska State Freight Plan
Nevada Department of Transportation	2022	Nevada Freight Plan Update
New Hampshire Department of Transportation	2019	New Hampshire Statewide Freight Plan
New Jersey Department of Transportation	2023	New Jersey Statewide Freight Plan
New Mexico Department of Transportation	2023	New Mexico 2045 Freight Plan Update
New York State Department of Transportation	2024	New York State Freight Plan
North Carolina Department of Transportation	2023	North Carolina Statewide Multimodal Freight Plan
North Dakota Department of Transportation	2023	North Dakota State Freight and Rail Plan
Ohio Department of Transportation	2023	Ohio State Freight Plan
Oklahoma Department of Transportation	2023	Oklahoma Freight Transportation Plan
Oregon Department of Transportation	2023	Oregon Freight Plan
Pennsylvania Department of Transportation	2023	Pennsylvania 2045 Freight Movement Plan
Rhode Island Department of Transportation	2022	2022 Freight and Goods Movement Plan
South Carolina Department of Transportation	2022	South Carolina Statewide Freight Plan Update
South Dakota Department of Transportation	2022	South Dakota Freight Plan
Tennessee Department of Transportation	2023	Tennessee Statewide Multimodal Freight Plan
Texas Department of Transportation	2023	Texas Delivers 2050
Utah Department of Transportation	2023	Utah Freight Plan 2023 Update
Vermont Agency of Transportation	2022	Vermont Freight Plan
Virginia Department of Transportation	2022	VTRans: Virginia’s Transportation Plan
Washington State Department of Transportation	2022	Washington State Freight System Plan

Washington State Department of Transportation	2023	Washington State Freight and Goods Transportation System Update
West Virginia Department of Transportation	2023	West Virginia State Freight Plan
Wisconsin Department of Transportation	2023	Wisconsin State Freight Plan
Wyoming Department of Transportation	2022	Statewide Freight Assessment
Metropolitan Planning Organization Plans and Reports		
Atlanta Regional Commission	2024	2024 Atlanta Regional Freight Mobility Plan Report
Charlotte Regional Transportation Planning Organization	2014	2040 Metropolitan Transportation Plan (Chapter 17: Freight)
Chicago Metropolitan Agency for Planning	2022	CMAP Strategic Direction
Delaware Valley Regional Planning Commission	2024	Freight Futures
Denver Regional Council of Governments	2024	Regional Multimodal Freight Plan
East-West Gateway Council of Governments, Missouri Department of Transportation, and Illinois Department of Transportation	2013	St. Louis Regional Freight Study
Houston-Galveston Area Council	2023	2023 Regional Goods Movement Plan
Los Angeles County Metropolitan Transportation Authority	2021	LA County Goods Movement Strategic Plan
Maricopa Association of Governments	2017	MAG Regional Freight Transportation Plan
MetroPlan Orlando, FDOT District Five, Lake-Sumter MPO, Space Coast TPO, and River to Sea TPO	2013	Central Florida Regional Freight Mobility Study
Metropolitan Council	2023	Urban Freight Distribution Study: E-Commerce Trends and Implications for Regional Planning
Metropolitan Transportation Commission	2016	San Franciso Bay Area Goods Movement Plan
Metropolitan Washington Council of Governments	2023	National Capital Region Freight Plan
Miami-Dade Transportation Planning Organization	2024	Freight Plan Update 2024
New Jersey Transportation Planning Authority	2020	2050 Freight Industry Level Forecasts Study Final Report
New York Metropolitan Transportation Council	2017	Plan 2045: Maintaining the Vision for a Sustainable Region Appendix 8, Regional Freight Plan 2018-2045
North Central Texas Council of Governments	2022	Freight North Texas 2022: A Freight Mobility Plan
Puget Sound Regional Council	2018	The Regional Transportation Plan – 2018 (Appendix J- Regional Freight and Goods Movement)
San Diego Association of Governments	2024	San Diego and Imperial Counties Sustainable Freight Implementation Strategy
Southeast Michigan Council of Governments	2012	Southeast Michigan Freight and Economic Analysis
Southern California Association of Governments	2022	Southern California Delivers the Goods
Southern California Association of Governments	2022	Curb Space Management Study
Municipal Agency Plans and Reports		
District of Columbia Department of Transportation	2023	District Freight Plan Update
City of Chicago	2021	Strategic Plan for Transportation
City of Dallas	2021	Connect Dallas: Strategic Mobility Plan

City of Minneapolis	2020	Transportation Action Plan
City of New York	2023	PlaNYC: Getting Sustainability Done
City of Portland Bureau of Transportation	2022	2040 Freight: Demographics, Equity, and Environmental Justice – Part 1
City of Portland Bureau of Transportation	2023	2040 Freight Plan
City of Portland Office of Transportation	2008	Designing for Truck Movements and Other Large Vehicles in Portland
City of Seattle	2016	Seattle Freight Master Plan
New York City Department of Transportation	2021	Delivering New York: A Smart Truck Management Plan for New York City
New York City Department of Transportation and New York City Economic Development Corporation	2021	Delivering Green: A Vision for a Sustainable Freight Network Serving New York City
Workshop Circulars		
Transportation Research Board (Rapporteur: Hancock)	2017	Transportation Research Circular E-C255: Innovations in Freight Data, 2017 Workshop
Transportation Research Board (Rapporteur: Hancock)	2019	Transportation Research Circular E-C255: Innovations in Freight Data, 2019 Workshop
Transportation Research Board (Rapporteur: Lawson)	2019	Transportation Research Circular E-C263: Conference on Performance and Data in Transportation Decision Making
Transportation Research Board (Rapporteur: Hancock)	2021	Transportation Research Circular E-C278: Innovations in Freight Data, 2021 Workshop
Transportation Research Board (Rapporteur: Conway)	2021	Transportation Research Circular E-C275: Measuring and Managing Freight System Resilience Workshop
Transportation Research Board (Rapporteur: Gick)	2023	Transportation Research Circular E-C288: Innovations in Freight Data, 2023 Workshop