Aggregation Errors in Life-Cycle Greenhouse Gas Assessments of Heavy-duty Trucks and Buses

by

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Abstract

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Heavy-duty trucks and buses represent one of the largest sources of greenhouse gas (GHG) emissions in the United States, yet the degree to which the GHG intensity of these vehicles varies is poorly understood. This dissertation improves the accuracy of GHG emission factors for heavy-duty trucks and buses by accounting for how these vehicles are utilized given the characteristics within infrastructure networks, and it provides details on how previous emissions inventories change in response to masking these features. The work focuses on the sensitivity of GHG emission factors to vehicle speed, vehicle productivity, and infrastructure topology.

To assess the influence of vehicle speed on GHG emission factor variability, we analyze the realtime activities of heavy-duty trucks on highways as well as buses in nine transit agencies across California. As expected, the results our case studies indicate that expected GHG emission rates are higher for vehicles operating within cities than along highways. For buses, the inclusion speed-corrected emission factors could improve the accuracy of previous emission inventories for transit agencies by upwards of 62%. In contrast, speed-corrected emission factors only marginally improve emission inventories for heavy-duty trucks across the state (<5% improvement). These findings suggest that speed-resolved emission factors should be used for transit buses, while a more narrow range of GHG emission factors for heavy-duty trucks could suffice.

Next, we assess the influence of variable vehicle loading factors (trucks: payloads, buses: passenger ridership) on GHG emission factor for heavy-duty trucks and buses. We present two case studies which examine (i) the fleet of heavy-duty vehicles in the United States and (ii) the performance of single bus network in the city of San Francisco. In each case study, we rely on highly resolved vehicle productivity data. Our results uncover systematic errors associated with assuming an average vehicle loading factors when estimating the GHG emission factors for heavy-duty vehicles. When this is the case, we show that emission factor estimation biases, described by Jensen's inequality, always result in larger-than-expected

environmental impacts (3% - 400%) and depend strongly on the variability and skew of truck payloads and bus ridership.

Lastly, we examine the influence of network topology (e.g., how individual portions of an infrastructure network's constituent parts are interrelated or arranged) on GHG emission factors for heavy-duty trucks participating in intermodal activities in the United States. To understand this relationship, we built a national truck and rail logistics model that quantifies the GHG emissions from freight shipments between counties. Using this model, we find that both network topology and GHG emission factors for heavy-duty trucks and intermodal rail differ across commodity types. These two factors in combination cause the GHG reductions associated with shifting freight shipments from trucks ($\approx$ 120 g $CO_{2,e}$ per ton-km) to rail ($\approx$ 20 g $CO_{2,e}$ per ton-km) to vary across the United States. As a proof of concept for the application of this model, we identify the counties with the greatest potential to reduce GHG emissions by switching freight shipments from truck to intermodal rail for two commodity types: meat/seafood and paper articles.

Collectively, this work advances the scientific community's understanding of how GHG emissions from heavy-duty vehicles vary on more resolved spatial and temporal scales, thereby improving decision-making on a case-by-case basis. Future work on this topic should be directed to integrating these findings into broader emissions mitigation decision tools and also considering other important environmental impacts.

To Molly

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List of Abbreviations

$CO_{2,e}$	carbon dioxide equivalents
GHG	greenhouse gas
km	kilometer
kph	kilometer per hour
LCA	life-cycle assessment
MJ	megajoule
mmt	million metric tons
pass	passenger
pass-km	passenger-kilometer
pkm	passenger-kilometer
ton	metric ton or 1,000 kg
ton-km	metric ton-kilometer
tkm	metric ton-kilometer
VKT	vehicle kilometers travelled
W2W	well-to-wheels

Glossary

Accessibility - The potential of opportunities for interaction about a point, given a discrete spatial limit or impedance over a distance.

Composite data - Data from the same operation or activity combined across locations.

Data aggregation - The process of transforming a range of data points into one measure of central tendency to represent the group as a whole.

Discrete scale - The decision-making scale for an individual vehicle and/or vehicle trip.

Emission factor - The ratio of pollutant emissions to the functional unit of activity.

Generic data - Data whose representativeness may be unknown but which are qualitatively descriptive of a process or technology.

Heavy-duty vehicle - A broad class of vehicles whose gross vehicle weight exceeds 3.85 metric tons in the federal jurisdiction and above 6.35 metric tons in California (model year 1995 and later).

Infrastructure topology - The manner in which individual portions of an infrastructure network's constituent parts are interrelated or arranged.

Intermodal rail - A type of freight transport that involves the combination of train and short truck trips to and from the rail network.

Level of specificity - The degree in the individual details of a product or system are described, considered, and/or modeled.

Loading factor - A term used in transportation life-cycle assessments to represent the ratio of goods or passengers on board a vehicle to the maximum allowable limit by mass or volume.

Local scale - The decision-making scale for a group of vehicles about a particular location (e.g., encompasses both a city and route specific perspective).

Regional scale - The decision-making scale for a complete fleet of vehicles within a larger geopolitical area (e.g., country, state).

Truck drayage - The short truck trips required to move goods between intermodal terminals, warehouses, or other destinations.

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Chapter 1

Introduction

1.1 Motivation and Goals

The demand for heavy-duty trucks and buses (i.e., heavy-duty vehicles[1]) is expected to increase in the coming decades across the United States [1, 2]. This has many implications for the nation's greenhouse gas (GHG) emissions. The U.S. Energy Information Administration estimates that heavy-duty vehicles consumes 2.8 million barrels of oil equivalents per day, and over the next 35 years this rate will increase by 12% [1]. This growth will occur even in light of new fuel economy regulations on heavy-duty trucks and buses [3]. By 2050, heavy duty vehicles will emit 670 mmt $CO_{2,e}$ per year and represent 38 percent of all on-road GHG emissions (10% increase in share since 2010) [1].

The forecasted increases in GHGs by heavy-duty trucks and buses suggest three major underlying trends in the future. First, the demand for these vehicles will outpace improvements in the average fuel efficiency under business-as-usual conditions, leading to an increase in GHG emissions. Second, the U.S. Environmental Protection Agency (EPA) and National Highway Traffic Safety Administration (NHTSA) projects that GHG emissions from heavy-duty vehicles will surpass passenger cars by 2030 [3, 4]. Thus, heavy-duty vehicles will remain a key area for consideration and policy focus for GHG abatement strategies in the decades to come. Lastly, if improvements to engine fuel economy can only reduce GHGs to a certain level, more comprehensive abatement strategies will be needed in the future. Addressing these future impacts on the global climate requires a full life-cycle approach.

Life-cycle assessments (LCA) aid the decision-making process by comparing the environmental footprint of competing abatement strategies on common terms and considering all stages of a product or system's life cycle: from extraction of raw materials through their production, distribution, and use phases until their disposal [5, 6]. Each assessment is carried out in the context of an intended goal and study scope [5], which is defined at the onset of the study. The comprehensive environmental assessment of competing GHG abatement

[1]Freight trucks make up the majority of vehicles in this category in terms of vehicle kilometers driven annually [1], although buses (e.g., transit, commuter, school, etc.) also fall under this distinction.

strategies, with scopes encompassing all of the direct and indirect processes relating to the system(s)-of-interest, is often data and time intensive. Costs of the study grow as the resolution of the study (i.e., level of specificity or aggregation level) increases, adding both complexity and data management challenges [7].

Within transportation policy, LCAs have been used to evaluate specific transport modes [8, 9, 10, 11, 12, 13], compare the impacts of different vehicle technologies [14, 15, 16, 11], perform cost-benefit analyses [17, 18], assess alternative fuel pathways [19, 20, 21, 22, 23], and evaluate other policies relating to the management of transportation networks and their supporting infrastructure systems [10, 24, 25, 26]. Life-cycle emissions factors for heavy-duty vehicles found in the literature [17, 27, 28, 8, 21, 10, 20, 19, 29] and within prominent LCA models [30, 31, 32] regularly reflect a generic or industry-average perspective, i.e., each model input constitutes generic or composite data for a global or regional context. (see, [33, 34]). This model formulation is intuitive since this scope is the decision-making level at which this sector is primarily regulated (e.g., countries and states). However, by maintaining a generic or industry-average focus, the results of LCAs on heavy-duty trucks and buses often lack the specificity to properly characterize the performance of the individual vehicles, which could lead to suboptimal GHG mitigation strategies at decision-making scales.

By collapsing over many individual vehicles to establish a formal emission factor, we believe that this aggregation process may restrict the explanatory power of the LCA model for individual cases by removing within-group information that may be useful for policy-making. This information includes knowledge of specific trip attributes (location, road type, time of day, etc.), vehicle attributes (gross weight vehicle rating, payload, and ridership), driving conditions (levels of congestion), and characteristics of their respective supporting infrastructure systems (location of critical infrastructure and route topology). While there are many angles which to approach this thesis, the scope of this research is limited to the study of emissions estimation errors and/or biases caused by variability in fuel economy due to vehicle speed[2], vehicle productivity (e.g., loading factor, tons delivered, passenger ridership, etc.), and infrastructure topology (e.g., how individual portions of an infrastructure network's constituent parts are interrelated or arranged).

The goals of this thesis are (i) to create more accurate heavy-duty truck and bus emission factors by increasing the dimensionality of the operational component of the LCA model, (ii) to understand how GHG emission factors vary based on how a vehicle is utilized given the characteristics within infrastructure networks, and (iii) to ultimately reduce uncertainty in LCAs of heavy-duty vehicles by identifying and correcting systematic biases in forming LCA emission factors.

The remainder of this chapter provides an overview of the current methodologies for conducting a LCA of transportation vehicles (*LCA Fundamentals*, Section 1.2), which serves as the context for the methodological components of this paper, followed by a review of literature frequently referenced in this thesis (*Review of Frequently Cited Literature*, Section 1.3). The chapter concludes with a review of the questions comprising the basis of this thesis.

[2]Vehicle speed and, by proxy, vehicle acceleration.

1.2 LCA Fundamentals

LCA provides a framework for evaluating energy use, emissions and wastes associated with direct, indirect, and supply chain processes in systems. The approach is composed of life-cycle inventorying (LCI), which quantifies the energy use, emissions, and generated waste of an activity (e.g., MJ or g per kilometer), life-cycle impact assessment (LCIA), which captures the environmental or human health impacts from the LCI (e.g., climate change, eutrophication, acidification, disability adjusted life years), and an interpretation phase [5]. The interpretation phase serves as a feedback loop so that once the LCI and LCIA have been completed, they are re-evaluated to reduce uncertainty and implement improvements to processes.

The interconnections between the many sectors of the economy are complex and practically infinite. The circular nature of these connections (e.g., the steel that is used to make trucks is shipped by trucks to the truck assembly plant) could lead to double counting of emissions, truncation errors from scope reduction, and other issues regarding emission allocation. Hence, there are methods to systematically help decision-makers construct consistent, thorough, and replicable LCAs. The three types of LCAs used in freight transportation LCAs are process-based LCA, economic input-output analysis-based LCA, and a hybrid LCA approach.

1.2.1 Process-Based LCA

Process-based LCA is a method for characterizing the life-cycle inventory of a product or system based on evaluating each segment of the direct process of interest as well as each supporting sub-process in the supply chain. The benefit of this approach is that it answers specific questions about processes (e.g., in a factory), specific product analyses (e.g., by brand, model year), product comparisons, and analyses in a geographic area, year, etc. An example application of process-based LCAs in freight transportation is the treatment of emissions during a vehicle's operation. During this phase, the environmental and human health indicators of interest are evaluated by quantifying the amount of fuel consumed by the vehicle (input) and measuring the amount of emissions resulting from its combustion (output). A shortfall of process-based LCAs is that they can be time and data intensive, which could make the costs of performing a full LCA increase [6].

1.2.2 Economic Input-Output Analysis-Based LCA

Economic input-output analysis-based LCA (EIO-LCA) utilizes the U.S. economy's input-output matrix to comprehensively map the interactions between economic sectors and define product and service supply chains [35]. These economic data are combined with publicly available environmental data (e.g., resource consumption and environmental emission and waste data) to produce supply-chain inventories associated with a product or service. The benefit of this approach is that produces national averages that are representative of any place in the US when economy-wide studies needed quickly and relatively cheaply. The approach is also effective at minimizing truncation assignment errors associated with selecting the boundaries of large and complicated systems. EIO-LCA has been used to estimate the emissions associated with vehicle maintenance and manufacturing within heavy-duty truck LCAs [28, 8, 10]. A major shortfall of EIO-LCA is that the model aggregates multiple commodities and industries at the level of economic sectors, so the resulting energy and emissions results may not reflect specific processes or capture economies of scale.

1.2.3 Hybrid LCA

Hybrid LCAs combine the benefits of process-based LCA and economic input-output analysis-based LCA (EIO-LCA), drawing from the strengths of both methods while curtailing their weaknesses. Hybrid LCA calls for process-based LCA to be used in evaluating the specific life-cycle components, and when sub-processes match economic sectors, the EIO-LCA approach can be used to capture the full upstream supply chain effects [35, 6]. The hybrid LCA approach has been used in several studies producing sometimes unexpected results in supply chains that may not have been unraveled with pure process-based LCA [28, 8, 10].

1.2.4 LCA Applied to Heavy-duty Vehicles

The use of any LCA approach requires selection of a system boundary and establishment of functional units to normalize results. There are five major life cycle stages or components that stand out as major contributors to the emissions footprint of a heavy-duty truck and bus. The first two life components characterize the well-to-wheels (W2W) processes (associated with fuel production, distribution, and storage) and the combustion of fuel. Other, non-use phase, emissions associated the operation of a heavy-duty vehicle include emissions from vehicle and trailer manufacturing and vehicle maintenance. The fifth component of a heavy-duty vehicles's life cycle is the emissions generated from the construction and maintenance of infrastructure systems (roads, weigh stations, bus stops, etc.) that support on-road goods movement. End-of-life emissions have been estimated as being less than 1 percent of the total emissions footprint of a heavy-duty vehicle [28, 8, 10], so this life phase is frequently omitted from truck and bus analyses.

The functional unit of comparison used to characterize the emissions generated by the freight industry is the ton-km (tkm) and by public transportation is the passenger-kilometer (pkm). This approach facilitates intermodal comparisons because it describes the efficiency in which goods or people are moved through infrastructure networks on a unit basis. In general, the total emissions footprint of a set of goods or passengers, i, measured in grams per functional unit, is [28, 8, 10]:

$$e_{f,T} = \sum_{i=1}^{n} \frac{I_i}{A} E_i \tag{1.1}$$

where,

$e_{f,T}$ = Emission factor for good or passenger (pollutant per functional unit)
n = Total number of components
I_i = Input (e.g., energy, USD)
E_i = Emission intensity of each input (g CO2-eq / I_i units)
A = Vehicle activity (ton-km or passenger-km)

1.3 Review of Frequently Cited Literature

The following section provides a detailed review of literature relevant to assessing the life-cycle GHG emission factors of heavy-duty vehicles. In order to distinguish the publications relating to a life-cycle perspective from studies focusing strictly on a narrower point of scope, we state the system boundaries for each respective study. The goal of sharing this literature prior to introducing each study in the following chapters is to orient the reader to the use of average input data in transportation LCA studies and models during a period in which other researchers noted the limitations of such approach. The studies herein are listed in chronological order.

Cohen et al. (2003)[17]

System Boundaries: Fuel extraction, production and distribution, and vehicle operation.

Summary:

The goal of this study is to assess the cost effectiveness of reducing criteria pollutants and greenhouse gases within transit bus fleets. Estimates for the well-to-wheel (W2W) emissions for conventional diesel and compressed natural gas (CNG) vehicles are based on dynamometer measurements for three specific engines models rather than fleet averages. While the study's primary focus is on costs, the authors' results show that bus operation GHG emissions represent the majority (>70%) of the W2W emission profile for both diesel and CNG-powered buses.

Silva et al. (2006)[36]

System Boundaries: Fuel extraction, production and distribution, and vehicle operation.

Summary:

The authors developed a numerical model to simulate fuel consumption and emissions for diesel-powered and alternatively fueled road vehicles. The model estimates engine loads using a resistive force mathematical program, which inputs include vehicle mass, speed, acceleration, and vehicle-specific properties (e.g., frontal area, rolling resistance, etc.). The authors couple their well-to-tank emission estimates with well-to-pump fuel emission estimates from conventional LCA software in a case study of transit buses operating in the city of Porto, Portugal. While the results capture the variability in CO2 emissions of urban transit buses, the results of the case study are based on standardized duty-cycles rather than location-specific simulations. Nonetheless, this is the earliest example of route-oriented W2W vehicle assessments. The methodologies in this paper have been implemented in the review of fuel pathways for light-duty modes (Torchio and Santarelli 2010,Ferreira, Ribau, and Silva 2011), however its application within heavy-duty vehicle fleets is limited to this study.

Facanha and Horvath (2007)[8]

System Boundaries: Fuel extraction, production and distribution, vehicle production, vehicle maintenance, vehicle operation, and infrastructure.

Summary:

The authors analyzed the life-cycle emission factors for air, rail, and road transportation of freight goods in the United States. The emission factors are based on an input-output analysis and process based modeling (e.g., hybrid LCA). Vehicle productivity and fuel consumption inputs are based on national averages. The carbon footprint of class 2b, class 6, and class 8 heavy-duty vehicles only includes carbon dioxide. The emission factors for these modes are 289 g CO2/ton-mi, 230 g CO2/ ton-mi, and 187 g CO2/ ton-mi, respectively. A parameter sensitivity analysis was performed to assess the influences of vehicle type, geography, and mode efficiency on the results. This research?s most relevant findings to this discussion are (i) well-to-wheel processes represent the bulk (80%) of the CO2 footprint of heavy-duty vehicles and (ii) CO2 emission factors therefore sensitive to small changes in fuel economy. With 39 citations, this paper the most cited LCA for freight emission factors on Web of Science and is still used as a reference in studies (8 citations between 2014-2015).

Pont (2007)[37]

System Boundaries: Fuel extraction, production and distribution, and vehicle operation.

Summary:

This report, which was commissioned by the California Energy Commission, performs a comprehensive analysis of well-to-wheel emission factors for a broad spectrum of road vehicles, including heavy-duty trucks and buses. Input put parameters, such as vehicle fuel economy, ridership, etc., are based on both national and state fleet averages. W2W emission factors are reported over ranges to represent the uncertainty in the results, which are primarily caused by variability in vehicle fuel economy. The most significant contribution of this report is it provides W2W emission factor estimates for many fuel types, which facilitates mode-specific emissions comparisons.

Ally and Prior (2007)[21]

System Boundaries: Fuel extraction, production and distribution, vehicle production, vehicle maintenance, and vehicle operation.

Summary:

The authors analyze the life-cycle emission factors of buses powered by diesel, CNG, and hydrogen fuel cell using a hybrid LCA modeling framework. The scope of the study is limited to fuel pathways found in Australia and the results are based on average emission rates for each vehicle technology. One of the major findings, in light of the purpose of this review, is that the life-cycle emissions footprint of transit buses is significantly dependent on vehicle fuel economy, which may vary widely on a route basis.

Chester and Horvath (2009)[10]

System Boundaries: Fuel extraction, production and distribution, vehicle production, vehicle maintenance, vehicle operation, and infrastructure.

Summary:

This research provides a broad comparison of life-cycle emission factors for passenger vehicles operating in the United State of America, which includes urban diesel buses. The authors find that the operational component of nearly all vehicles represents the dominant contribution to their respective life-cycle GHG footprint. Results from a sensitivity analysis also show that the normalized GHG emission factors for urban diesel buses are extremely sensitive to assumption of passenger occupancy (50 g $CO_{2,e}$ / pkm, high ridership; 410 g $CO_{2,e}$ / pkm, low ridership). The authors base these values on a US fleet-average estimate of vehicle fuel economy. This paper is one of the most cited studies on the life-cycle footprint of passenger vehicles on Web of Science (54 citations) and is still used as a reference in studies analyzing the GHG emissions of urban transit systems (6 studies on urban bus networks and 19 total citations between 2014-2015).

CA-GREET (2009)[38]

System Boundaries: Fuel extraction, production and distribution, and vehicle operation.

Summary:

CA-GREET is a life-cycle emissions model for fuels that was contracted by the California Energy Commission specifically for fuels used within the state. The model is the primary policy analysis tool used to assess scenarios relating to California?s Low Carbon Fuel Standard. The CA-GREET model does not include pathways for heavy-duty vehicles. However, the well-to-wheel emissions tool bases life-cycle emission factors on average fuel economy estimates for the light-duty vehicles it models (e.g., cars, electric plug-in vehicles, etc.). Fuel pathways include conventional petroleum-derived products, biofuels, and gaseous fuels.

Sathaye et al. (2010)[24]

System Boundaries: Vehicle operation and infrastructure rehabilitation.

Summary:

The authors estimate the GHG emissions associated with varying the interval between pavement overlays based on vehicle weights and vehicle mileage. The case studies for this research focus on a select number of interstate highways and arterial roads in northern California. The methods presented in this paper demonstrate the relationship between payload size, axle configuration, and the resulting infrastructure-related GHG emissions: GHG emissions grow by a fourth order relative to truck payload. While Facanha and Horvath (2007) estimate that infrastructure maintenance emissions represent the approximately 10% of the total CO2 footprint class 8 truck, the results from this assessment indicate that this value is much smaller.

Meyer et al. (2011)[20]

System Boundaries: Fuel extraction, production and distribution, and vehicle operation.

Summary:

The authors estimate the well-to-wheel emission factors for class-8 heavy-duty trucks powered by diesel, biofuels, and natural gas and operated in the United States. The implemented model assumes an average payload and fuel for each respective fuel, which is reflective of national fleets. The article states, "It is noted that, in practice, fuel consumption is a function of truck payload, just as fuel consumption is a function of driver behavior, speed, terrain, and other factors. Furthermore, the persistence of a legacy fleet or variabilities in engine design, technology, and performance can affect energy consumption and emissions. In this analysis, the relationship between these factors and fuel consumption is constrained to reduce uncertainty; the purpose of this analysis is not to capture all of these effects, but to compare emissions across a spectrum of fuels." Overall, the paper advances our understanding of the average emissions savings associated with adopting alternatively fueled vehicles. Other than uncertainties regarding data availability and accuracy, the major limitation of this paper is the application of these emission factors on a route-level, given the use of average input parameters.

GREET Fleet(2012)[39]

System Boundaries: Fuel extraction, production and distribution, and vehicle operation.

Summary:

The GREET Fleet - Carbon and Petroleum Footprint Calculator is a Microsoft Excel model produced by researchers at Argonne National Laboratory that calculates well-to-wheel petroleum use and GHG emissions. This tool is exclusively for modeling medium and heavy-duty vehicles, including buses, operating in the United States. For each mode and fuel type, GREET Fleet provides baseline estimates for annual miles travelled, average fuel economy, and vehicle loading factors (e.g., tons and passengers). Well-to-pump emissions are based on estimates from the more compressive GREET model [30], which like CA-GREET [38], only reports fuel pathways for light-duty vehicles. Fuel pathways include conventional petroleum-derived products, biofuels, and gaseous fuels.

McKenzie and Durango-Cohen (2012)[19]

System Boundaries: Fuel extraction, production and distribution, vehicle production, vehicle maintenance, and vehicle operation.

Summary:

This study analyzes the marginal abatement costs of switching from diesel-powered transit buses to two potential low-carbon alternatives: diesel hybrid and CNG transit buses. Life-cycle emission factors for each mode were estimated using a hybrid LCA method. Well-to-tank emissions were based on various values estimated in the literature, including Pont (2007) and Chester and Horvath (2009). Vehicle fuel economy for each vehicle types is based on specific transit bus demonstrations in New York City andAlameda County, California. While previous studies report a single central estimate for life-cycle emission factors, the authors publish their findings over a range of values that reflect variability in key parameters - most notably passenger ridership. In a parameter sensitivity analysis of passenger demand, the authors find that, "emissions for each bus type is highly dependent on the [passenger]-load factor, as well as the capacity of the bus. At low [passenger]-load factors, the per [passenger]-mile emissions are greatest for the diesel bus, however the higher capacity of this bus means that it has the lowest per [passenger]-mile emissions at higher load factors." The authors do not relate increased passenger loads with increased emissions, however. Overall, the researches show that vehicle loading factors influence the cost-effectiveness of vehicle mode-switching or technology adoption policies.

Xu et al. (2013)[40]

System Boundaries: Fuel extraction, production and distribution, and vehicle operation.

Summary:

The authors of this study compare the well-to-wheel emissions footprint (including GHGs) for five transit bus vehicle technologies, conventional compression ignition, parallel hybrid electric, series hybrid electric, battery electric and fuel-cell electric, in combination with three fuel types, diesel, compressed natural gas (CNG), and 20% biodiesel. Each vehicle's fuel consumption was based on power requirements estimated through combining in-field measurements of the vehicles speed, acceleration, and road grade with power-dependent emission rates provided in the US EPA's MOtor Vehicle Emissions Simulator (MOVES) model. The case study is limited to only a few vehicle trips monitored in Atlanta, Georgia. The results of their study show the GHG savings achieved from switching from conventional (e.g., diesel) to low-carbon (e.x., CNG) vehicle technologies is "highly dependent upon the route characteristics." This study illustrates the advantages of coupling route-based emissions models with regionally-based fuel models in order to improve the accuracy of life-cycle emission factors. While the study offers new methods and tools to evaluate individual heavy-duty vehicles, it does not address the issue of how these results could improve decisions regarding the management of vehicle fleets where collecting 'real-time' operational data isn't possible.

NEAT: Non-Light Duty Energy and GHG Emissions Accounting Tool (2014)[32]

System Boundaries: Fuel extraction, production and distribution, and vehicle operation.

Summary:

Argonne National Laboratory's Non-Light Duty Energy and GHG Emissions Accounting Tool (NEAT) allows analyst's to estimate the well-to-wheel energy usage of every major freight mode in the United States. The model delineates each mode based on commodity classes listed in the U.S. Census Bureau's Commodity Flow Survey. Vehicle input parameters are based on a 2002 survey of freight vehicles. Well-to-wheel energy estimates are based on the GREET model. The model currently ignores all other environmental indicators, such as GHG emissions and criteria air pollutants. In the model, heavy-duty vehicles are represented as a single class: class 8 trucks. Medium-heavy duty vehicles are not included in the tool.

CA-GREET (2015)[38]

System Boundaries: Fuel extraction, production and distribution, and vehicle operation.

Summary:

The 2015 version of the CA-GREET tool is identical in structure and scope as the 2009 version. While the tool does not review heavy-duty vehicle fuel pathways, it does include additional fuel types, which are considered "next-generation fuels (cellulosic alcohols, hydrogen, drop-in fuels, etc.) or first-generation fuels produced using innovative production processes."

Matute and Chester (2015)[18]

System Boundaries: Fuel extraction, production and distribution, vehicle production, vehicle maintenance, vehicle operation, and infrastructure.

Summary:

The authors examine the energy and GHG emissions payback period, e.g., the period of time required to recoup the environmental burdens expended during infrastructure construction, for select urban transit projects in the city of Los Angeles. Bus rapid transit (BRT) was one of the modes considered. Life-cycle emission factors for BRT are based on the "best available technology buses today (effectively a 23% improvement from today's buses [in the United States])." The studies results indicate that buses with greater vehicle loading factors (e.g., higher ridership) have shorter payback periods, since the GHG emission savings from switching to BRT from automobiles are greater when buses are fuller (e.g., lower normalized emissions footprint). The biggest limitation of this paper is it assumes that BRT fuel consumption rates are a constant across the network and therefore GHG emissions are linearly proportional to vehicle distance travelled.

Tong et al. (2015)[29]

System Boundaries: Fuel extraction, production and distribution, and vehicle operation.

Summary:

The authors in this recent study aim to estimate the well-to-wheel emission factors for medium and heavy-duty trucks and buses for natural gas fuels. Other conventional fuel pathways (diesel and gasoline) are also analyzed. The results for each vehicle mode were based on Monte Carlo analysis to account for the variability and uncertainties associated with each fuel pathway. This paper shows both the strengths and the potential weaknesses of LCAs of heavy-duty vehicles. The strengths include providing decision-makers with information useful for comparing the climate footprint of heavy-duty vehicles. However, given issues of data availability and uncertainty, these values represent only what can be expected across vehicle fleets on average. The authors note that one of the paper's biggest limitations is its "inability to consider real-world conditions in actual operations of [heavy-duty vehicles], especially the drive cycles (e.g., speed, idling, road grade) and payload profiles." They follow with an optimistic view of the future in which "vehicle tests and innovative method to factor duty cycles onto assessments of vehicle [life-cycle] emissions" are available to further refine the scope of these types of fuel pathway assessments.

1.4 Problem Statement and Questions

By 2050, heavy-duty trucks and buses are forecasted to represent 38 percent of all on-road GHG emissions in the United States (10% increase in share since 2010). This trend in growth is expected to continue into the next century [1]. We need comprehensive strategies to allocate the emissions from these vehicles to specific commodities and passengers, accounting for all direct and indirect processes associated with their complete life cycle of vehicles, fuels, and infrastructure. During the policy selection process, life-cycle assessments inform decision-makers (e.g., fleet owners, regulators, etc.) by quantifying all relevant GHG or other emissions from the extraction of raw materials for these vehicles through their production, distribution, and use phases until ultimately their disposal. While comprehensive, the results of LCAs are subject to both uncertainty and variability, especially for dynamic systems like heavy-duty vehicles, which increases the risk of selecting suboptimal environmental mitigation strategies.

This dissertation aims to improve the accuracy of LCAs of heavy-duty vehicles and the decisions they inform by addressing the following questions:

- **As of 2015, what are the fleet-scale GHG emission factors for heavy-duty trucks and buses?**
  - With California as a focus, we seek to provide individual well-to-wheel GHG emission factors for heavy-duty vehicles based on (i) the state's designated vehicle categories, (ii) gross vehicle weight rating (truck only), and (iii) commodity type for trucks.
- **To what extent can GHG emission factors and inventories derived from a generic LCA model be applied to individual trucks and buses?**
  - We seek to present new knowledge on the uncertainties surrounding the use of generic data, specifically generic fuel economy, vehicle productivity, and infrastructure topology data, in the generation of GHG emission inventories for heavy-duty vehicles.

  - We seek to conduct original case studies on (i) trucks monitored in the Caltrans Performance Measurement System, (ii) real-time operations of buses in nine public transit agencies in California, (iii) each classification of trucks operating in California, and (iv) intermodal truck activities across the United States.
  - We seek to provide policy directives that guide LCA modelers as to when it is appropriate to use generic, fleet-scale GHG emission factors to calculate the carbon footprint of heavy-duty vehicles and when more precise emission factors are needed.

- **Are there systematic biases associate with the use of average productivity data (e.g., freight tonnage and bus ridership) in fleet-scale LCAs?**
  - We seek to evaluate the relationship between the variability and skew of truck payload and bus ridership distributions on the expected results of LCA models.

- **Does the interrelation or arrangement of a freight system's constituent parts (i.e., topology) affect the environmental footprint of goods movement?**
  - We seek to understand how the proximity to critical supply chain infrastructure, e.g., intermodal terminals, affects environmental performance of trucks and intermodal rail.
  - We seek to improve our understanding of the GHG footprint of intermodal freight systems by providing county-to-county GHG footprints for each county in the U.S.
  - We seek to analyze this effect across commodity types and its influence on consumers' accessibility to goods from an environmental perspective.

1.5 Organization

The rest of the chapters are organized as follows.

Chapter 2 presents a study that estimates the aggregation errors in terms of percent deviation from the average, associated with assuming a fleet-wide fuel economy in LCA models of heavy-duty vehicles. We assess these errors across regional, local, and discrete level of specificity (i.e., aggregation level) for trucks operating along highways and buses operating in 9 different public transit agencies in California.

Chapter 3 presents a study that quantifies the GHG emissions bias associated with assuming a fleet-wide loading factor (i.e., payloads and ridership) in LCA models of heavy-duty vehicles. We assess these biases for all truck classes operating in California, considering the vehicle size and configuration (i.e., body and trailer types). We also conduct a case study for San Francisco's MUNI bus network. This chapter is based on our study published in *Environmental Science & Technology*[41].

Chapter 4 presents a study that assesses the GHG emissions errors associated with ignoring network topology (e.g., geometric and spatial properties of the infrastructure) in LCA models of heavy-duty freight trucks. In contrast to Chapters 2 and 3, this chapter primarily focuses on these formulation of GHG emission inventories rather than solely emission factors. We analyze how the GHG reduction potentials associated with switching from truck to rail (e.g., modal switch) differ across different product supply chains and between specific locations across the United States. This chapter is based on our study published in *Environmental Science & Technology* [42].

Finally, in Chapter 5, we conclude with an overview of the work presented, its implications on environmental decision-making, and directions for future research.

Chapter 2

Aggregation Errors in LCAs of Heavy-Duty Vehicles: Speed Variability

2.1 Introduction

Spatial and temporal variability of greenhouse gas (GHG) emission factors for heavy-duty vehicles is primarily determined by variability in fuel economy. A recent study by Taptich et al. (2015) found that over 95% of life-cycle GHG footprint of a heavy-duty trucks and buses results from the extraction, production, distribution, and combustion of transportation fuels (i.e., well-to-wheel processes, W2W)[13]. The same is true for other environmental impacts [8, 19, 20]. The allocation of these emissions is based on the rate at which fuel is consumed by a vehicle and the process-specific energy-to-emissions conversion factors [8]. Other supply-chain processes, such as vehicle production, maintenance, end of life, and infrastructure support, contribute less to the overall variability of life-cycle emissions factors for heavy-duty vehicles because their total impacts are amortized over the lifetime of the vehicle [8]. Given the significant proportion of GHG emissions tied to the well-to-wheel processes, fuel economy variability is an important driver for overall life-cycle impact variability.

The well-to-wheel emission factors for heavy-duty vehicles found in the literature [17, 27, 28, 8, 21, 10, 20, 19, 29] and within prominent LCA databases [30, 31, 32, 38, 39] reflect a generic or industry-average perspective, i.e., each model input constitutes generic or composite data for a global or regional context. For instance, Argonne National Laboratory's *GREET Fleet - Carbon and Petroleum Footprint Calculator* (2012) (one of the aforementioned tools) allows heavy-duty truck and bus owners to evaluate the energy usage and GHGs emissions of their fleet based on one central estimate for fuel economy among other inputs, e.g., payload and annual vehicle kilometers traveled. The process of using mean input values to predict the mean values of outcomes is called aggregation. Data aggregation is one way to reduce the dimensionality of LCAs (i.e., the number of random variables under consideration), which is often essential for reducing the complexity of LCAs for a general audience or group of decision-makers [43]. Moreover, aggregating fuel economy data is akin to stating that the marginal influence of vehicle attributes such as vehicle speed, acceleration, and mass, have no significant relation to the overall decision-making process (i.e., life-cycle footprint). While fuel economy variability is often encapsulated in sensitivity analysis [8, 20, 19, 29], the results of LCAs of heavy-duty trucks and buses often lack the specificity to properly characterize the performance of the individual vehicles [17, 27, 28, 8, 21, 10, 20, 19, 29].

Though route-oriented emissions assessments exist, their methodologies have not been broadly integrated within LCA models such as the *Greenhouse Gases, Regulated Emissions, and Energy Use in Transportation Model (GREET)* [30] or the *Ecoinvent Database* [31]. Vehicle traveling speed [44, 45, 46, 47, 48, 49, 50], terrain [51, 40, 52], vehicle payload [53], driver behavior [54], road conditions [55, 24], among other factors [56, 36] all have an impact on fuel economy and subsequently tailpipe emissions. These variations are amplified when well-to-pump emissions are also considered, which are linearly scaled with fuel consumption rates (g $CO_{2,e}$ / MJ) [30, 38]. Each of these factors is important for understanding how fuel economy is influenced by discrete-scale vehicle activities.

Uncertainties relating to data aggregation are a reasonably well-researched topic in the field of life-cycle assessment [7, 6, 57]. However, there is an emerging need to understand how aggregation bias affects the accuracy of transportation-specific LCAs [58]. It is important for decision-makers, i.e., those using life-cycle emission factors, to know the extent to which generic or aggregated emission factors apply. Bridging this analytical gap may allow the decision-makers to more efficiently and accurately answer important questions, such as, "are drayage trucks traveling within urban networks causing more GHG emissions than line-haul trucks," "does increasing truck payloads or bus ridership always improve the life-cycle GHG footprint," or "are the benefits from introducing alternatively-fueled trucks or buses uniform across the country?"

The focus of this chapter is to evaluate whether it is appropriate to use generic well-to-wheel emission factors under different levels of specificity or aggregation. Broadly, there are four major decision-makers interested in knowing and reducing the GHG footprint of heavy-duty vehicles: governments, fleet owners, and individual firms or people employing their services. LCA practitioners rely on life-cycle GHG emissions factors for heavy-duty vehicles to calculate the overall emissions from other products and systems. The utility each stakeholder gains by knowing the carbon intensity of heavy-duty vehicles varies, which influences the way decisions are made and policies are formed. For example, governments may want a fleet of heavy-duty trucks and buses to reduce GHG emissions, while a company may be only interested in vehicles that they utilize. The optimal decision in the former case may be different than the latter, but both are not currently equipped with the appropriate tools to make the correct assessment. In this chapter, we select three levels of specificity in which we assess aggregation bias: a regional scale that is closely associated with the geographic scope of most available, generic, or industry-average data, a local scale that encompasses both city- and route-specific perspectives, and a discrete scale that reflects the scale of individual vehicle trips.

To summarize, the main goal of this analysis is to compare the explanatory power of aggregate emission factor models on more spatially and temporally resolved scales (e.g., sub-regional, city, etc.), so we perform a quantitative evaluation of aggregation bias resulting from the use of fleet-wide average fuel economy data. Based on a careful review of openly available data on heavy-duty vehicle transportation systems and transportation emissions models, we chose to only analyze the effect speed variability has on emission factor aggregation errors, though other driving conditions (e.g., vehicle acceleration, road grade) are also important contributors to emissions variability and should be explored in the future. In doing so, this analysis aims to contribute insights into LCA model formulation as well as the appropriate use of secondary data in LCA models. A secondary goal is to highlight underutilized yet publicly available data sources that could be integrated into current LCA models.

2.1.1 Scope of Case Studies and Chapter Organization

California serves as the basis for the following case studies. In California, always at the forefront of transportation policies, there have been recent attempts that piece wise aim to reduce the well-to-wheel emissions footprint of on-road vehicles. Efforts include incentivizing fuel-efficient vehicles [59, 60], setting a carbon-intensity limit on fuels sold within the state [61], advancing tailpipe emissions standards [62], and others state bills directly addressing climate change [63]. An important aspect of regulating the well-to-wheel emissions is establishing methods to monitor the well-to-wheel footprint of vehicles currently on the road, especially within a temporal and spatial context, and use such information to better inform local policy.

The chapter is partitioned into four sections: (i) a background and further motivation section to provide a review of literature and to establish the geographic setting (California) for the case studies; (ii) a methods section which defines in detail the decision-making scales analyzed in this study, formalizes both heavy-duty truck and bus emission factors, and presents the basis for our selection of representative vehicles; (iii) a case study of heavy-duty trucks operating along highways in California; and, (iv) a case study of heavy-duty buses operating within 9 transit agencies in California. We conclude the chapter with a summary of the chapter's findings, then a discussion of the results, and their impact on the life-cycle emission factor formulation and selection process for heavy-duty vehicles.

2.2 Methods

2.2.1 Decision-Making Scales

In this study, decision-making scales include (i) a regional scale, where vehicles are modeled as fleet-wide averages, (ii) a local scale, which represents a small subsample of the larger fleet,

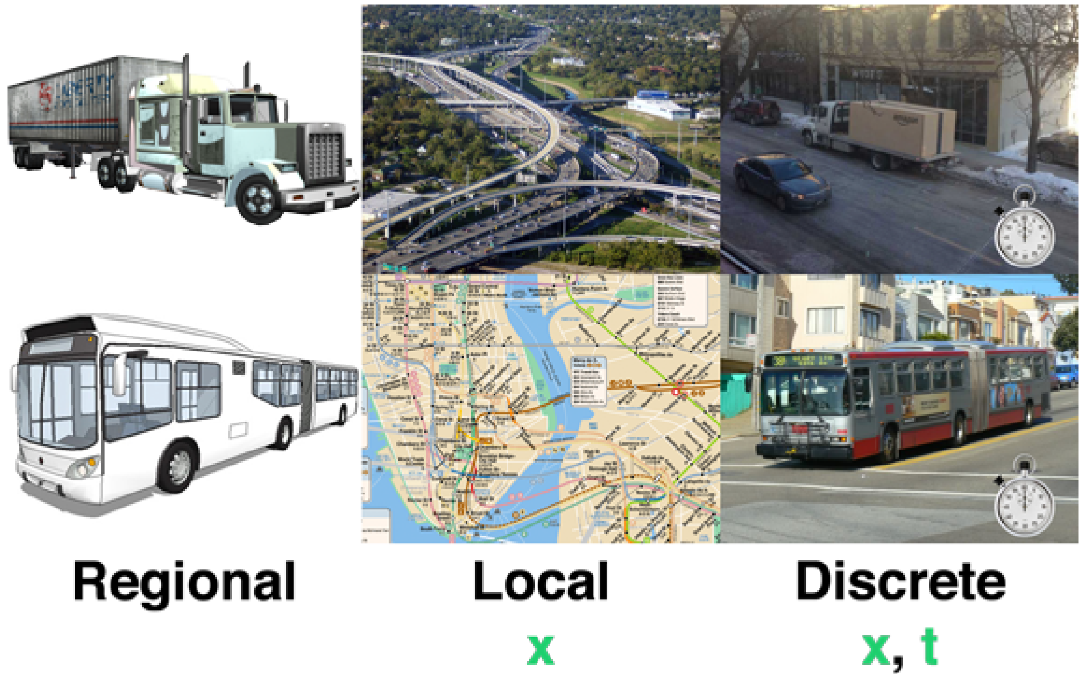


Figure 2.1: The different scales at which environmental assessments of heavy-duty vehicles are characterized. Vehicles in regional assessments are represented in abstract as a generic or fleet averaged vehicle. Vehicles in local assessments are characterized by a small subsample of a larger fleet. These vehicles are classified as being within geopolitical boundaries (e.g., cities, zones) or along specific routes. Vehicles in discrete assessments are characterized on a trip-by-trip basis.

and (iii) a discrete scale, which represents the movement of vehicles on a trip-by-trip basis (Figure 2.1). For each of the levels of specificity, Figure 2.1 indicates whether additional geographic (x) or temporal (t) information is available to differentiate a heavy-duty vehicle from the rest of the fleet. The common assumption across the regional and local levels of specificity is that obtaining information at more resolved scales might be costly, but not prohibitively. That is, information may exist, but the modeler may opt to use fleet-wide averages and trade off some amount of uncertainty. The goal of the case studies is to assess the uncertainties in these decision pathways and guide modelers to the correct emission factors at each scale.

2.2.2 Emission Factor Formulation

The scenarios presented evaluate whether fleet-average estimates of truck and bus emission factors are appropriate for modeling the GHG emissions footprint of vehicles at a local (e.g., district, city, agency) and discrete (e.g., route, bus line) resolution. To simplify the problem,we analyze the extent to which speed variability [44, 45, 46, 47, 48, 49, 50] contributes to emission-factor aggregation bias at each of these decision-making levels, though other driving conditions and vehicle attributes could also be explored [51, 40, 52, 53, 54, 55, 24, 56, 36]. Given the significant shares (>95%) of emissions relating to the production, distribution, and ultimate combustion of transportation fuels [13], we limit the scope of the assessment to only these system processes, ignoring GHG emissions from vehicle production, maintenance, infrastructure, and end-of-life [8, 24].

Formally, we first restructure the current well-to-wheel impact equations (Eq. 2.1) to account for this, now endogenous variable by amending the pump-to-wheel energy consumption rate (Eq. 2.2):

$$E_{f,avg} = E_{MJ,avg} \times (\pi + \gamma) \tag{2.1}$$

$$E_{f,s} = E_{MJ}(V) \times (\pi + \gamma) \tag{2.2}$$

where,

$E_{f,avg}$: Well-to-wheels emissions rate (g pollutant /km), fleet average
$E_{MJ,avg}$: Pump-to-wheel energy consumption rate (MJ/km), fleet average
$E_{f,s}$: Well-to-wheels emissions rate (g pollutant /km) as a function of speed, V
$E_{MJ}(V)$: Pump-to-wheel energy consumption rate (MJ/km) as a function of speed, V
π: Tank-to-Wheels emissions rate (g pollutant /MJ)
γ : Well-to-pump emissions rate (g pollutant /MJ)

Tailpipe or tank-to-wheels emission rates for GHGs were modeled using the California Air Resources Board (CARB) EMFAC 2011 model [50]. The EPA's MObile Vehicle Emission Software (MOVES) model [48], among other models used in the literature [3, 36, 56, 52], could have also been used in this assessment. EMFAC was designed specifically to model the emissions from Californian vehicle fleets and the model results for CO_2 emissions from heavy-duty vehicles are comparable to those found in MOVES [64, 48]. For these reasons, we rely only on this model for the assessment. CARB models heavy-duty emission rates across varying speeds using speed correction factors (SCF) [45, 49]. The SCFs scale emission factors to reflect average emissions measurements collected as trucks execute both federal (e.g., Urban Dynamometer Driving Schedule, the Creep mode, the Transient mode, the Cruise mode, and the High Speed Cruise mode test cycles) and state (e.g., ARB 4-Mode cycle) standardized duty cycles [49]. Since vehicles are not traveling at constant speeds across the duty cycles, these SFCs also reflect changes in emissions caused by periods of acceleration. Thus, the following emission factors reflect average, rather than instantaneous, emissions with respect to speed.

A comparison of the SCFs across the vehicle classes is presented later in this section. The EMFAC model offers emission rates estimates for heavy-duty vehicles powered by gasoline, diesel, and natural gas [49]. Electric heavy-duty vehicles, which represent <<1% of the total vehicle stock in the state, are excluded from the EMFAC. Given this data limitation, we assume that electric heavy-duty vehicles have similar SFCs to gasoline, diesel, and natural gas vehicles, which is supported in part by SCFs offered by vehicle manufacturers [65].

CARB's official annual baseline results for total emissions rates and tailpipe emission facts are openly published in an online database. In addition to carbon dioxide, the database also includes estimates for criteria air pollutants (NO_x, particulate matter, carbon monoxide, sulfur dioxide) as well as ozone precursors (e.g., volatile organic compounds). While the EMFAC database offers a basis for conducting state-level, pump-to-wheel emissions assessments, it does not report fuel consumption rates as a function of speed. To correct for this exclusion, we estimate the pump-to-wheel energy consumption rate (MJ/km) as a function of speed based on a carbon-balance method. Given standard properties of low-sulfur diesel and CARBOB [38], the energy consumed per distance driven was determined for heavy-duty trucks and buses, as follows:

$$E_{MJ} = E_{f,CO2} \times \Big(44/12 * w_c * \times Y_{CO2}/(Y_{CO2} + Y_{CO} + 3 * Y_{HC}) * \gamma_d\Big)^{-1} \times LHV \qquad (2.3)$$

$$E_{MJ}(V) = E_{f,CO2}(V) \times \Big(44/12 * w_c * \times Y_{CO2}/(Y_{CO2} + Y_{CO} + 3 * Y_{HC}) * \gamma_d\Big)^{-1} \times LHV \qquad (2.4)$$

where,
$E_{f,CO2}$ = Carbon dioxide emission rate (g CO_2/km), fleet average
$E_{f,CO2}(V)$= Carbon dioxide emission rate (g CO_2/km) as a function of speed, V
Y_{CO2}= Mole fraction of CO_2 in tailpipe exhaust
Y_{CO}= Mole fraction of carbon monoxide in tailpipe exhaust
Y_{HC}= Mole fraction of hydrocarbons in tailpipe exhaust
w_c= Carbon intensity of fuel, (g C/g fuel)
γ_d= Density of diesel fuel, (g diesel fuel/liter fuel)
LHV= Lower heating value (MJ/liter fuel)

The three in front of Y_{HC} denotes the conversion of hydrocarbons as propane equivalents to carbon atoms [66]. The calculated energy consumption rate per distance traveled was then used to determine the well-to-pump GHG emissions for each respective vehicle type. The final well-to-wheels GHG emissions rates were calculated (Eq 2.1) by combining the results from the EMFAC2014 model (g pollutant per km) [50] with the results of our model runs using the GREET model (g pollutant per MJ) [30].

2.2.3 Estimation of Emissions Errors

In this research, the primary interest is estimating the relative emissions deviation (δ) as an indicator of aggregation errors, which we define as the relative difference between the fleet average emission factor, $E_{f,avg}$, and the more resolved, speed-corrected emission factor, $E_{f,s}$:

$$\delta = \frac{E_{f,s} - E_{f,avg}}{E_{f,avg}} \qquad (2.5)$$

In practice, the costs (e.g., time, financial, computational) of gaining extra precision may lead LCA practitioners to accept some level of uncertainty in emission factor estimators. This threshold tolerance for δ could be estimated by performing a cost-benefit analysis on an individual case basis. We were unable to find any supporting literature delineating a generalizable method for defining an allowable emissions deviation threshold since these decisions are made on a case-to-case basis [5]. Therefore, in the following case studies, we arbitrarily picked $|\delta| = 0.2$ to be a representative threshold based on a target accuracy of 80%. We assume that any deviation less than this threshold would imply that a fleet average emission factor could suffice as a reasonable substitute for its speed-corrected counterpart. Though this approach is admittedly subjective, establishing an arbitrary threshold value facilitates both the discussion of the results as well as the comparison between heavy-duty trucks and buses. Again, establishing a threshold $|\delta|$ would be and should be done on a case-by-case basis [5].

2.2.4 Representative Vehicles

This subsection outlines the process for selecting the representative vehicles used in the chapter's case studies. The section presents an intermediate analysis of heavy-duty vehicle well-to-wheel emission factors and their variability across speeds, vehicle categories, and model years.

CARB reports emission factors for various types (e.g., car, bus, truck), subclasses (e.g., passenger, in-state, urban), and model years of vehicles in the EMFAC database [50]. Table 2.1 provides an overview of each vehicle class as well as the calculated fleet-average well-to-wheel GHG emission factor.[1] Figure 2.2 summarizes the speed-resolved well-to-wheel GHG emission factors for each of the vehicle categories. For each category, the vehicle type with the highest annual vehicle kilometers traveled in California is shown.

We base the selection of vehicles based on cumulative annual vehicle kilometers traveled. In California, diesel non-neighboring out-of-state trucks (HHD NNOOS) class represents the most VKT, so this was used as the case study's representative vehicle for heavy-duty trucks. These trucks are often associated with intercity travel on highways. The $E_{f,s}$ profile for this vehicle class is the same for diesel neighboring out-of-state trucks (HHD NOOS), diesel tractor trucks (HHD Tractor), and diesel California International Register Plan trucks (HHD CAIRP) (Table 2.1). Collectively, these vehicle classes represent 52% of VKT by all heavy-duty trucks in California and 77% of all class-8 tractor-trailers in California [50]. Other vehicles were also suitable candidates within the HHDs if we were to consider the type of commodity being transported (e.g., agricultural products, construction). The representative model year is 2012. For heavy-duty buses, we select UBUS as the representative vehicle class as it represents urban transit buses, which is the basis of our case study. Based on total

[1]GVWR refers to Gross Vehicle Weight Rating.

[3]Diesel-powered unless reported otherwise.

[3]Electric bus emission factors are based on studies independent of CARB (72).

Table 2.1: Well-to-wheel emission factors for heavy-duty vehicles listed in EMFAC.[2]

Vehicle Class	**Description**	**Model Year**	$E_{f,avg}$
MHD Ag	Medium-Heavy Duty (MHD) Diesel Agriculture Truck	1999	1390
MHD CAIRP heavy	MHD Diesel CA Int'l Reg. Plan Truck with GVWR>26000 lbs	2012	1370
MHD CAIRP small	MHD Diesel CA Int'l Reg. Plan Truck with GVWR≤26000 lbs	2014	1330
MHD OOS heavy	MHD Diesel Out-of-state Truck, GVWR>26000 lbs	2012	1370
MHD OOS small	MHD Diesel Out-of-state Truck, GVWR≤26000 lbs	2014	1330
MHD Public	MHD Diesel Public Fleet Truck	2013	1440
MHD instate construction heavy	MHD Diesel instate construction Truck, GVWR>26000 lbs	2008	1370
MHD instate construction small	MHD Diesel instate construction Truck, GVWR≤26000 lbs	2012	1430
MHD instate heavy	MHD Diesel instate Truck with GVWR>26000 lbs	2012	1380
MHD instate small	MHD Diesel instate Truck with GVWR≤26000 lbs	2012	1430
MHD utility	MHD Diesel Utility Fleet Truck	2013	1430
MHD TS	MHD Gasoline Truck	2008	1500
HHD Ag	Heavy-Heavy Duty (HHD) Diesel Agriculture Truck	1995	1950
HHD CAIRP	HHD Diesel CA Int'l Reg. Plan Truck	2012	1830
HHD CAIRP construction	HHD Diesel CA Int'l Reg. Plan Construction Truck	2008	2050
HHD NNOOS	HHD Diesel Non-Neighboring Out-of-state Truck	2012	1830
HHD NOOS	HHD Diesel Neighboring Out-of-state Truck	2012	1830
HHD POAK	HHD Diesel Drayage Truck in Bay Area	2008	2120
HHD POLA	HHD Diesel Drayage Truck near South Coast	2008	2130
HHD Public	HHD Diesel Public Fleet Truck	2013	1940
HHD Single	HHD Diesel Single Unit Truck	2008	2060
HHD other port	HHD Diesel Drayage Truck at Other Facilities	2008	2100
HHD single construction	HHD Diesel Single Unit Construction Truck	2008	2050
HHD tractor	HHD Diesel Tractor Truck	2012	1850
HHD tractor construction	HHD Diesel Tractor Construction Truck	2008	2050
HHD utility	HHD Diesel Utility Fleet Truck	2012	1930
HHD IS	HHD Gasoline Truck	2007	2310
All Other Buses	All Other Buses	2008	1390
OBUS	Other Buses, Gasoline	2006	1520
SBUS	School Buses	2008	830
UBUS	Urban Buses	2001	2120
UBUS-NG	Urban Buses, Natural Gas	-	1590
UBUS-electric[3]	Urban Buses California Electricity)	-	320
UBUS-electric-sf	Electric Urban Buses in San Francisco (Hydropower Only)	-	4

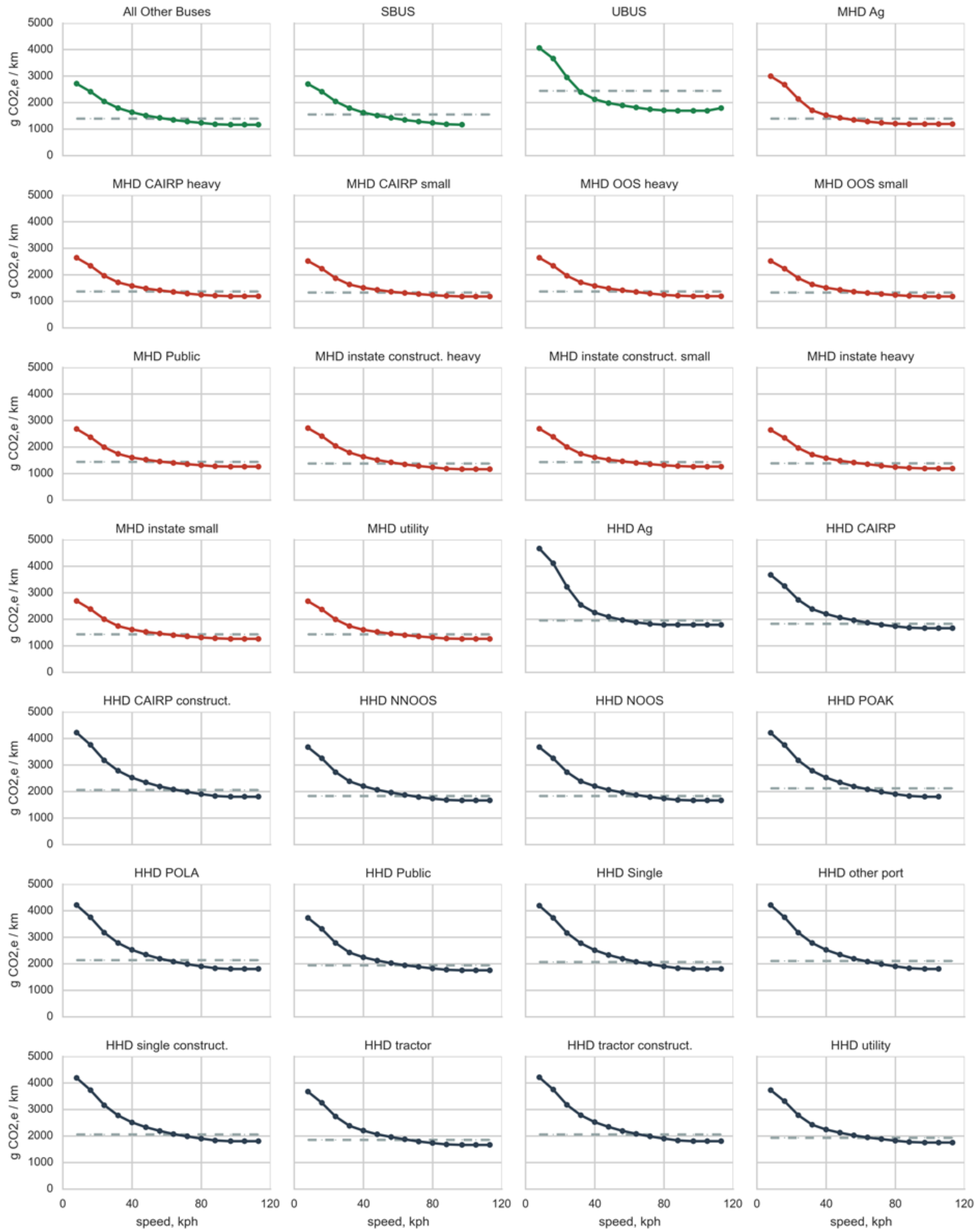


Figure 2.2: Speed-corrected emission factors for buses, MHD trucks, and HHD trucks. Each value represents the vehicle model year with the most annual VMT. Also shown are the well-to-wheel baseline emission factors that are based on average fleet parameters (dashed line, grey).

annual VKT driven in the state, this vehicle class's representative model year is 2001. These statistics were derived from the EMFAC 2011 database [50].

There are two issues associated with representing the emissions deviation from a fleet of vehicles with a single vehicle class and model year. The first issue stems from interclass differences. Figure 2.3 compares the magnitude of the emissions deviation, δ, across vehicle traveling speeds for the representative vehicles selected for this study as well as other heavy-duty vehicles listed in the EMFAC database. Each value represents the vehicle model year shown in Figure 2.2, which is based on the greatest annual VKT. CARB assigns the same SFCs to natural gas fueled vehicles as diesel vehicles, and we assume that the same SFCs apply to electric vehicles based on data from manufacturer's tests [65]. Therefore, these emission deviation estimates reflect the errors for alternatively fueled vehicles as well.

The level of error (positive or negative) varies across traveling speeds, with large negative deviations occurring at reduced traveling speeds and positive deviations for higher speeds. Since the $E_{f,s}$ profile for the representative heavy-duty truck class is the same for HHD NOOS, HHD Tractor, and HHD CAIRP, the relative difference in estimates across vehicle traveling speeds are identical. Since a single vehicle class in EMFAC represents transit buses, the first issue does not affect this mode.

The second issue arises from possible differences in emissions deviation between model years. Figure 2.4 illustrates the standard deviation of the emissions deviation, std(δ), reported across vehicle traveling speeds to examine the variability across vehicle model years. Since vehicle model years extend back to 1971, only model years representing the top 80% of fleet VKT are represented in the sample. Results show that emissions deviation at lower speeds (e.g., <40 kph) is more sensitive to vehicle model year than at higher speeds. Overall, variability in emissions factor deviation estimates are generally small, so relying on a single model year is justified.

2.3 Long-Haul Trucking in California Case Study

2.3.1 Vehicle Speed Data

The Performance Measurement System (PeMS) network served as input data to model the movement of heavy-duty trucks along California highways [67]. PeMS is a traffic management network used by the state's Department of Transportation (Caltrans) to record the movement of vehicles around the states. The network consists of over 39,000 remote traffic detectors, which record real-time information on vehicle counts, vehicle occupancy, vehicle speeds, and more. Caltrans also provides an archive of data spanning 10 years for each of the PeMS network sensor stations. The PeMs reporting systems offers many valuable pieces of information that can be used to assess the environmental performance of vehicles, such as traveling speeds, vehicle counts, lane widths, and is aggregated over numerous time scales. For the purpose of this study, we chose a full week of PeMS stations reports (June 7, 2015 - June 13, 2015), which was reported in 5-minute intervals. Station samples were removed

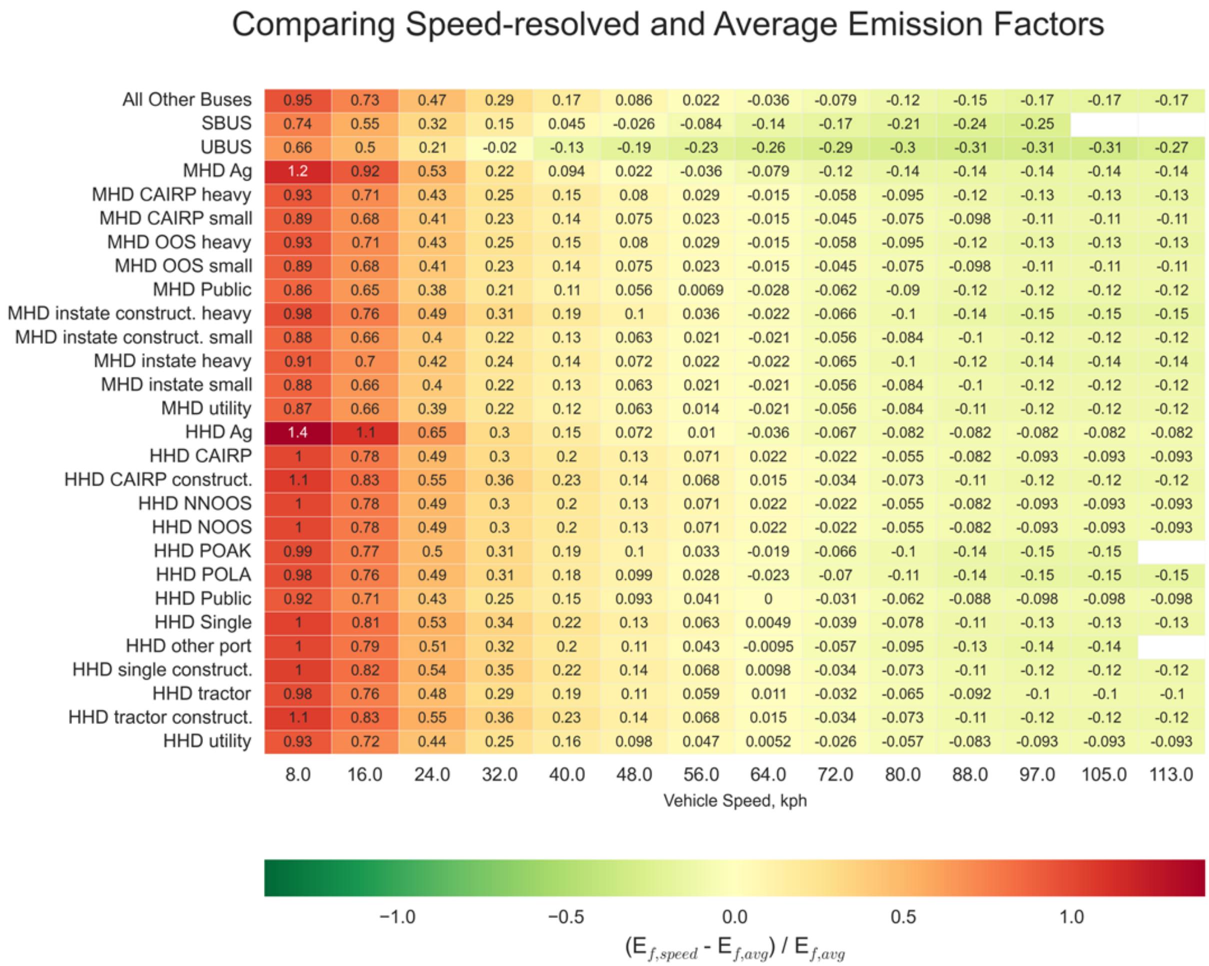


Figure 2.3: Results for a comparison of speed-resolved and average W2W emission factors show the relative difference in estimates across vehicle traveling speeds. Each value represents the vehicle model year shown in Figure 2.2, which is based on the greatest annual VKT.

from the dataset when there was no observed flow or there were equipment failures. At each of the reporting stations, we rely on the cross-lane average speed to estimate W2W emission rates and assume these values represent traveling speeds for cars. However, since heavy-duty trucks must adhere to a different set of speed limits ($\leq$ 88 kph) on California freeways [68], speeds were constrained to these limits. Due to lack of data, the case study assumes that truck traffic is proportional to total VKT.

During these periods of congestion, emission factors increase due to more frequent periods of acceleration and lower vehicle traveling speeds. Since one goal of our case study is to show how well-to-wheel emission factors vary over time and space, we choose to isolate periods

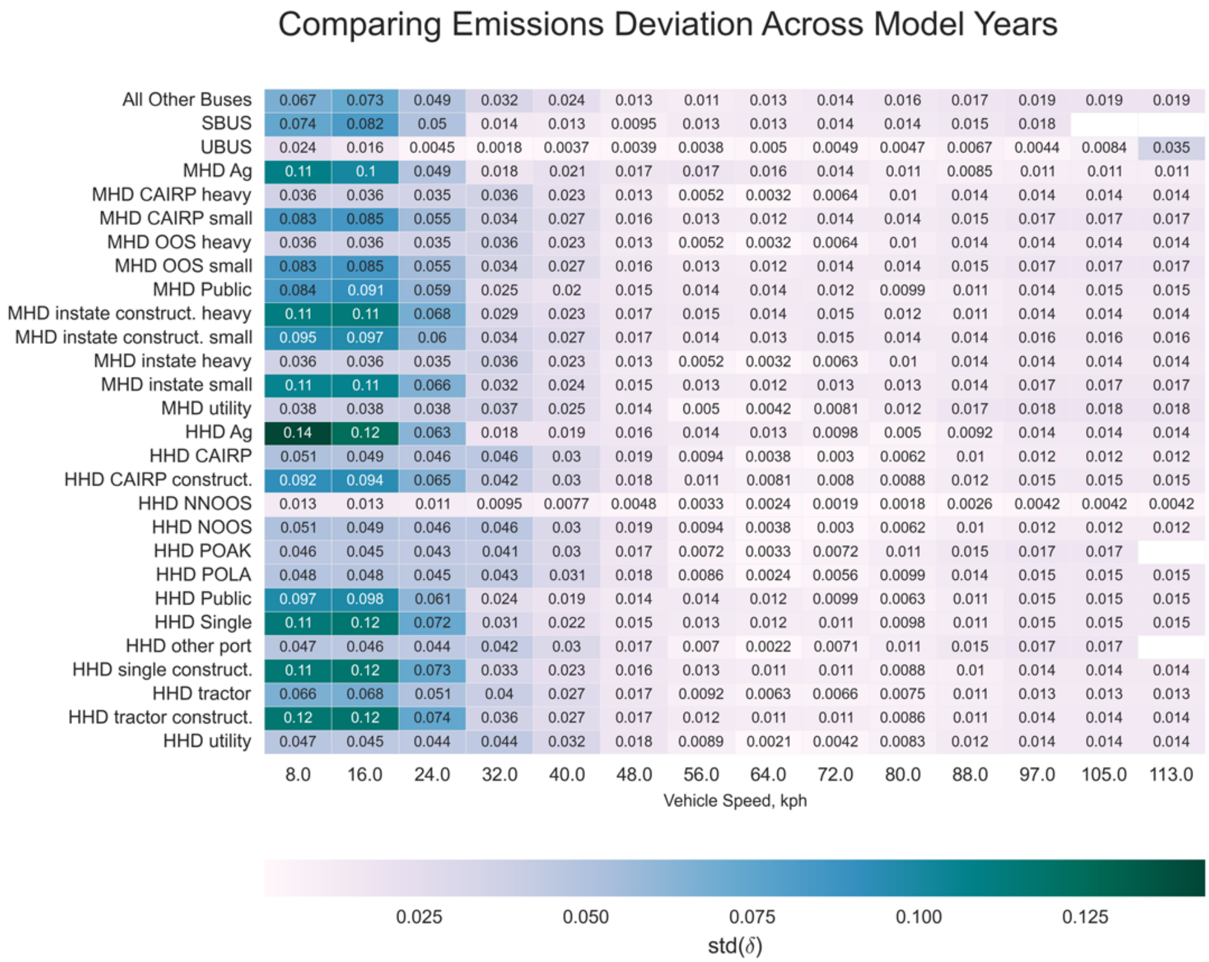


Figure 2.4: For each vehicle class, the standard deviation of the emissions deviation, std(δ), is reported across vehicle traveling speeds to examine the variability across vehicle model years.

of congestion (on-peak) from periods when cars are traveling at free-flow speeds (off-peak). We assume on-peak periods of congestion correspond to morning (7:00 - 9:30) and afternoon (15:00 - 19:00) commutes.

Stations are not uniformly distributed along routes within the PeMs network, which could bias aggregation statistics if not corrected. Therefore, when averaging across sample time periods or aggregating up to route-level assessments, we weighted the emission factors at each station based on VKT. For example, the weighted-average, well-to-wheel emission factor,$\bar{E}_{f,s_i}(t)$, along a generic route at time interval, t, is:

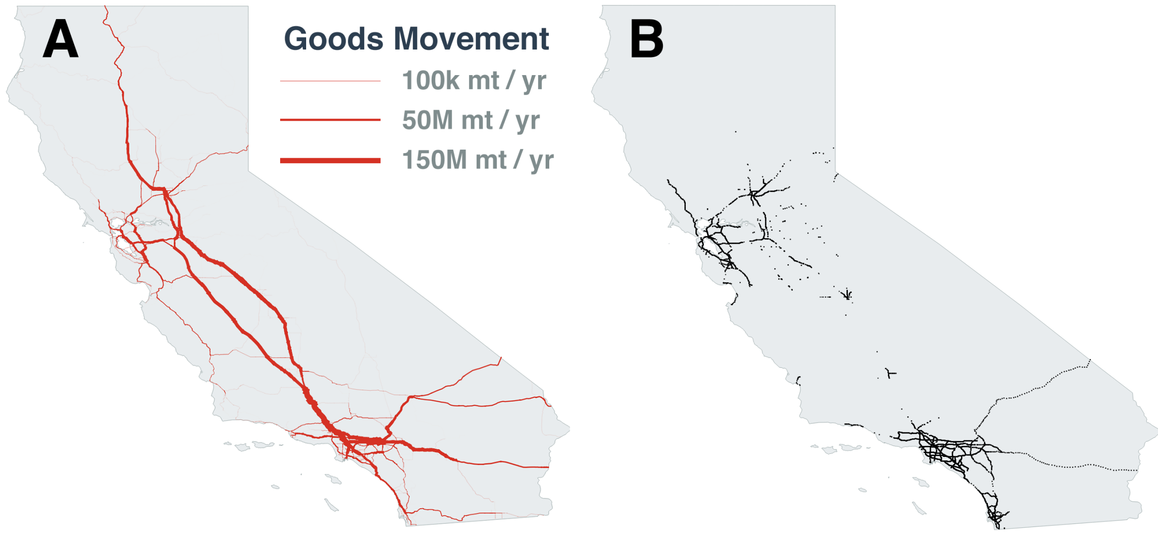


Figure 2.5: (A) Tonnage flows by heavy-duty truck along major freight corridors (2007). (B) Sensor locations for Caltrans PeMS vehicle monitoring network.

$$\bar{E}_{f,s_i}(t) = \sum_{i}^{n} \left(\frac{E_{f,s_i} L_i f_i}{L_i f_i} \right) \tag{2.6}$$

where

L_i = Representative vehicle sensor recording distance at station i, (km) (e.g., its
f_i = Vehicle flow at station i, (veh / time-interval)
n = Total number of station samples along the route at time t

One limitation of using the PeMS network to estimate emission factor aggregation bias is the network primarily records the flow of vehicles along major highways. The lack of intercity detectors implies that truck movements, particularly among smaller truck classes, associated with the "last mile" of goods movement [69] are significantly under-sampled. Though important contributors to environmental impacts [24], these truck activities represent only a small fraction of California's total, on-road freight turnover [50]. Figure 2.5 compares the annual tonnage (2007) moved by trucks in California [2] as well as the locations of the PeMS network sensor stations [67]. Moreover, the results of this case study reflect primarily, if not entirely, the movement of goods over large distances (i.e., intercity, interstate, transnational).

2.3.2 Results

Aggregation bias was assessed across 9 Caltrans districts, where PeMS monitoring stations were available, and the results of this regional assessment are presented in Figure 2.6. Results

	Caltrans Districts, Monitored distance (%)								
Emission Deviation	3	4	5	6	7	8	10	11	12
$-0.1 < \delta$	0	0	0	0	0	0	0	0	0
$-0.05 > \delta \geq -0.1$	98.19	95.51	96.97	99.40	91.74	97.41	99.49	96.55	94.45
$0 > \delta \geq -0.05$	0.67	1.13	0.73	0.39	1.95	0.82	0.32	0.88	1.47
$0.05 > \delta \geq 0$	0.36	0.71	0.52	0.10	1.29	0.50	0.09	0.58	0.87
$0.1 > \delta \geq 0.05$	0.20	0.65	0.46	0.04	1.17	0.36	0.04	0.46	0.66
$0.15 > \delta \geq 0.1$	0.13	0.54	0.26	0.02	0.87	0.25	0.02	0.36	0.51
$0.2 > \delta \geq 0.15$	0.12	0.39	0.16	0.01	0.69	0.19	0.01	0.29	0.40
$\delta > 0.2$	0.34	1.07	0.90	0.03	2.29	0.48	0.03	0.87	1.64
Weekday									
$\delta > 0.2$ (7:00am – 9:00am)	0.80	3.39	0.71	0.03	6.23	0.76	0.01	2.85	4.65
$\delta > 0.2$ (5:00pm – 7:00pm)	1.61	4.24	3.69	0.04	8.94	1.52	0.11	3.74	8.08

Figure 2.6: Scenario results for district-level emission variability across California show that only a small percentage of monitored VKT are subjected to periods of congestion (e.g., high δ).

indicate that speed variability on these spatial scales does not significantly lead to variability in GHG emissions on a weekly basis. For the select representative vehicle categories, the average deviation between the fleet-wide average emissions factor (1,840 g $CO_{2,e}$ / tkm) and the speed-corrected emission factor (1,700 g $CO_{2,e}$ / tkm) was ≈7%. This error is consistent with the errors associated with trucks operating at unconstrained or free flow speeds (i.e., 88 kph). Approximately 91-99% of VKT across the districts reported this level of GHG emissions error.

Given the low overall variability, we report the results for this analysis as a percentage of VKT within emission deviations bins across each district (Figure 2.6,) to better capture the frequency of emission deviations. Here, outliers were selected based on our decision-making threshold tolerance (e.g., $|\delta| = 0.2$), which was discussed in a preceding section. Results show that Caltrans District 7, which encompasses both Los Angeles and Ventura counties, reported the greatest share of emissions deviation, 2.3% of total VKT, above our selected threshold tolerance. Generally, emissions deviations breach this threshold more frequently during weekday periods of peak travel demand. Across the districts, evening periods of congestion caused higher levels of deviation than morning periods.

The overall low deviations within and across Caltrans districts suggest that fleet wide average emission factors would suffice for LCAs at the regional level of specificity. The higher deviations during periods of congestions, however, suggest that peak and off-peak emission factor subclasses could improve the accuracy of these models. Continuing the previous assertion, freeway-level (i.e., local specificity) emission variability across California during weekday travel periods was explored in more detail.

From analysis of 89 freeways across California [67], results again suggest that speed variability on these spatial scales does not significantly lead to variability in GHG emission on a weekly basis. Expected emissions deviations reflect the errors common to trucks traveling at free flow speeds. Over 90% of VKT across the highways recorded within the PeMS network reported this error. This, again, suggests that a single speed-resolved W2W emission factor (typically average free-flow speed) can be used to represent overall vehicle travel within this network.

Figure 2.7 shows that the largest errors occur among a smaller portion of vehicles during weekday on-peak periods. The top 60 of the top 89 freeways based on recorded VKT are shown. Two major trends are apparent. First, nearly all of the emissions deviation occurs within the designated periods of congestion. Trucks operating during off-peak periods of the day along every route recorded within the network emit GHGs at a rate of approximately 1,700 g $CO_{2,e}$ / tkm. Second, evening periods of congestion do not always report higher levels of deviation than morning periods, which was the finding reported at the regional level of specificity. In fact, along freeways such as Route 170 in Burbank (Los Angeles County), morning emissions deviations can be far greater than their evening counterparts. At this level of specificity, the percentage of emissions deviation above our selected threshold tolerance during peak demand periods ranges from 0-17%. Along routes with higher emissions deviation, peak and off-peak emission factor subclasses could improve the accuracy of these models.

Next, analysis was performed to evaluate emissions deviation within studies where trip-levels emission estimates are performed (i.e., discrete specificity). Figure 2.8 shows a time-location emissions deviation diagram for the study's representative truck class along southbound I-405 in Los Angeles. At this discrete scale, results along this 77 km stretch of freeway show that large emission deviations (e.g., $|\delta| > 0.2$) are spatially and temporally correlated, corresponding to locations of reduced speeds caused by congestion. Analysis suggests that during on-peak periods of congestion well-to-wheel emission factors often deviate from average conditions within clusters or deviation hotspots.[4] Within the congestion-induced clusters

[4]Clusters can be identified both visually and computationally using machine-learning algorithms, such as k-means or DBCAN. For more formation, see `http://scikit-learn.org/stable/auto_examples/#clustering`

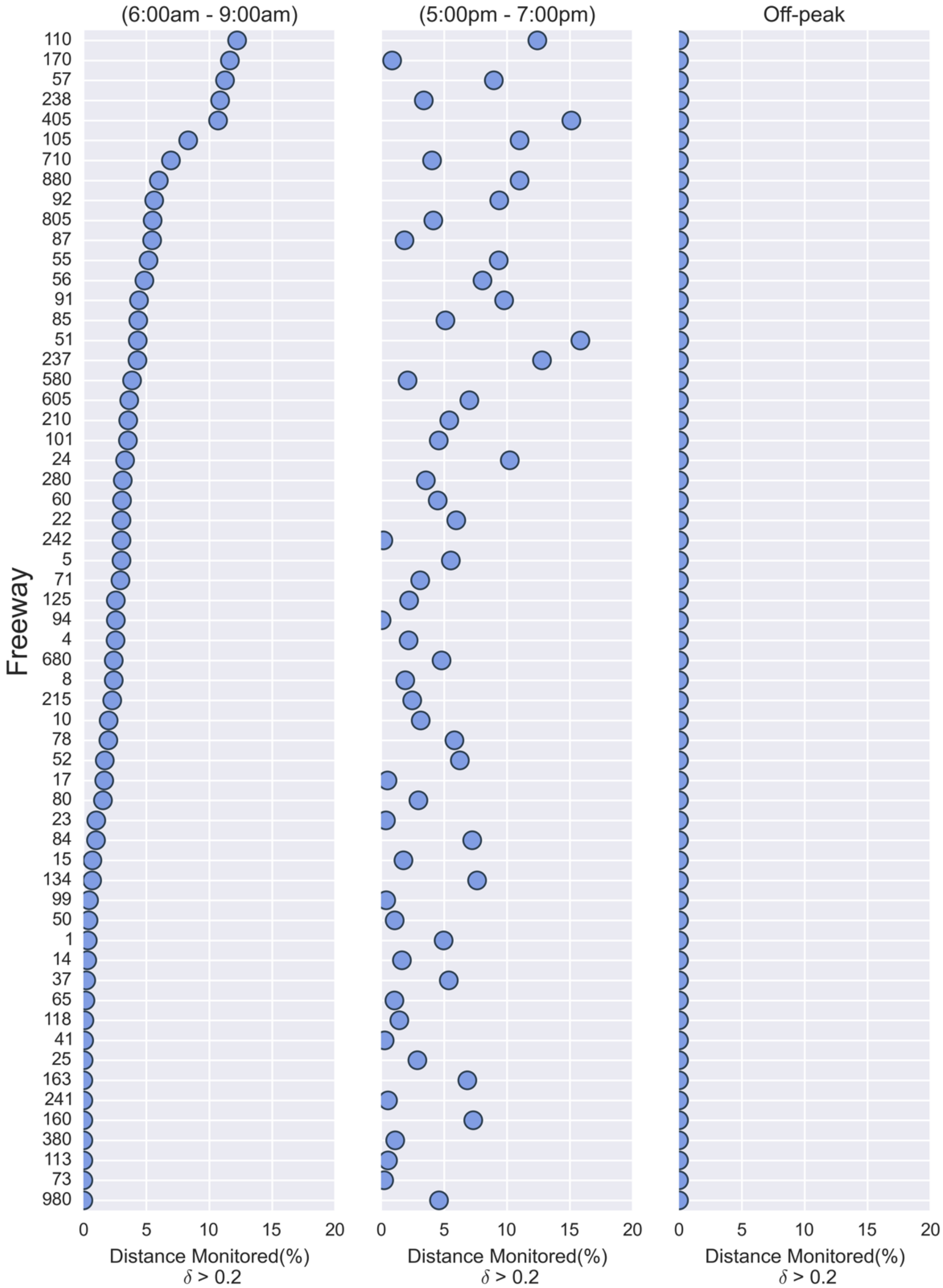


Figure 2.7: Freeway-level emission variability across California during weekday travel periods. Results are reported as the mean percentage of monitored VKT where truck emissions deviation (δ) is greater than 0.2.

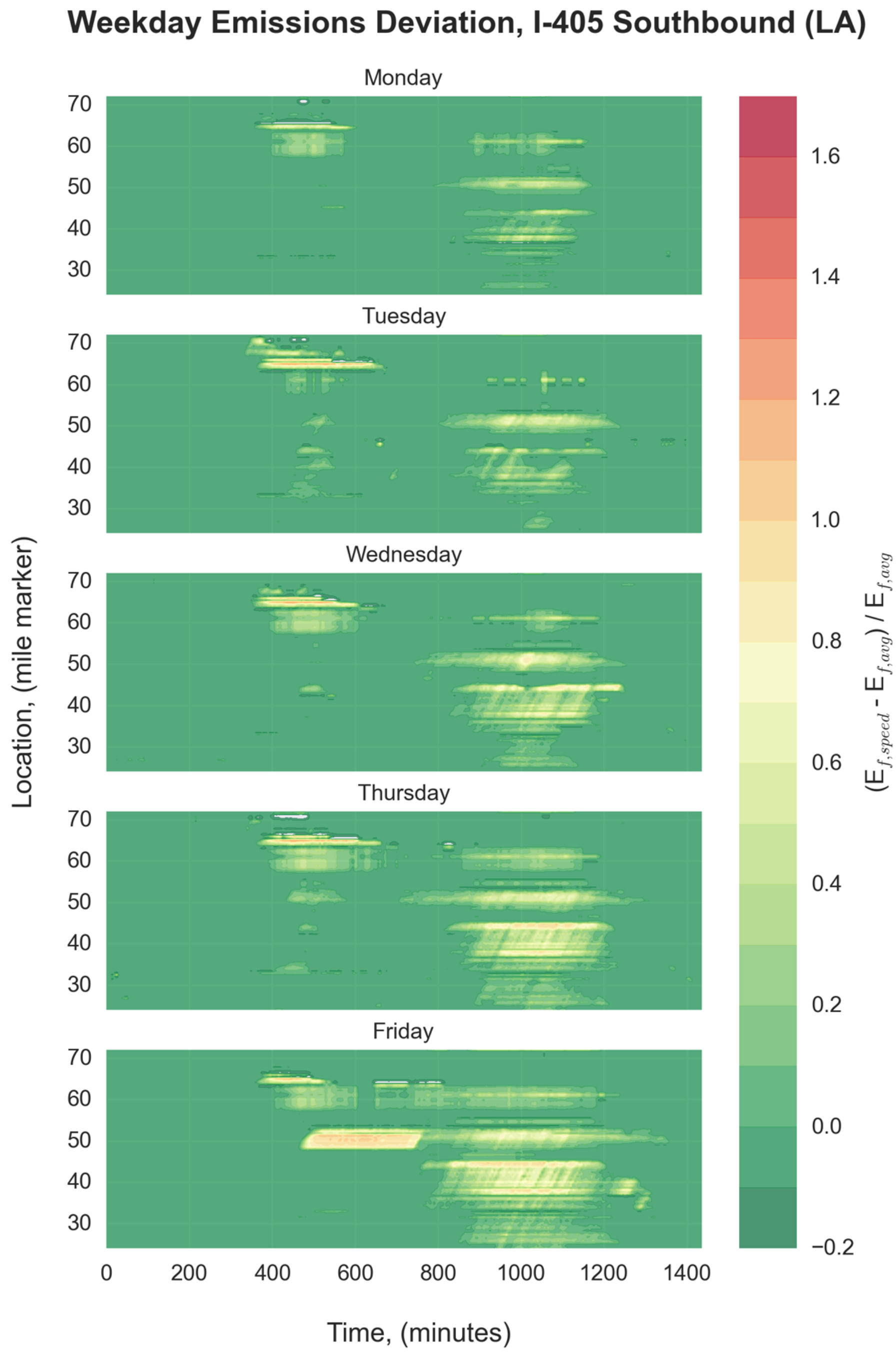


Figure 2.8: Time-location diagram along southbound Interstate 405 through western Los Angeles illustrates how W2W emission hotspots, or neighboring stations with emission rates that deviate from average emission factors may form along portions of routes.

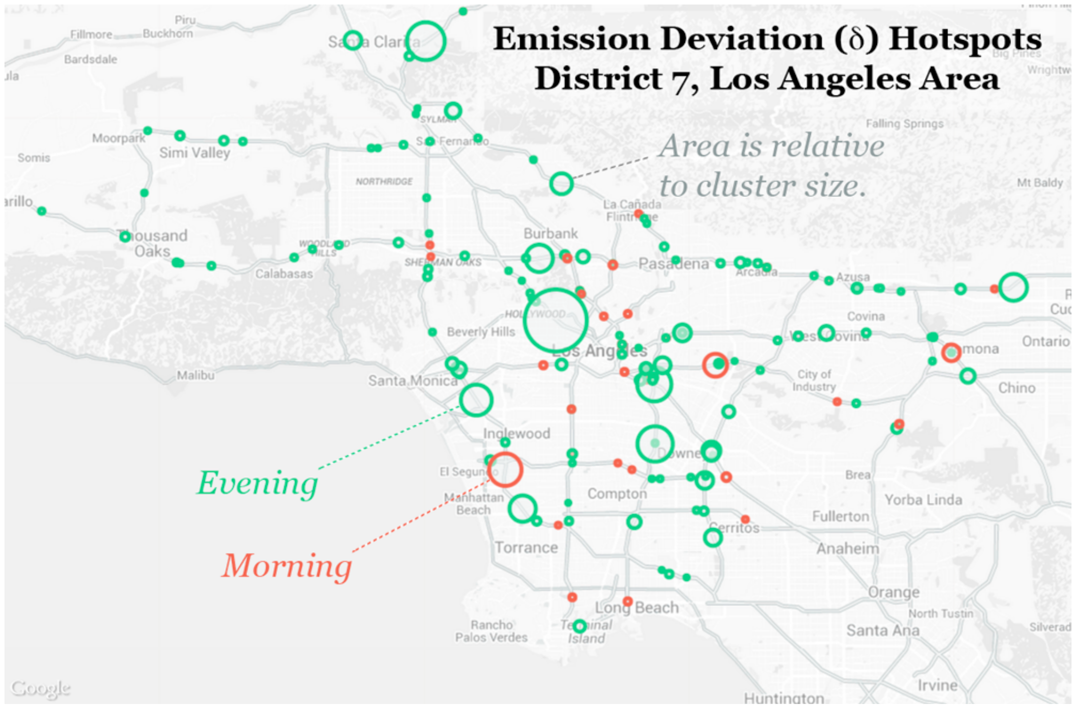


Figure 2.9: Map depicts clusters of high emissions deviation (e.g., $|\delta| > 0.2$) across District 7 on Friday, June 12, 2015. The clusters are partitioned into morning and evening classifications. The area of each data point represents the total number of PeMS recording sensors reporting high deviations at a particular time and location. Clustering was performed using the DBSCAN algorithm and plotted with Google Maps.

shown in Figure 2.8, emissions deviations reach as great as $\delta = 1.8$. Figure 2.8 also indicates that hotspots along this section of highways vary in frequency throughout the week. Figure 2.9 illustrates the frequency of congestion-induced emission deviation hotspots across District 7 (Los Angeles and Ventura Counties) on Friday, June 12, 2015. Clustering records allows modelers to retain some information regarding when and where emissions deviations occur while aggregating the data to a local level of specificity (e.g., Los Angeles area).

Only a small percentage of reported VKT along this stretch of highway deviates from what would be expected at larger aggregate levels (e.g., regional and local specificity). However, identifying and accounting for these isolated instances of emission deviation could improve the accuracy of GHG inventories on a trip basis. For example, Figure 2.10 shows the total W2W emissions for vehicles traveling southbound on I-405 (see also Figure 2.8) as they enter the freeway at different times of the day. During on-peak periods of congestion, W2W emissions footprint of a trip will rise as high as 47% greater than estimates based on average W2W emission factors. Avoiding the W2W emission hotspots that form during on-peak periods can lower the overall GHG emissions. For example, if a truck were removed from the southbound I-405 on Friday during evening morning rush hour traffic (17:00) and instead

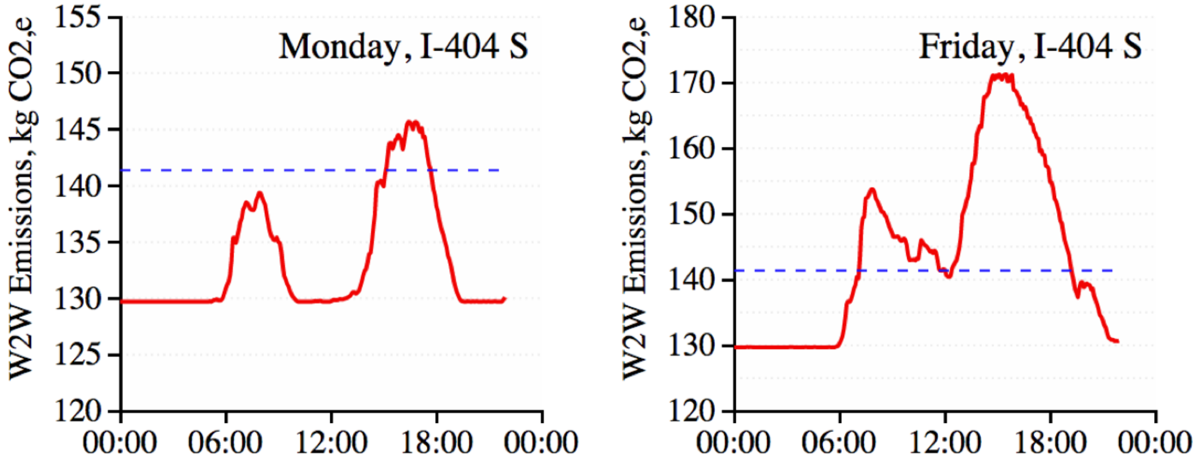


Figure 2.10: The well-to-wheel emissions footprint of a vehicle depends on when it enters a freeway network and travels the length of I-405 (77km). The graphs above show the total well-to-wheel emissions for GHGs associated with the time a truck enters the southbound I-405 throughout the day. Well-to-wheel emissions estimates based on average emission factors (blue line) are also shown.

began its trip during the late evening (21:00), net GHG W2W emissions would be reduced by 40 kg $CO_{2,e}$ per trip, a 23% reduction in GHG emissions. However, this example may only represent a small fraction of total freight turnover within the state, as 7% of total ton-km fall within 161 km of total trip distance on average across the United States, while 51% of all goods are moved within this distance on a mass basis (78).

While this example suggests that incorporating speed-corrected emission factors into discrete level of specificity could reduce the overall uncertainties relating to congestion's influence on life-cycle emission factors for heavy-duty trucks, modelers should also relate these uncertainties in relative to the total emission inventory. For example, if the analysis results shown in Figure 2.10 include an additional 200-km portion of truck travel at free flow speeds, then shifting a truck trip to evening traffic would only amount to a 9% reduction in total GHGs. In this case, a fleet-average average emission factor would suffice. Ultimately, determining the appropriate selection of emission factor models at a discrete level may depend on when, where, and for how long a heavy-duty truck is operating.

2.4 California Transit Bus Case Study

2.4.1 Vehicle Speed Data

In this case study, bus speeds were estimated using real-time GPS feeds provided by NextBus during a 7-day period from 8/28/2015 to 9/5/2015 [70]. NextBus is a private real-time passenger information provider that works with public transit agencies to monitor, assess, and disseminate data regarding the performance of their vehicle fleets. Real-time data systems could be considered the most advanced technological system for informing both agencies and their riders about the current performance of public transit systems (i.e., bus, bus rapid transit, light rail, and subway). Through its application program interface (API), NextBus provides GPS feeds that track the location, orientation, and speeds of active buses, which it updates cyclically at various time intervals (e.g., seconds to minutes). This information serves as the basis for the vehicle speed dataset.

The primary benefits of utilizing this data source are: (i) it more accurately details the current operational performance of transit systems in comparison to the more readily adopted General Transit Feed Specification (GTFS) vehicle scheduling system [71] (ii) like GTFS, this information is often available for third-party applications free of change; and, (ii) real-time data feeds can be stored to analyze historical trends in the performance of transit systems. While informative, real-time data systems are only available for a select number of public transit agencies [70]. These data feeds also lack important information about route schedules, which are commonly offered under the GTFS. Given its limited availability, only nine California public transit agencies were assessed, though the top four agencies in the state [73] are represented.

The following sections provide a brief description of the locations in which samples were collected for each public agency. The agencies are presented in descending order based on the size of their respective bus fleets. Information on bus fuel types is also included.

Los Angeles County Metropolitan Transportation Authority

The Los Angeles County Metropolitan Transportation Authority (lacmt) is a public transit agency supporting the greater Los Angeles County (Figure 2.11). The agency manages a number of transit services (bus, bus rapid transit, light rail, and subway), though the NextBus data collected for this system was limited to only buses. In total, the lacmt transit network spans 2,300 km, encompasingg 169 bus routes and 2,738 buses (2,301 are represented in the sample) [70]. Of the nine public transit agencies reviewed, lacmt is the largest in terms of annual passenger kilometers traveled (PKT). Nationally, the agency is ranked 2nd in annual PKT by bus with 2.4 billion pass-km per year in 2011[73]. During the week-long sample period, 2.04 million vehicle speed measurements were recorded. The agency manages a fleet of both natural gas- and diesel-powered buses [74].

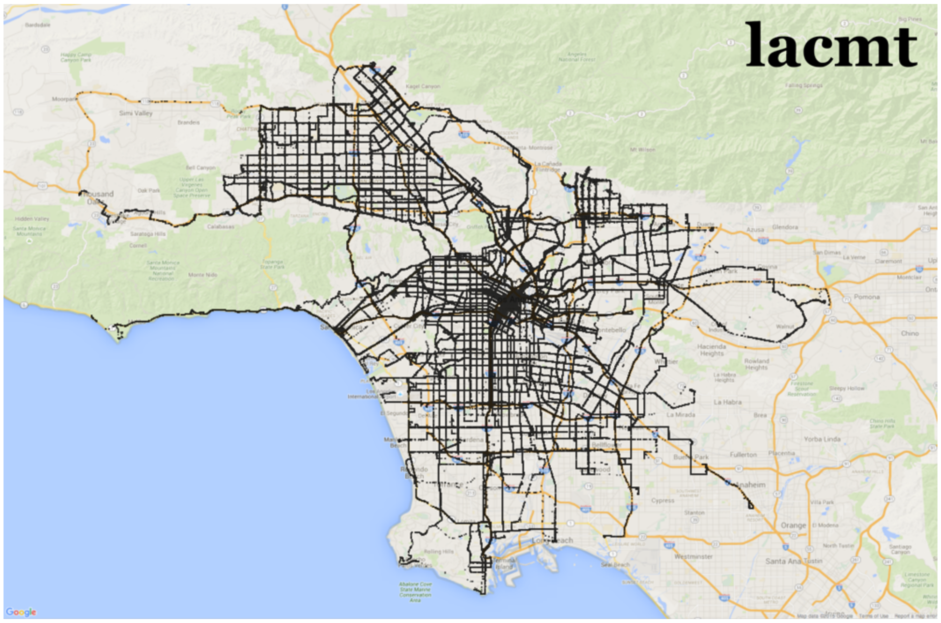


Figure 2.11: An overview of the samples collected for the Los Angeles County Metropolitan Transportation Authority (lacmt) plotted on Google Maps [72].

San Francisco Municipal Transportation Agency

The San Francisco Municipal Transportation Agency (sfmuni) is a public transit agency supporting the city of San Francisco (Figure 2.12). Like the lacmt, the sfmuni agency manages a fleet of public transit modes, however, only buses were considered within the week-long study period. The sfmuni network is the second largest transit system in our dataset in terms of annual passenger kilometers (325 million pass-km per year, 21st nationally) [73]. It offers 71 unique bus routes, including bus rapid transit and commuter bus services). From the sample data, we estimate that the agency's 967 active buses traverse a total of 142,000 km on average during weekdays [70]. During the sample period, 3.98 million vehicle speed measurements were recorded. The agency manages a fleet of both diesel- and electric-powered buses [75].

Alameda-Contra Costa Transit District

The Alameda-Contra Costa Transit District (actransit) is a public transit agency supporting Alameda and Contra Costa counties (Figure 2.13). The public transit network serves many cities in the East Bay (e.g., Oakland, Hayward, Richmond, etc.), including other major cities in San Francisco, San Mateo, and Santa Clara counties. The actransit network is ranked 25th nationally (2011) in terms of total PKT by bus with 300 million pass-km per year [73]. The agency has the third largest bus fleet among the nine agencies measured in the case study. In total, actransit operated 547 buses during the week sample period across 107 bus

Figure 2.12: An overview of the samples collected for the San Francisco Municipal Transportation Agency (sfmuni) plotted on Google Maps [72].

Figure 2.13: An overview of the samples collected for the Alameda-Contra Costa Transit District (actransit) plotted on Google Maps [72].

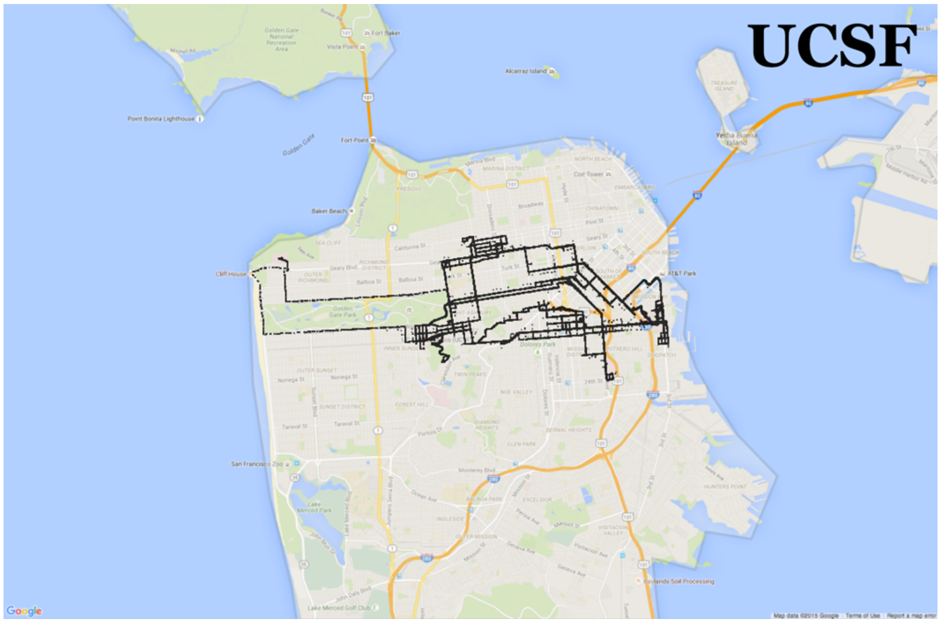


Figure 2.14: An overview of the samples collected for the University of Californa — San Francisco (ucsf) Transportation Department plotted on Google Maps [72].

routes. 596,000 vehicle speed measurements were recorded during this period. The agency manages a fleet of both diesel- and hydrogen-powered buses [76].

University of California — San Francisco

The University of California — San Francisco (ucsf) Transportation Department is a bus shuttle service that transports students between the multiple university campuses in the city (Figure 2.14). Both ucsf and sfmuni are located in the city of San Francisco. The ucsf network is one of two public transit networks in the dataset that primarily supports a university. The department operates 50 diesel-powered buses [77] along a total of 16 routes [70]. During the week-long sampling period, 596,000 vehicle speed measurements were recorded.

University of California —Davis University Transportation

The the University of California —Davis University Transportation (unitrans) department is a public transit agency that serves both the university as well as the adjacent communities in northern California (Figure 2.15). Unitrans is well-known for their London double decker-style buses. The buses, 37 recorded in total during the sampling period, are primarily run by compressed natural gas (CNG), but a small portion of the fleet is powered by diesel engines [78]. The unitrans network is composed of 19 routes. During the week-long sampling period, 166,000 vehicle speed measurements were recorded.

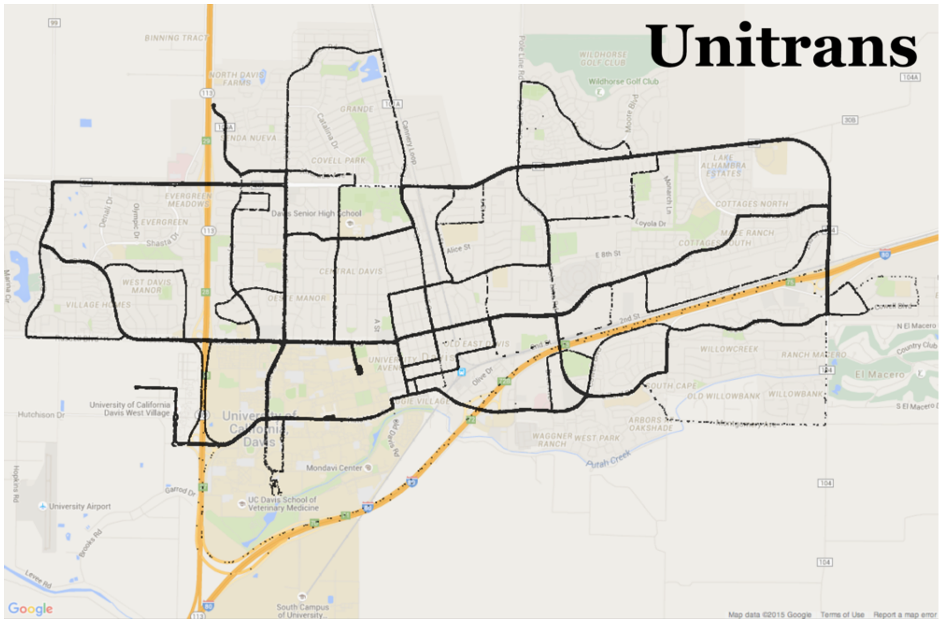


Figure 2.15: An overview of the samples collected for the University of California —Davis University Transportation (Unitrans) system plotted on Google Maps [72].

Ventura County Transportation Commission — Intercity

The Ventura County Transportation Commission — Intercity (vista) is a public transit agency supporting intercity transport services for the county in southern California (Figure 2.16). The vista bus transit network is unique within the sample because the network is primarily along major state and interstate highways, while the other networks are composed of mostly urban arterial roads. The agency maintains a fleet of 25 diesel buses [79], which operate 8 routes between the cities of Ventura, Santa Barbara, Camarillo, and Thousand Oaks. During the week sampling period, 138,000 vehicle speed measurements were recorded [70].

Emeryville Transportation Management Association

The Emeryville Transportation Management Association (emery) is a public transit agency supporting intercity transport services for the city of Emeryville in northern California (Figure 2.17). The service area for emery is the smallest among the 9 agencies examined in this study. The bus fleet is comprised of 16 diesel buses that operate along 5 routes [80]. Many of the routes transport riders to and from the MacArthur BART Station to various locations throughout the city. During the week sampling period, 77,000 vehicle speed measurements were recorded [70].

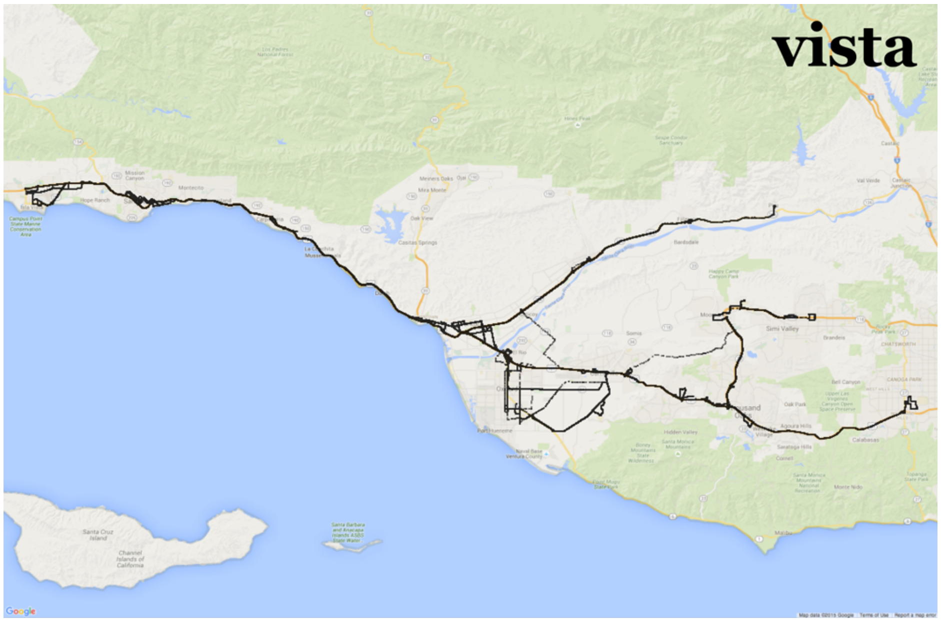


Figure 2.16: An overview of the samples collected for the Ventura County Transportation Commission Intercity (vista) bus service plotted on Google Maps [72].

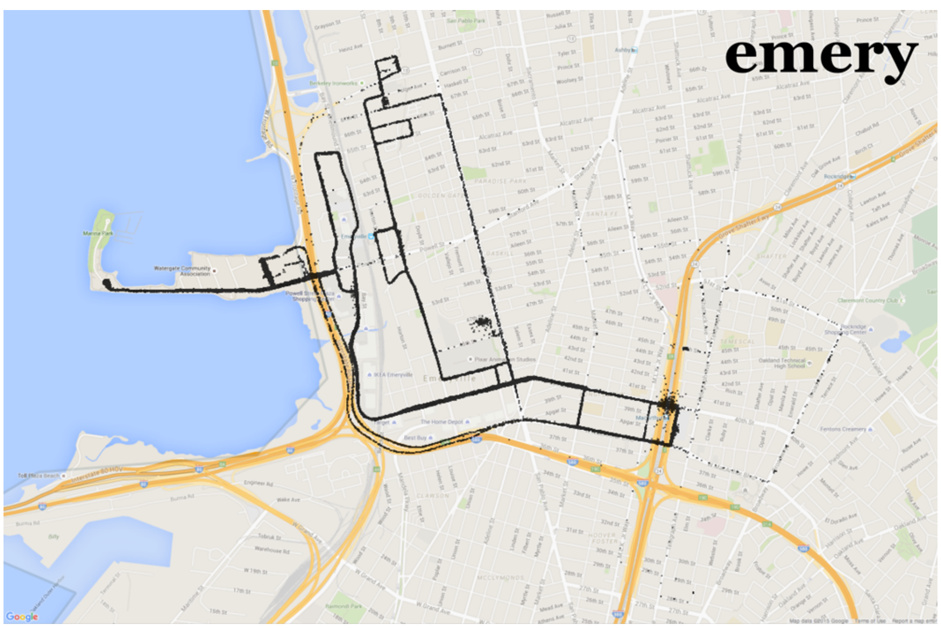


Figure 2.17: An overview of the samples collected for the Emeryville Transportation Management Association Emery Go-Round bus (emery) bus service plotted on Google Maps [72].

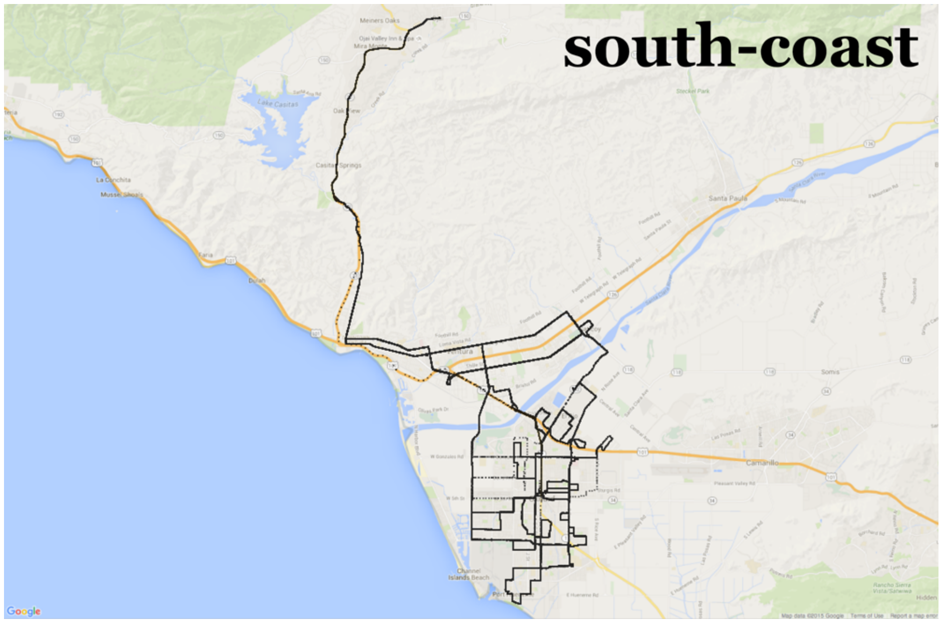


Figure 2.18: An overview of the samples collected for the Gold Coast Transit District, formerly known as South Coast Area Transit (south-coast) system plotted on Google Maps [72].

Gold Coast Transit District, formerly known as South Coast Area Transit

The Gold Coast Transit District, formerly known as South Coast Area Transit (south-coast) is a public transit agency supporting transport services for the cities of Oxnard, Ventura, and Port Hueneme, among others, in southern California (Figure 2.18). The south-coast agency manages a mixed fleet of both CNG and diesel buses (11 in total) along 21 routes [81]. During the sampling period, 61,000 vehicle speed measurements were recorded for south-coast [70].

Thousand Oaks Transit

The Thousand Oaks Transit (thousand-oaks) is a public transit agency supporting transport services for the city of Thousand Oaks in southern California (Figure 2.19).The agency schedules only four routes that are serviced by two CNG buses [82]. During the week-long sampling period, 6,800 vehicle speed measurements were recorded for thousand-oaks [70].

2.4.2 Results

Figure 2.20 illustrates the frequency of speeds reported during the 7-day sampling period across the state (A, top) and by individual agencies (B, bottom). In this figure, we partition the respective dataset into 1 kilometer per hour (kph) bins and exclude samples in which

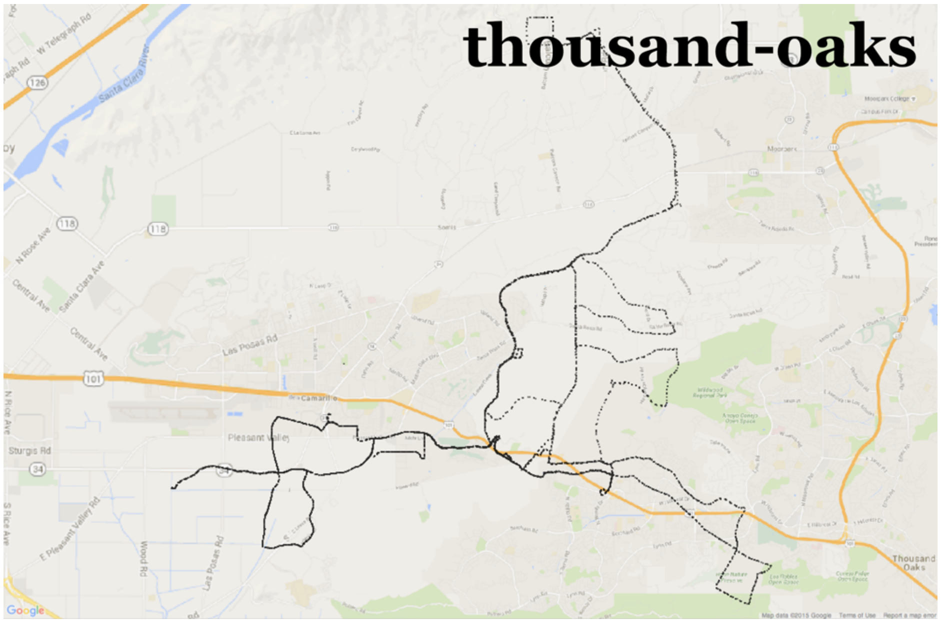


Figure 2.19: An overview of the samples collected for the Thousand Oaks Transit (thousand-oaks) system plotted on Google Maps [72].

buses were idling (i.e, 0 kph). Idling vehicles fall within the scope of this study since these emission rates are not recorded on a VKT basis. For a point of reference, the bus traveling speed in the EMFAC model that corresponds to δ equal to zero is 30 kph [50, 49], which is approximately the expected value (28 kph) and mode (27 kph) when jointly considering the collective nine agencies (A, top).

By disaggregating the samples by agency, we show that each agency has speed distribution profile that is unique in overall expectation, mode, and skewness. The expected vehicle traveling speeds for each agency in ranked order are 12.0 kph (actransit, lowest), 19.2 kph (lacmt), 19.9 kph (sfmuni), 21.8 kph (ucsf), 26.5 kph (emery), 29.0 (unitrans), 36.1 (south-coast), 43.5 (thousand-oaks), and 64.5 (vista, highest). The most frequently occurring vehicle traveling speeds in ranked order are 5 kph (actransit, lowest), 25 kph (sfmuni), 31 kph (ucsf), 38 (unitrans), 40 kph (emery), 41 (south-coast), 43 kph (lacmt), 52 kph(thousand-oaks), and 106 kph(vista, highest).

Figure 2.20 (B) shows that each agency's speed frequency distribution is asymmetric, with two agencies displaying large skewness (actransit: positively; vista: negatively). Vista's skewness is the easiest to explain, as most of the VKT for this agency occur on highways. The mode for this agency's distributions (106 kph) aligns with typical operating conditions along these road types (e.g., freeflow speeds range from 88 kph — 120 kph). The skewness in the actransit network is less clear. As described previously, the majority of the actransit network is situated along urban arterial roads, where speed limits range from 32 to 40 kph. The mode for this agency's sample data (5 kph) falls well below these limits, which suggests

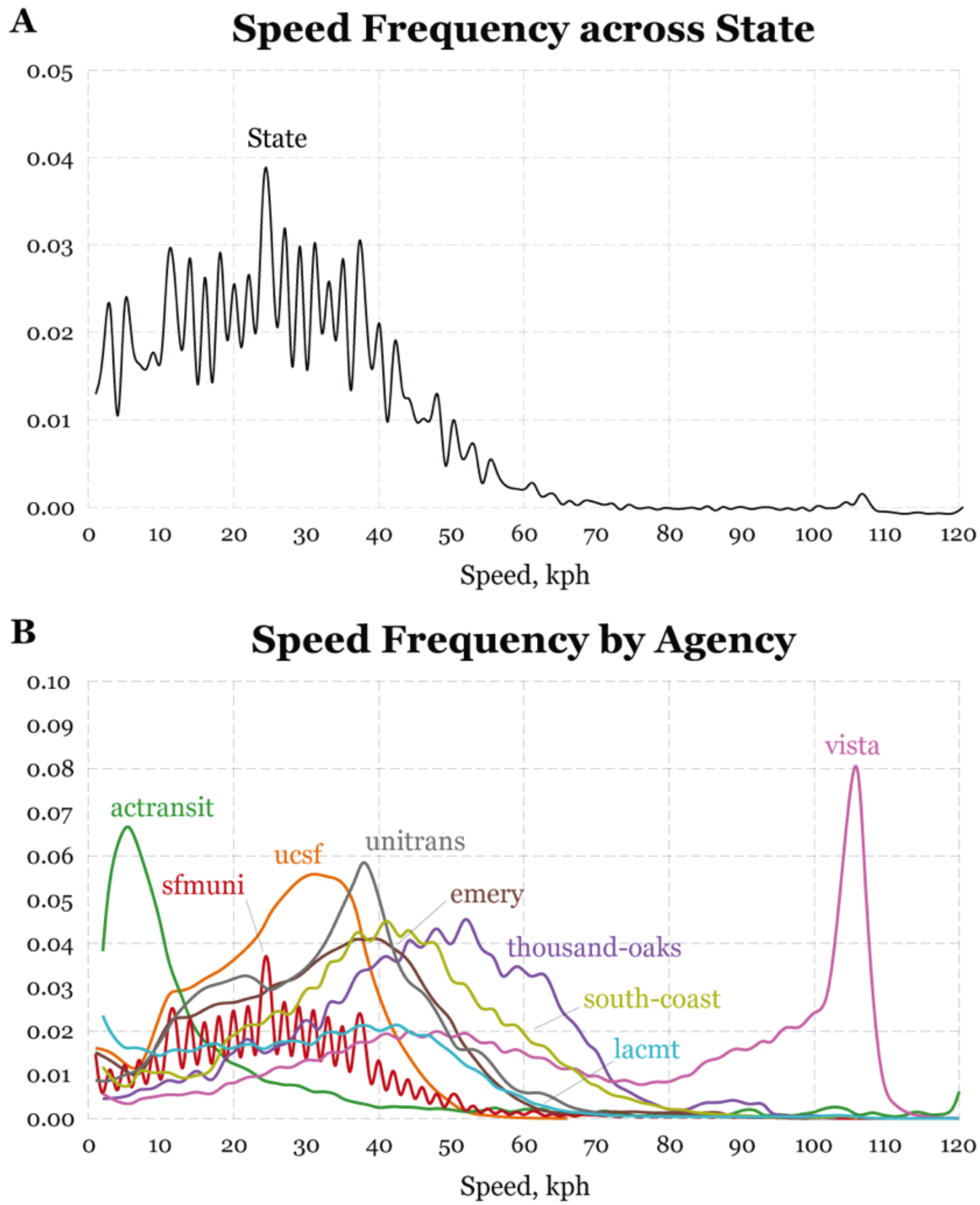


Figure 2.20: The distribution of vehicle traveling speeds across all nine agencies (e.g., state) (A) and by each individual agency (B).

that other factors may be at play. Further analysis is provided in the following discussion of the emission deviation results.

After transforming the vehicle speed data into speed-corrected emission factors, we analyzed the range of emission deviations for each agency in order to determine where fleet-average emission factors were appropriate at this level of specificity. Figure 2.21 shows the

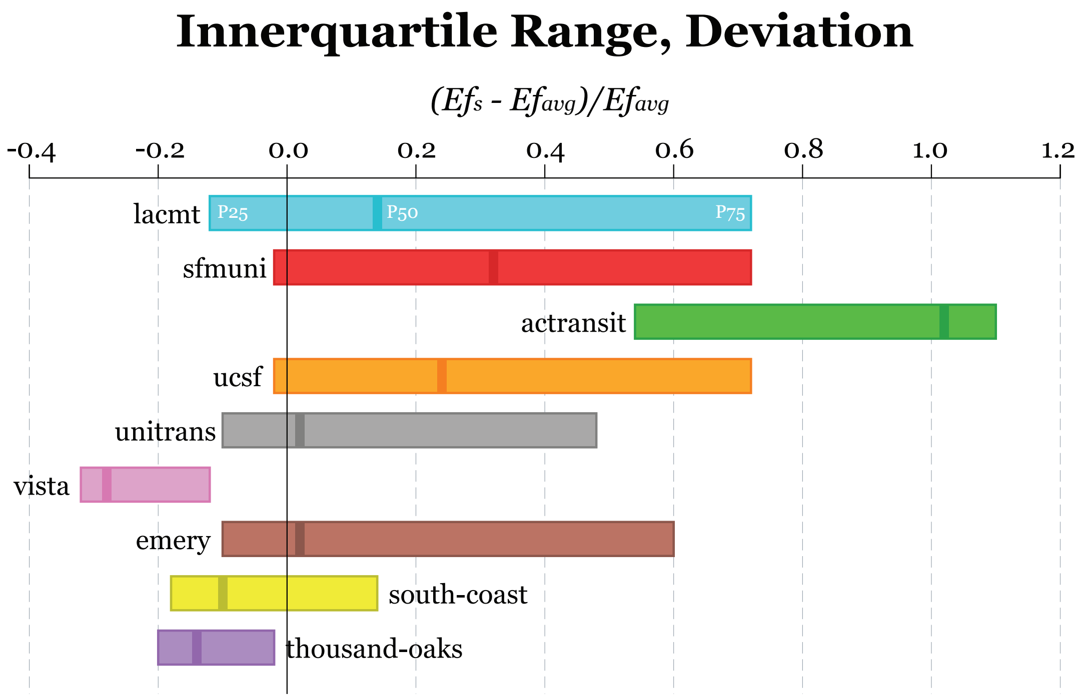


Figure 2.21: The overall magnitude and distribution of emissions deviations varies between agencies, as show by the interquartile ranges above. The agencies are listed in descending order based on total bus stock. The overall trend suggests that agencies servicing large metropolitan populations have generally larger emissions deviation.

results of this assessment. Again, the emissions from idling buses were not considered as these emissions can be considered in a separate category. For each agency, we report the 25th (P25), 50th (P50), and 75th (P75) percentiles. The rectangular area in each graph represents represents the inner 50% of all bus samples during the week sample period. To illustrate a sense of scale in the results, we report agencies in descending order based on total bus stock (i.e., largest agencies on top).

The results from the regional analysis show that over 60% of the buses had emission deviation scores beyond the study's threshold limit for variability, $|\delta| > 0.2$ (lacmt: 52%, sfmuni: 63%, actransit: 91%, ucsf: 53%, unitrans: 43%, vista: 73%, emery: 44%, south-coast: 43%, thousand-oaks: 49%). Agencies that operate buses at low traveling speeds (e.g., <30 kph) have larger positive emission deviations errors. This is true for the top four agencies listed in Figure 2.21, where each are situated in a major metropolitan area. These agencies also have the greatest emissions variability as the marginal change in emissions due to a change in speed is larger for slower rates of travel (<30 kph; Figure 2.3). For instance, actransit, i.e., the agency with the lowest expected speeds, reported over half of its samples at a deviation level greater or equal to $\delta > 1$, which would imply emission rates are 2 times

Table 2.2: Expected route-level emissions deviation.

Agency	Expectation, $\mathbb{E}(\delta)$	Stand. Dev., $std(\delta)$
vista	-0.131	0.012
thousand-oaks	-0.008	0.072
emery	0.210	0.079
unitrans	0.246	0.080
lacmt	0.303	0.089
south-coast	0.080	0.092
ucsf	0.397	0.103
sfmuni	0.382	0.137
actransit	0.618	0.38

greater than what would be expected at the level of specificity of the entire state.

In contrast, agencies with higher average speeds (the bottom 5 agencies in Figure 2.21) tend to have a greater share of negative emission deviation. Since the marginal change in emissions due to a change in speed is comparatively smaller for higher rates of speeds, agencies with bus traveling speeds similar to those found on highways tend to show lower emission deviation variability. This is true for both vista and thousand-oaks, which offer bus services primarily along highways. Thousand-oaks and south-coast agencies have a large share of emissions estimates within the study's threshold limit for variability, $|\delta| > 0.2$, so a case could be made that the statewide fleet average emissions factors are sufficient for these agencies. Nonetheless, Figure 2.21 suggests that a single statewide average emission factor for buses may not be appropriate at a local (e.g., agency) level of specificity.

Next, we consider the variability in emission factors at a route level across each of the nine agencies. Figure 2.22 shows the results of a route-level analysis and indicates that emissions deviation varies by individual bus route, though the scale of variability depends on the agency. Each line in the figure represents the cumulative percentage of emissions deviation for an individual route during the 7-day sampling period. The figure shows that bus routes take on a range of emissions deviations value, resulting from the fact that buses along routes hardly maintain a constant speed. Table 2.2 estimates the variability in emissions deviation across each agency.

While a single statewide average emission factor for buses may not be appropriate for estimating an agency's emissions inventory due to accuracy concerns, adjusting the $E_{f,avg}$ based on an expected emissions deviation statistics is a better alternative. Even so, this may still lead to varying amounts of inaccuracy in emissions inventory as Table 2.2 standard deviation scores indicate (i.e., vista vs. actransit). If a study's scope is set to a local level of specificity, we suggest to adjust fleet average emissions based on route-estimated expected deviation. To assist future analyses of bus greenhouse gas emissions at this level of specificity,

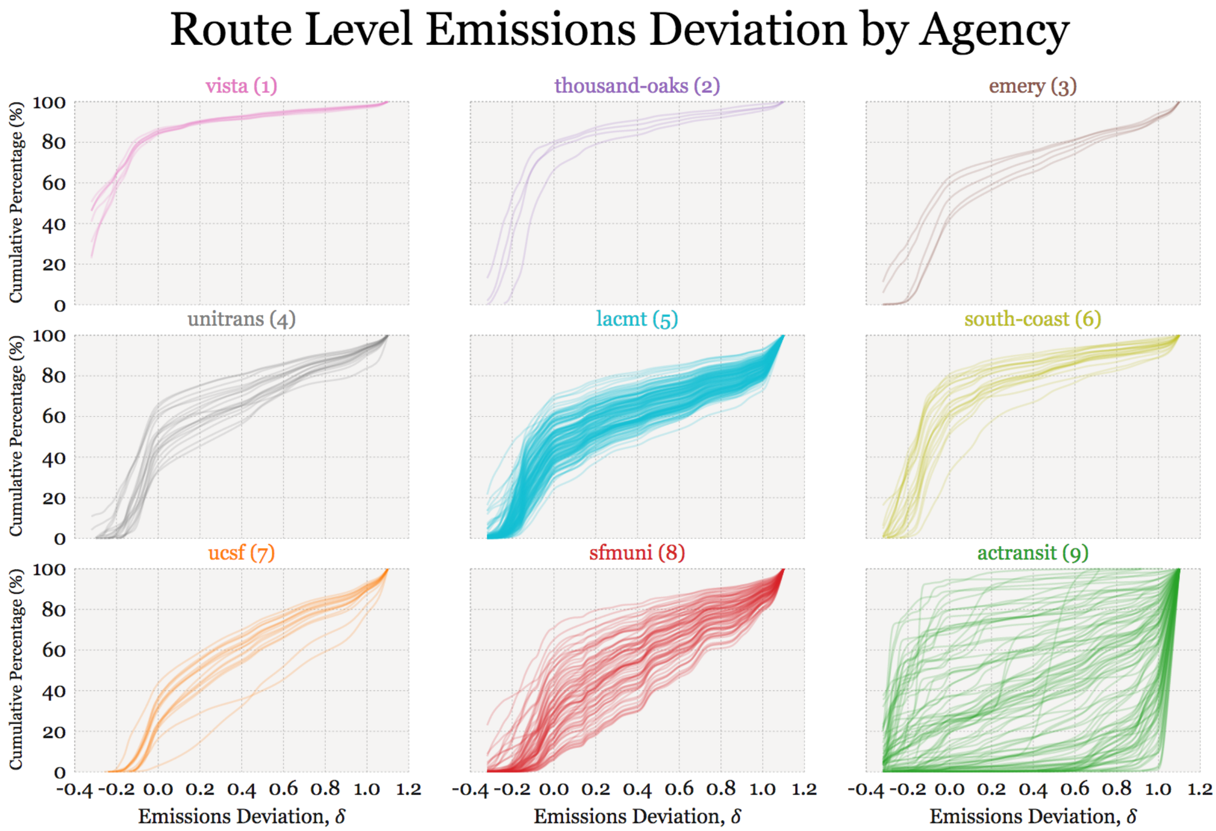


Figure 2.22: Results indicate that emissions deviation vary by individual bus route, though the scale of variability depends on the agency. The cumulative distribution depicts the percentage of total samples (y-axis) recorded at increasing emissions deviation for individual routes (lines). Agencies are presented in order of increasing emissions deviation variability.

we provide an appendix to this dissertation (*Appendix A*, Table A.1) that lists the expected emissions deviation values for all of the routes examined in the dataset.

We complete this bus case study by observing the variability of emissions deviation at a discrete level of specificity. For this example, we narrow the scope of the study to only buses operating within the sfmuni bus network. Given large gaps in time between samples taken from NextBus (latency ≈ 30 seconds), it was not possible to model a single bus traveling along a route within sfmuni or any other of the agencies examined. To overcome this limitation, we instead partition the bus road network into 50-meter segments and analyze the variability in emissions deviation within each segment as a proxy for an individual bus trip.

Figure 2.23 illustrates some of the spatial trends in emission deviation found within the sfmuni bus network. After reviewing the data, results suggest that there are three major factors that influence emission variability. The first factor involves the process of passengers entering and leaving the bus transit network. Across the dataset, regression analysis suggests that routes with higher bus stop density (e.g., stop-to-stop distance) tend to have higher expected emissions deviation, presumably due the fact that closer stops reduce the potential for a bus to travel at higher rates of speed. The second major factor is road type. Figure 2.23 (B) highlights the noticeably negative emissions deviation along a section of highway 101 (≈100 kph highway speed limit) while contrasts the noticeably positive emissions deviation along the arterial roads transecting the Mission and Potrero Hills neighborhoods (≈40 kph arterial road speed limit). However, literature suggests (38, 41) that other factors, such as vehicle density (e.g., congestion) which was not directly observed in the dataset, also lead to differences between these road types. The third factor influencing bus speeds and therefore emission deviation is route topology. Data suggest that buses navigating between road types (Figure 2.23 C) and entering intersections (Figure 2.23 A) often reduce their speeds during these activities, resulting in a change in their expected emissions deviation.

To conclude the case study, we aim to give perspective on how emissions deviation affects local GHG emissions inventories. We estimate the bias in bus emissions for an average weekday across sfmuni. Unfortunately, the NextBus dataset and other prominent public data sources (e.g., GTFS) do not provide the type of fuel used to powered buses along routes. This information is known within agencies, however, and we were able to acquire it through personal correspondence with the San Francisco Municipal Transportation Agency (sfmuni).

After scaling the respective emission factors using bus schedule data [71], we estimated that the resulting emissions estimation errors in the city-wide GHG emission inventory is 72 metric tons of $CO_{2,e}$ per day, or a roughly 35% underestimation of total, daily bus-related GHG emissions in San Francisco. Figure 2.24 summarizes the results of this analysis. The plotted dotted line represents the cumulative estimate of total daily GHG emissions (e.g., well(grid)-to-wheel only) using an average emission factor. In contrast, the plotted dashed line represents the results of the same assessment, using the respective speed-resolved emission factors. The gap between the two lines, shown as the grey area, represents the cumulative aggregation bias associated with using an average emission factor, which grows and shrinks based on the route-based emission deviation.

The routes in the figure are shown in ranked-order by increasing VKT and colors by fuel type (i.e., diesel: red, electric: pink). For a point of reference, the average GHG emission factors for diesel and electric buses is 2,120 g $CO_{2,e}$ / km and 4 g $CO_{2,e}$ / km, respectively. Total estimation errors for electric buses represents only 0.05% of the total error since electric buses are multiple orders of magnitude lower than diesel buses due to sfmuni sourcing 100% of its electricity from the Hetch Hetchy hydropower plant in Yosemite National Park,, CA (91). If the buses were powered by the average California energy mix (280 g $CO_{2,e}$ / kWh) (92), the total estimation errors within this network would be 5.7 tons per day higher, a 4% increase. These results suggest that emissions deviation may only result in significant errors if the average bus emissions are relatively large and represent a significant fraction of the fleet activity.

Overall, the results from the assessment on discrete level of specificity show that bus speeds are highly variable, leading to high variability in bus emissions rates. As a result, LCA modelers should seek to implement speed-resolved emission factors.

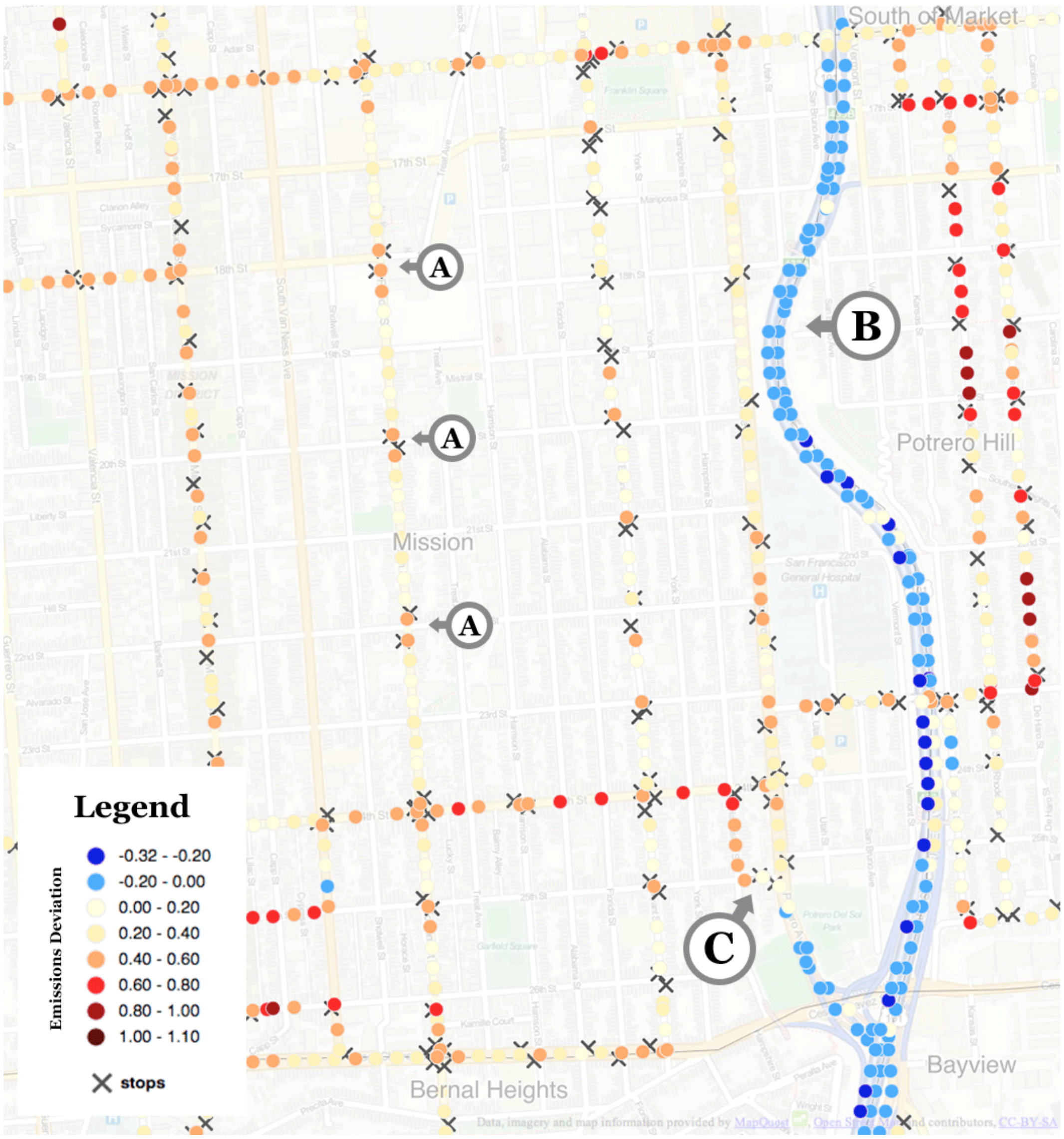


Figure 2.23: An annotated map of San Francisco's Mission neighborhood highlights three factors that influence bus speeds and therefore emission deviation. (A) Emission deviation around bus stops (shown in the map as X's) tends to be greater as buses lower their speeds to complete pickups. (B) Emissions deviation varies based on route type. Across the sf-muni network, bus routes along highways (shown here) and bus rapid transit (e.g., 38R, not shown) tend to have lower expected emission rates compared to arterial roads since bus speeds are generally higher along these road types. (C) Network topology also affects emissions deviation. Data suggest that buses changing road types (shown) and/or entering intersections (see A) often reduce their speeds during these activities, resulting in a change in their expected emissions deviation scores.

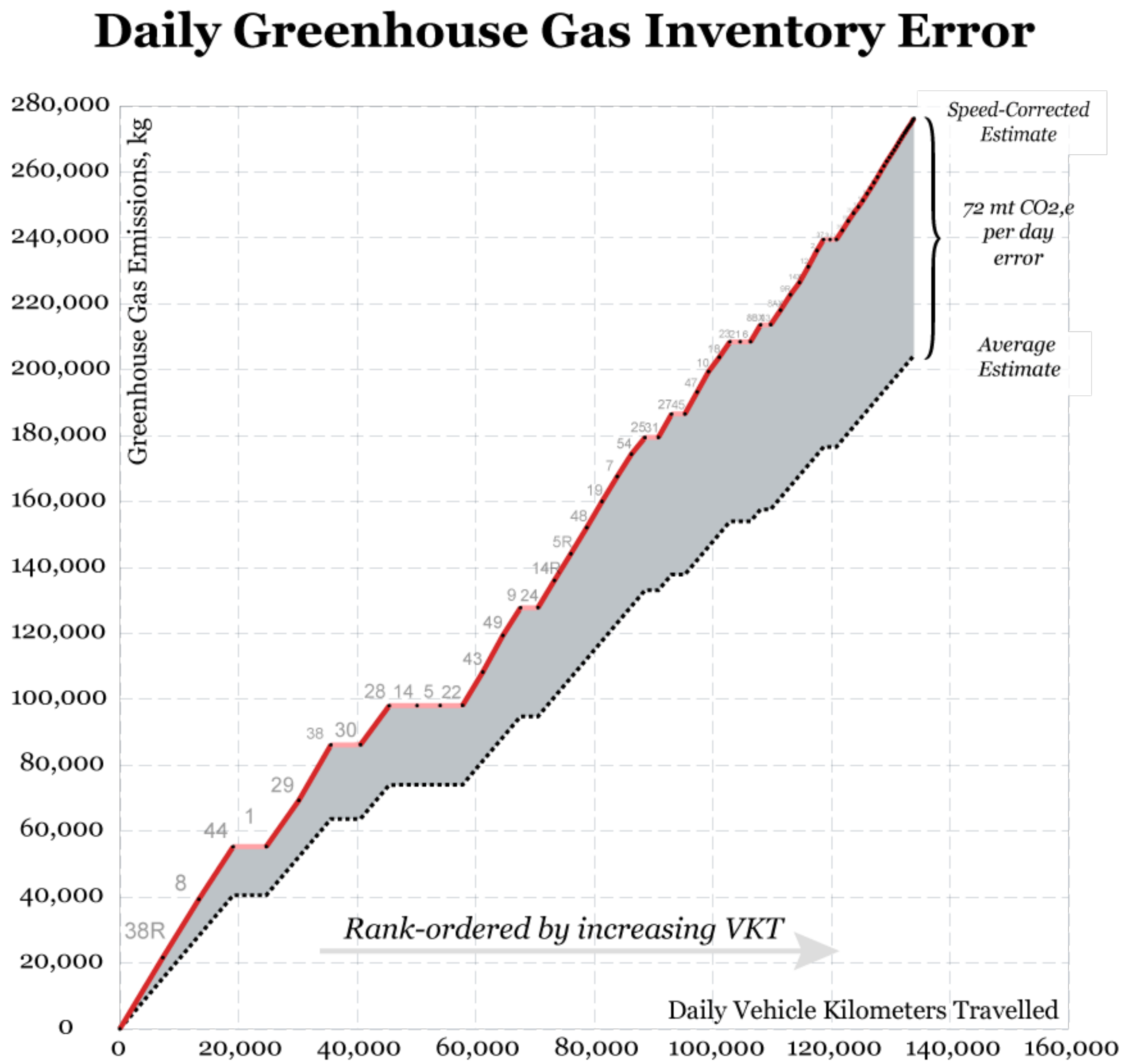


Figure 2.24: Estimates of total bias in kilograms of $CO_{2,e}$, for the daily, well-to-wheel GHG inventory for the San Francisco MUNI transit network. Bus routes were rank-ordered by daily vehicle kilometers traveled and colored by fuel type (i.e., diesel: red, electric: pink).

2.5 Chapter Summary

Life-cycle emissions factors for heavy-duty vehicles found in the literature [17, 27, 28, 8, 21, 10, 20, 19, 29] and within prominent LCA models [30, 31, 32, 38, 39] estimate well-to-wheel greenhouse gas emission factors based on fleet-average fuel economy. In recent years, however, studies have shown that these emission factors are greatly influenced by operational variability [51, 40, 52, 53, 54, 55, 24, 56, 36], especially vehicle traveling speeds

[44, 45, 46, 47, 48, 49, 50]. In this chapter, we quantified the expected difference between GHG emission factors based on fleet averages with emission factors estimated at a regional, local, and discrete level of specificity (aggregation level). The purpose of the chapter is to formally provide decision-making directives to LCA modelers to indicate if average emissions factors are appropriate, should be considered under specific conditions, or be avoided when conducting an LCA of heavy-duty vehicles. The scope of the study was limited to heavy-duty trucks (diesel) operating along California's highway network ad heavy-duty buses (diesel, gasoline, electric, and natural gas) operating within nine public transportation agencies in the same state.

In order to reorient the reader to the key findings of this current chapter prior to the chapter's ending discussion, the following summarizes the chapter:

- The level of emission estimation errors (positive or negative) vary across traveling speeds, with larger errors occurring at reduced and elevated traveling speeds.
- As would be expected, there is more variability in speeds along urban arterial road networks than on highways. As a result, our case study results show that emission estimation errors are greater for buses operating in cities than heavy-duty trucks operating along highways.
- For heavy-duty trucks operating along highways, congestion (resulting in low vehicle speeds) is the biggest driver of emission estimation errors since vehicle speed limits presumably cap emissions deviation caused at high traveling speeds. For the week sampling period, data indicate that congestion is primarily limited to the peak traffic hours of the day (7am-9am and 5pm-7pm) and along only certain sections of the observed interstate highway network.
- Bus speeds differ across public transit agencies, which subsequently causes each agency to have a unique GHG emissions rate distribution. The range of emission factors expected also varies by agency. On a discrete level of specificity, network features such as road type, bus stops, route topology, and aspects of congestion all drive emissions variability.

2.6 Discussion

Policies based on route-oriented hybrid trucking LCA methodologies have numerous advantages over those applying traditional LCA models. Speed-resolved GHG emission factors can be integrated into current transportation network models to provide valuable information about how the GHG footprint of trucks and buses may change within specific settings. Until now, heavy-duty vehicle LCAs have primarily been a way of modeling the footprint of moving goods and passengers from a generic or industry-average perspective [17, 27, 28, 8, 21, 10, 20, 19, 29]. By including the influence average speed has on fuel economy, this approach allows decision-makers to manage the GHG footprint of heavy-duty trucks and buses in a more localized context using route-based modeling techniques. Removing the constraint of utilizing average data, new statistics can be formed given additional information that is readily available today. We find that increasing the dimensionality of heavy-duty vehicle fuel economy models reduces overall aggregation errors in GHG emissions inventories.

Overall, we see many applications for this method to be implemented within current transportation systems monitoring and environmental management. We have shown that well-to-wheel emission factors can be incorporated into existing vehicle monitoring networks, since these systems already report vehicle speeds. Data collected from networks such as PeMs or Nextbus can be used to better record well-to-wheel emissions variability over time and space, helping to identify and mitigate emissions"hot-spots" through targeted mitigation policies. The incorporation of well-to-wheel emission estimates within transportation monitoring networks could also make emissions data more accessible to parties unfamiliar with environmental analyses but who have intimate knowledge of how vehicle networks function and how they are managed. In addition, speed-resolved emission factors can also be incorporated into trip-level decision-making, such as vehicle routing optimizations. One of the major limitations of this study is that speed-resolved emission factors are based on an a priori vehicle duty cycle. In reality, vehicle operational conditions (e.g., speed, mass, ac-

Table 2.3: Summary Decision-Making Directives.

	Level of Specificity		
Mode	Regional	Local	Discrete
Trucks (Highways)	Approximately 91-99% of VKT across the districts reported an error less than 7%. Therefore, an average emission factor will suffice.	Emissions deviation only occurs during on-peak periods of the day, though only a few highways are affected. An average emission factor will suffice.	Emission deviation could be large, but this only occurs when trucks hit congestion. Speed-resolved emission factors are preferred, but should take into account the fraction of the total trip that experience periods of high emissions deviation.
Buses (Arterial Roads and Highways)	Emissions deviation will vary across agencies. In some cases, the bulk majority of buses could be characterized using the statewide average emission factor. The only way to determine would be to assess bus speeds, however. Given this requirement, speed-resolved emission factors are preferred but could be substituted for average emission factors when appropriate.	Emissions deviation is highly variable on an individual route basis. In some cases, the differences between the expected emissions deviation across routes may be small. In these cases, an agency-specific emission factor corrected to reflect an expected δ could suffice. Otherwise, speed-resolved emission factors are recommended.	Again, emissions deviation is highly variable across bus networks. The major factors that influence this variability are road type, locations of bus stops, congestion, and route topology. Speed-corrected emission factors should always be used when referring to the carbon footprint of an individual bus trip.

celeration, grade) and vehicle configurations vary. Future work should focus on improving emission factors so that they reflect true operational variability.

To conclude this chapter, we outline specific decision-making directives for governments, fleet owners, companies, and LCA practitioners to help evaluate whether it is appropriate to use generic or industry-average GHG emission factors (e.g., fleet scale) under different levels of specificity or aggregation. Table 2.3 summarizes the major findings of the heavy-duty truck and bus case studies in the form of a stoplight diagram. The table cells, which reflect the vehicle mode and study's level of specificity, are colored to indicate if generic or industry-average emissions factors are appropriate (green), should be considered under specific conditions (yellow), or be avoided (red) when conducting an LCA of heavy-duty vehicles. Overall, we find the fleet-average emission factors to be more appropriate for heavy-duty trucks than buses.

Moreover, integrating speed-corrected emission factors into LCA models can allow decision-makers to identify when, where, and how often heavy-duty truck emission rates deviate from fleet-wide averages. Average emission factors have the potential to mask vehicles that are more environmentally burdensome. Targeting vehicles with higher emissions rates may be an effective way to minimize emissions and their subsequent impacts in a cost effective manner, assuming the unit cost of mitigation is uniform across vehicles. Since increased emissions can be very localized, we find that assessments at finer resolutions (local and discrete) may be best to capture this variability and provider better context regarding the value of removing vehicles from the vehicle networks.

Chapter 3

Aggregation Errors in LCAs of Heavy-Duty Vehicles: Vehicle Payloads and Ridership Variability

3.1 Introduction

[1] The interactions between infrastructure systems (e.g., roads, transportation, water distribution, waste collection, etc.) and the environment are highly complex due to the heterogeneous nature of these systems' design, operation, and scale of coverage. Life-cycle assessment (LCA) has been a powerful analytical process used to evaluate the environmental impacts across all stages of a life cycle, which include material extraction, manufacturing, use, maintenance, and end of life. The results of the study, normalized by a functional unit, inform policy by allowing different parts of a system and its alternatives to be compared on equivalent terms.

While comprehensive, LCAs of infrastructure systems are not without their own methodological challenges [43], many of which arise from the fact that our knowledge about the connections between these systems and our environment is constantly evolving [83, 84, 85, 86]. Conducting a thorough LCA of infrastructure systems is data and time intensive. As a result, LCA practitioners often construct models based on average characteristics of systems and emission factors, such as secondary data found in published studies and LCA databases. This appears in the literature for environmental assessments of goods movement [87, 27, 8, 20, 88, 89], transit buses [10, 90, 19], other passenger transportation modes [11], water and wastewater systems [91, 92, 93], infrastructure materials [94, 24, 25, 26], buildings [95, 96, 97], telework [98], solid waste [99], as well as in tools used in life-cycle footprinting. The

[1]Reproduced in part with permission from Taptich, MN. Horvath, A. Bias of Averages in Life-Cycle Footprinting of Infrastructure: Truck and Bus Case Studies. *Environmental Science & Technology*, 2014, 48 (22), pp 13045-13052. Copyright 2014 American Chemical Society. Weblink to Article: `http://pubs.acs.org/doi/abs/10.1021/es503356c`

resulting average evaluations are important to understanding the magnitude of environmental burdens, and offer insights into possible energy and emissions tradeoffs between different system alternatives. However, uncertainties resulting from model configuration, data quality, data availability [100], and location of and population exposure to impacts [101, 102, 103] have lead some researchers to call into question the representativeness of results from average assessments under varying spatial and temporal scales [104, 57, 105, 106, 58].

Variability in life-cycle emission factors can be the result of heterogeneity in emission rates or level of service across like systems. The inherent randomness of these parameters is an irreducible form of uncertainty and its influence on emission factors is often, but not always, addressed in LCAs through sensitivity analyses, quantitative ranges, or process scenarios and simulations [100]. Interpreting the results of these assessments of variability and integrating them into future LCAs is challenging, specifically when it is unclear if the systems of interest represent the 'average' or typically modeled system. A very good example of average versus marginal comparisons is electricity production in the United States, where environmental impacts vary by production output, fuel type, efficiency, year-specific regulations, etc. [107]. In these situations, inherent errors are likely to exist.

The literature offers insights how to address these uncertainties when forming policies regarding infrastructure systems [108, 109, 110], and a few studies have attempted to quantify the level of errors associated with the use of average emission rate data over varying spatial and temporal scales [106, 58]. However, there is no study addressing the errors introduced by normalizing emissions based on average levels of service across systems, as opposed to averaging emission factors that apply across various levels of service (Jensen's inequality). This form of estimation bias is a function of both the variability of infrastructure system outputs (i.e., normalizing unit) and emission rates. We sought to examine the influences of the former in the context of two transportation systems where services are highly variable over time and space.

This study explored scenarios for estimating the well-to-wheels (W2W) greenhouse gas (GHG) emissions associated with on-road goods movement by medium- and heavy-heavy-duty trucks and bus travel. We present two case studies which examine (i) the fleet of heavy-duty vehicles in the United States and (ii) the performance of a single bus network in the city of San Francisco over the course of a week. Previous studies that reported the GHG footprint of these modes normalized to the ton-km [27, 28, 8, 20] and passenger-km [10], respectively, did so based on average levels of service (i.e., the number of tons or people transported) while accounting for parameter variability through a sensitivity analysis or reporting emission factors over a range of system outputs [19]. Each study found that GHG emission factors are sensitive to levels of service when GHG emission rates are assumed constant (i.e., the vehicle's total emissions per kilometer are not a function of the level of service).

By focusing the scope of our scenarios only on the variability in productivity for trucks and buses, we show that traditional methods for reporting the normalized GHG footprint of these services give biased "average" estimates by undervaluing the influence of under-productive or inefficient trips. These biases stem from the linear approximation of the nonlinear relationship shared between emission factors and the functional units used to normalize life-cycle energy and emissions inventories. While there are many conceivable policy implications, we focus on the underlying mathematics driving these estimation errors, and comment on their potential applications to other infrastructure systems. In addition, we provide updated well-to-wheel GHG emission factors as well as estimates of bias resulting from scenario analyses.

3.2 Methods

3.2.1 Well-to-wheel Emission Factor Formulation

The allocation of well-to-wheel (W2W) greenhouse gas (GHG) emissions to passenger travel or goods movement can be described by a convex function [8] that is dependent upon an emissions rate and level of activity,

$$e_f = \frac{E_f}{A} \tag{3.1}$$

where,

E_f = well-to-wheels emissions rate for activity (g $CO_{2,e}$ /km, $CO_{2,e}$: CO2, CH4, N2O)
A = functional unit associated with activity, (personal travel: passengers; freight: metric tons, mt)
e_f = well-to-wheels emissions factor, (personal travel: g CO2/passenger-km; freight: g CO2/ metric ton-km, t-km)

Previous LCAs of heavy-duty trucks have included the distance driven without payload (e.g., the dispatch and backhaul portions of a delivery) within the scope of A [27, 8]. The emissions generated during this portion of a delivery are shared equally among the goods transported along the trip. Therefore,

$$A = p \times (1 - e) \tag{3.2}$$

where,

p = The amount of goods transported, (metric ton)
e = The proportion of empty driving associated with each delivery, (%)

Empty-driving has not been considered in previous LCAs of buses [10, 19] and is not considered a part of this study.

Emissions are allocated to passengers and goods on a proportional basis, and the allocation takes into consideration the distances traveled while empty. For vehicles, we describe A in terms of levels of service (i.e., truck payloads and bus riders). When fuel economy and subsequently well-to-wheel GHG emission rates are assumed to be constant over a range of A [27, 28, 8, 10, 20, 19], the environmental efficiency of a vehicle increases as it becomes more productive (as A increases). However, previous studies have noted that negative feedbacks to energy consumption and infrastructure emissions occur with high vehicle payloads [24, 53]. These externalities should be accounted for. When these feedbacks are incorporated, the levels of bias that we describe herein would likely be smaller. In this study, we mirror the assumptions of previous W2W assessments of trucks and buses [27, 28, 8, 10, 20, 19] and do not consider these factors within the scope of the following scenarios.

Well-to-wheel (W2W) emissions include the direct and indirect pollutant releases associated with fuel production, distribution, storage and then the ultimate release of the fuel emissions at the tailpipe. Different fuel pathways and vehicle engine technologies will have unique W2W profiles. Due to certain rights granted within the Clean Air Act, the state of California is able to regulate vehicles and fuels beyond what is required based upon federal standards, and therefore have fuel pathways that are distinct from other states across the country [61]. In our case studies, we only consider the well-to-pump GHG emissions for ultra-low sulfur diesel sold within California. These emissions, which are reported in g $CO_{2,e}$ per mmBTU, were modeled using Argonne National Laboratory's GREET model [30] with a 2015 scenario year.

Tailpipe carbon dioxide emissions were modeled using the California Air Resources Board (ARB) EMFAC2011 model [50]. ARB reports GHG emission factors (g CO_2 per mile) for various types (e.g., car, bus, truck), subclasses (e.g., passenger, in-state, urban, etc.), and model years of vehicles. ARB also reports emission rates by vehicle traveling speeds, which are based on dynamometer studies. In our case studies, we assumed medium-heavy duty trucks, heavy-heavy duty trucks, and buses fall within 'T-6 Instate Small', 'T7 California IRP', and 'UBus' subclasses, respectively. There were other suitable subclasses which we could have used in this study, which is a limitation of this research. However, the variability in CO_2 tailpipe emission rates reported by ARB is small across subclasses and would not have significantly affected the final results.

The final well-to-wheels GHG emissions rates were calculated by combining the results from the EMFAC2011 model (g CO2 per mile) with the results of our model runs using the GREET model (g $CO_{2,e}$ per mmBTU) by carbon balance. Given standard properties of low-sulfur diesel, the energy consumed per distance driven was determined for heavy-duty trucks and buses:

$$E_{BTU} = E_{CO2} \times (44/12 * w_c * \times Y_{CO2}/(Y_{CO2} + Y_{CO} + 3 * Y_{HC}) * \gamma_d)^{-1} \times LHV \qquad (3.3)$$

where

E_{BTU} = Energy consumption rate for activity, (BTU / km)
E_{CO2} = Carbon dioxide emission rate for activity, (g CO2 /km)
Y_{CO2} = Mole fraction of carbon dioxide in tailpipe exhaust

Y_{CO} = Mole fraction of carbon monoxide in tailpipe exhaust
Y_{HC} = Mole fraction of hydrocarbons in tailpipe exhaust
w_c = Carbon intensity of Diesel, (g C per g diesel fuel)
γ_d = Density of diesel fuel, (g diesel fuel / gal diesel fuel)
LHV = Lower heating value for diesel fuel (BTU / gal diesel fuel)

For low-sulfur diesel, we assumed w_c= 0.871 and LHV = 129,500 BTU / gal of diesel fuel (9). The three in front of Y_{HC} denotes the conversion of hydrocarbons as propane equivalents to carbon atoms [66]. The calculated energy consumption rate per distance traveled was then used to determine the well-to-pump GHG emissions for each respective vehicle type.

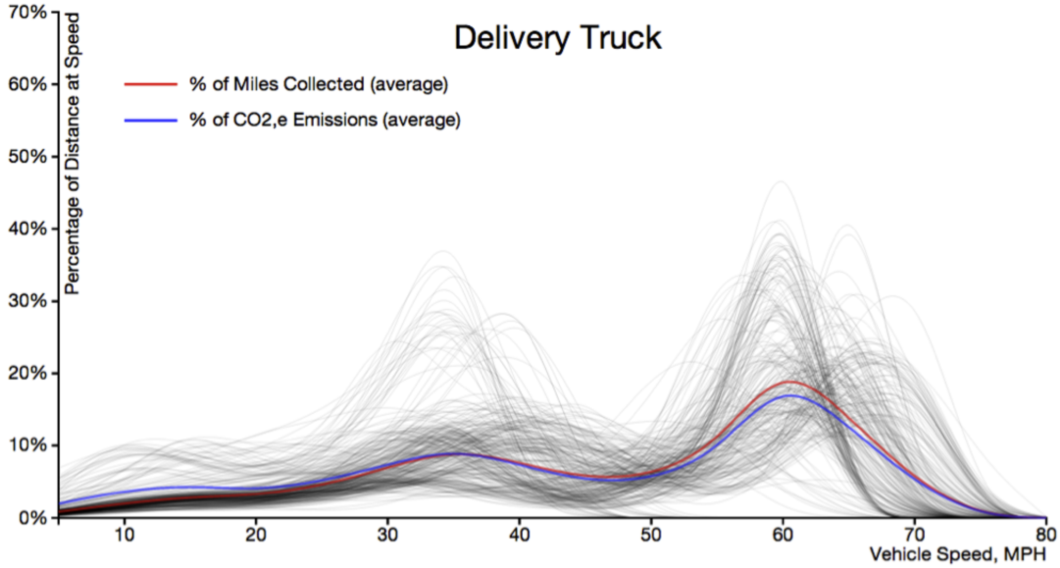
The expected well-to-wheel GHG emission rates were corrected to reflect the varying emissions rates at different traveling speeds [50]. We assume a standard profile for heavy-heavy duty (truck modeled: class 8) and medium-heavy duty (truck modeled: class 6 delivery) trucks [111]. Figure 3.1 shows that the smaller delivery trucks spend a larger percentage of their total trip distances traveling at lower speeds than the larger class 8 trucks. This is primarily due to the services each truck type provides. The average percentage of miles traveled at each speed is reported (red line) as well as the average percentage of $CO_{2,e}$ emissions (blue line). Fuel consumption rates reported in the EMFAC2011 model are the greatest at lower traveling speeds; therefore, $CO_{2,e}$ emission rates are highest at these speeds [50]. Overall, the well-to-wheel GHG emission factors were estimated to be on average 1350 g $CO_{2,e}$ per km and 840 g $CO_{2,e}$ per km for medium- and heavy-heavy duty trucks, respectively.

For urban transit buses, we compare the change in emission factors based on a relative value for E_f. At the time in which this study was submitted to and ultimately published in *Environmental Science & Technology*, we were unable to find a public source of information that completely listed the fuel types for the buses in our case study of the San Francisco Municipal Transportation Agency (SFMTA) MUNI bus network. We do provide on example calculation for diesel buses to discuss the impact of emission bias in nominal terms. Since we did not have real-time data on bus speeds during the time period when the passenger data was recorded, which were the basis for the previous chapter's case study, we instead needed to first estimate traveling speeds at each of the bus stops. We accomplished this by mapping bus stop arrival times to distances along route using transit stop and schedule data:

$$V_{i+1} = \frac{d_{i+1} - d_i}{t_{i+1} - t_i} \tag{3.4}$$

where,

V_{i+1} = Average velocity at bus stop i, kph
d_i = Distance along route at bus stop i, km
t_i = Time along route at bus stop i, hour



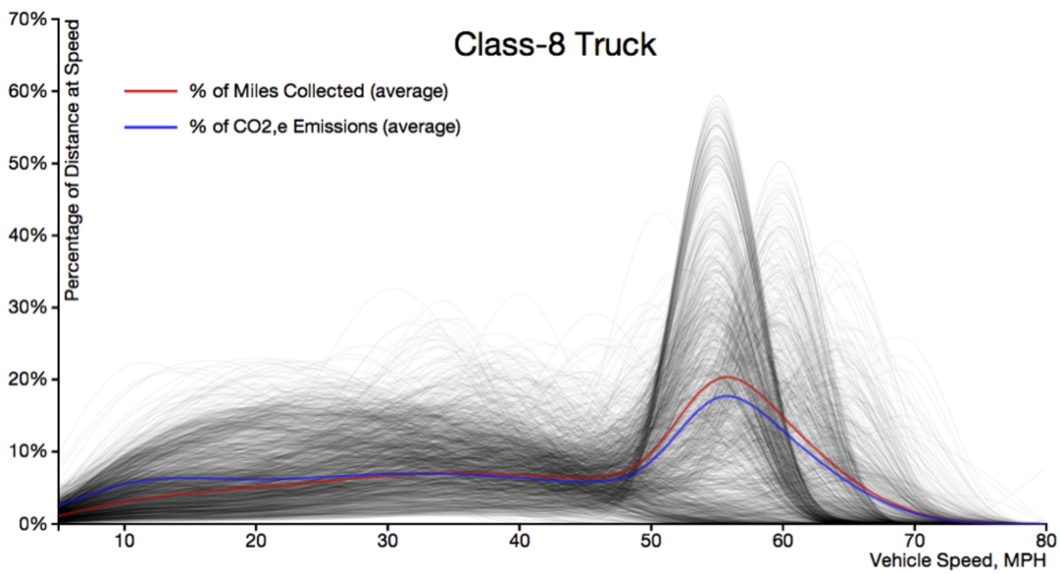


Figure 3.1: The distance-weighted speed profiles for medium-heavy duty (top) and heavy-heavy duty (trucks) based on data collected from the National Renewable Energy Laboratory's Fleet DNA project [111].

3.2.2 Estimating Aggregation Bias

It is important to consider the distribution of productivity when developing vehicle emission factors. Based on our assumptions, the marginal change in W2W emission factor $\frac{\partial e_f}{\partial A}$ monotonically increases with increasing A, signifying that small changes in productivity at low A have a disproportionally higher impact on average emission factor estimates than at high A (Figure 2). Since in our scenarios $\frac{\partial e_f}{\partial A}$ is not constant, using average values for A rather

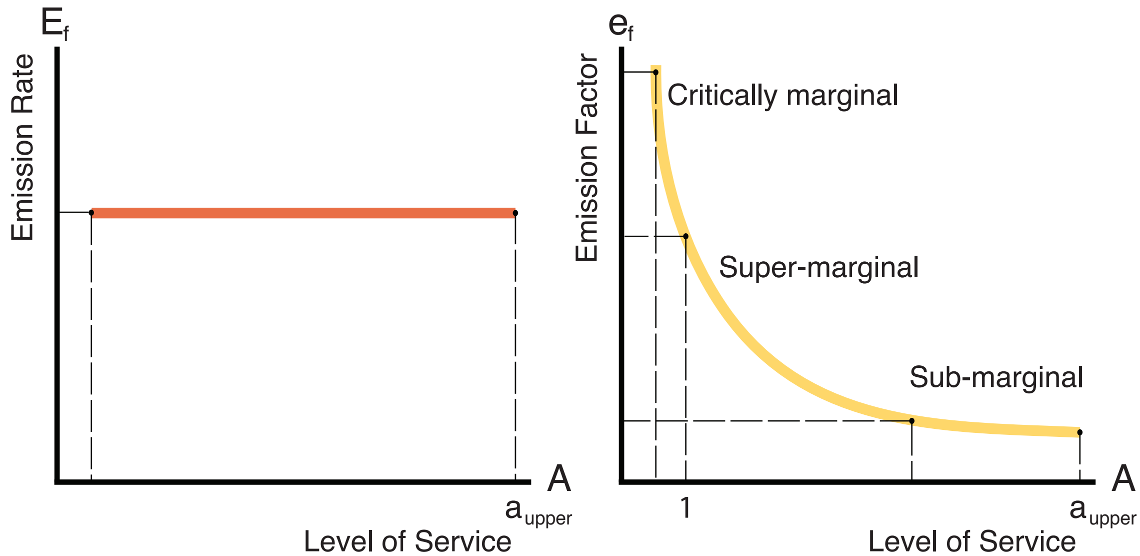


Figure 3.2: When emission rates E_f are assumed to be fixed over a range of system outputs A, average level of service estimates may suffice when activity parameters are contained within the sub-marginal region. Higher errors are possible if productivity drops into either super- or critically-marginal regions, where unit changes in outputs have large effects on emission factors.

than distributions has the potential to underestimate the true average e_f by undervaluing the impact of less productive trips (e.g., low truck payloads or bus trips with few riders).

As described by Jensen's inequality (and explained on an example in Figure 3.2), the average W2W emission factor will always be greater than estimates based on average productivity. The difference δ between the expected value of the W2W emission factor $\mathbb{E}_A[e_f(a)]$ (i.e., the unbiased estimate) and the mean after convex transformation $e_f(\mathbb{E}_A[A])$ (i.e., the estimate based on average productivity) depends on the extent and distribution of A as well as E_f:

$$\delta = \mathbb{E}_A[e_f(a)] - e_f(\mathbb{E}_A[A]), \forall a \in A \tag{3.5}$$

The bias δ, or Jensen's gap, will vary across different products and services and is largely dependent upon the minimum and maximum values of A. Figure 3.2 simplifies average versus marginal comparisons for when emission rates and levels of service are assumed independent of each other by dividing the emission factor function e_f into three regions we call sub-marginal, super-marginal, and critically marginal over increasing levels of service. Without knowing the precise distribution of A, the relative level of estimation error can be gauged based on where the range of A falls on the $e_f - A$ graph. Within the sub-marginal region, the level of bias is relatively small because e_f can be approximated as linear within this region. Thus, variations in productivity have limited influence on the final emission factor estimate. In super-marginal and critically marginal regions, improving productivity by a unit will noticeably improve emission factors. The threshold between critically marginal and super-marginal occurs when productivity is equal to one unit (e.g., one ton). Below this limit, the emission factors change exponentially with even small changes in productivity.

The transition between super- and sub-marginal regions may not be defined simply in terms of A. Different analyses will have different reduction thresholds, where improving A beyond these points yields negligible reduction in emissions. For example, the marginal improvement in an emission factor by increasing A incrementally is less than 5 percent beyond $A \approx 5$ and less than 1 percent beyond $A \approx 14$. Defining this threshold in studies may be subjective, but should take into consideration levels of uncertainty as well as scale. In our case studies, the transition between super-marginal and sub-marginal depends on the magnitude of E_f,while in situations where emission rates are considered a function of levels of service, the structure of E_f should also be considered.

Incidentally, the same marginal evaluations can also be made for indirect supply chain emissions within the scope of an LCA. In some stages of an infrastructure system's life cycle, such as those associated with manufacturing, construction, and end of life, large portions of emission rates are independent of the lifetime output. Previous studies for buses and truck have allocated emissions from vehicle production and end of life based on lifetime output in terms of ton-km or passenger-km, respectively [27, 28, 8, 10]. With years of operation, the share of these burdens in the total GHG footprint of the vehicle quickly diminishes as W2W emissions increase, and in time, represents only a small fraction of the total footprint (<5%). This is an example of operating within the sub-marginal region of the $e_f - A$ graph. We have not considered these emissions in our study because the biases are likely small.

3.2.3 Case Scenarios

To analyze the variability of level of service on W2W GHG emission factor estimates, we describe a goods movement and a personal travel case study using data from California. For goods movement, we focus on medium- and heavy-heavy trucks, which account for the majority of on-road freight turnover (280 billion ton-km in 2012) in the state [2] and emit 49 million metric tons of CO_2 (mmtCO_2) annually (tailpipe only) [50]. For context, the total direct GHG emissions in California are estimated to be 460 million metric tons of CO_2 equivalents [112]. GHG emissions from heavy-duty trucks are likely to rise in the coming decades as increased on-road freight demand is projected [2] to raise total fuel consumption [50], even in light of stricter federal fuel economy standards [113].

Statistics on average payload size and their standard deviations within truck classifications were taken from the US Environmental Protection Agency's (EPA) SmartWay program [114]. A full description of the truck equipment analyzed in this study (49 in total) is provided in the *Supporting Information* of Taptich and Horvath (2014) [41]. We assume payload distributions follow a truncated normal distribution that is bounded between zero metric tons and each truck's maximum payload capacity [115]. Trucks are driven empty for 29 percent of their operational lifetime on average, though this range will likely vary depending on the commodity type [116]. The truck duty cycles used in this study are based on measurements taken from the National Renewable Energy Laboratory's Fleet DNA project [111] for class 8 trucks (heavy-heavy duty) and delivery trucks (medium-heavy duty).

For personal travel, we estimate the W2W GHG emission factor bias δ for buses operating in San Francisco. We obtained a complete inventory of bus ridership at each of the city's 3,341 bus stops for a week through one of the city's open governmental data initiatives [117]. This allowed us to measure W2W emission factor variability along routes throughout the city caused by variable ridership. Since we were unable to identify each bus's fuel type (e.g., diesel or electric), we report bias δ as a percentage of $e_f(\mathbb{E}_A[A])$.

We report only the W2W greenhouse gas emissions for ultra-low sulfur diesel manufactured for California according to the Low Carbon Fuel Standard [61]. Tailpipe CO_2 emissions are taken from the ARB's EMFAC2011 model [50]. Emissions associated with the material extraction, production, distribution, and storage of diesel fuel powering trucks in California are based on estimates from the GREET model for 2015 [30].

3.3 Results

3.3.1 Heavy-duty Trucks in California

Heavy-duty trucks represent a range of vehicle sizes and performance capabilities. In the United States, they are classified based on their Gross Vehicle Weight Rating (GVWR), which bin trucks based on the manufacturer's suggested maximum operating weight [115]. They may also be designated as light (class 2b-3), medium (classes 4-6), or heavy-heavy duty (classes 7-8b) [116]. The size of a truck influences the types of services it can provide and its truck-body/trailer configuration (50, 48). In the United States, medium-heavy duty trucks have smaller payloads and are driven over shorter distances than the larger heavy-heavy duty trucks [116].

Statistics published by the EPA SmartWay program [114] indicate that truck payloads vary over different ranges across GVWR classes. participants in SmartWay, they were unable to provide further information regarding the shape and skew of payload distributions. Therefore, we assume that truck payloads follow a truncated normal distribution that is bounded between zero metric tons and each truck's respective maximum suggested payloads [115] and estimate the distribution via Monte Carlo Analysis. For some of the larger specialty trucks, average payloads exceeded the suggested maximum payload values provided by Oak Ridge Laboratory's Energy Databook and could not be appropriately bounded. For this reason, we excluded these trucks from our results.

Figure 3.3 shows that the average payload distribution varies by GVWR class and trailer type [114, 116][2]. Statistics from the EPA SmartWay[3] program indicate that trucks the aver-

[2]VIUS, though now-dated, is useful for obtaining state and national level data on the physical and operating characteristics of fleets in the United States Many freight logistic models utilize this data for planning and forecasting purposes.

[3]The EPA's SmartWay program has been working with shippers and carriers for over 10 years in order

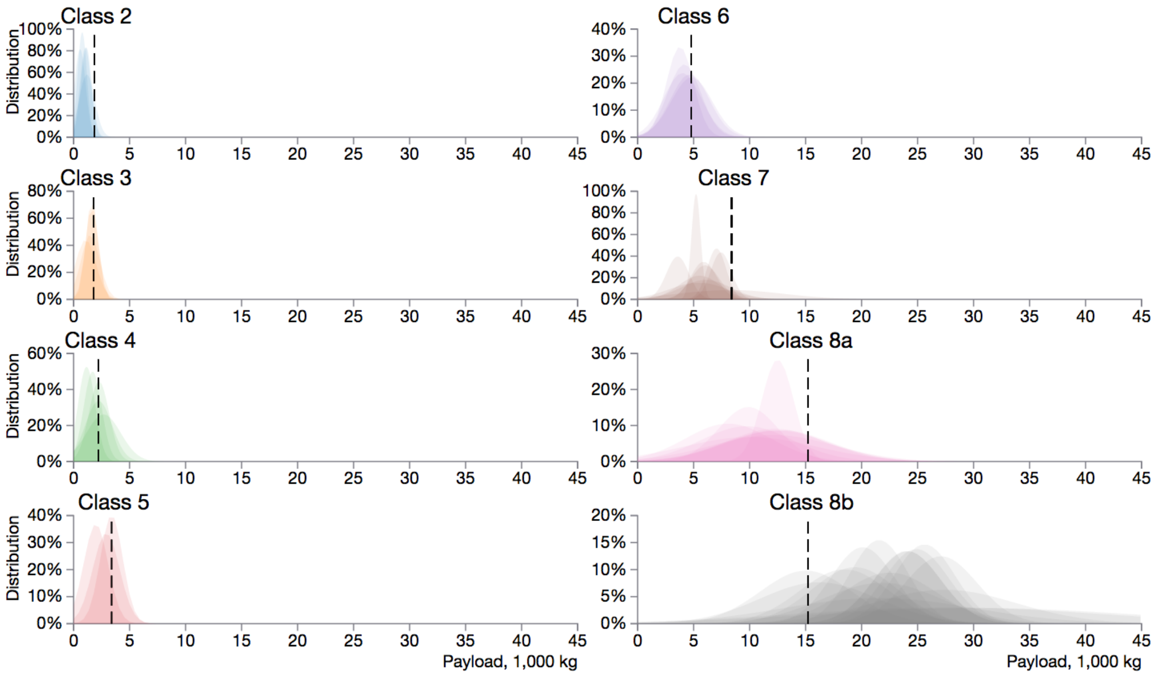


Figure 3.3: Average truck payload varies within GRWR classes. This variability may due to differences in the types of goods being shipped. The shaded area shows the distributions by different truck + trailer combinations (EPA 2013) versus average VIUS payload statistics (line).

age payload estimates from the now dated Vehicle Use Survey fall in line with current fleet estimates for most GVWR classes. A few additional characteristics about US trucking fleets can be gleaned from the figure. First, trucks with high capacity see the largest variations in payloads (tons). Second, different trailer types achieve a different distribution of payloads within classes of trucks. For example, among SmartWay participants, class 8 trucks that transport tanker trailers typically carry double the payload of trucks providing less than truckload services. Lastly, Figure 3.4 indicates that larger trucks carry a proportionally higher volume of goods per trip. Trucks with larger payloads allocate emissions over a larger amount of goods.

For each truck class, a feasible cumulative distribution function (CDF) range for truck payloads was reported (Figure 3.4). Again, we constructed a payload CDF for each truck type by creating a random number generator based on the truncated normal distribution and sorting in increasing order the results of 10,000 sample iterations. The bounds of the payload area graphs were determined by taking the lower and upper estimated CDF functions within each truck GWVR class.

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to evaluate truck fleet performance in terms of criteria air and CO2 pollutant performance metrics. The EPA recently (2013) published fleet-specific statistics on the over 3,500 trucking and logistic companies participating in the program. Prior to SmartWay, VIUS was the most comprehensive freight data source.

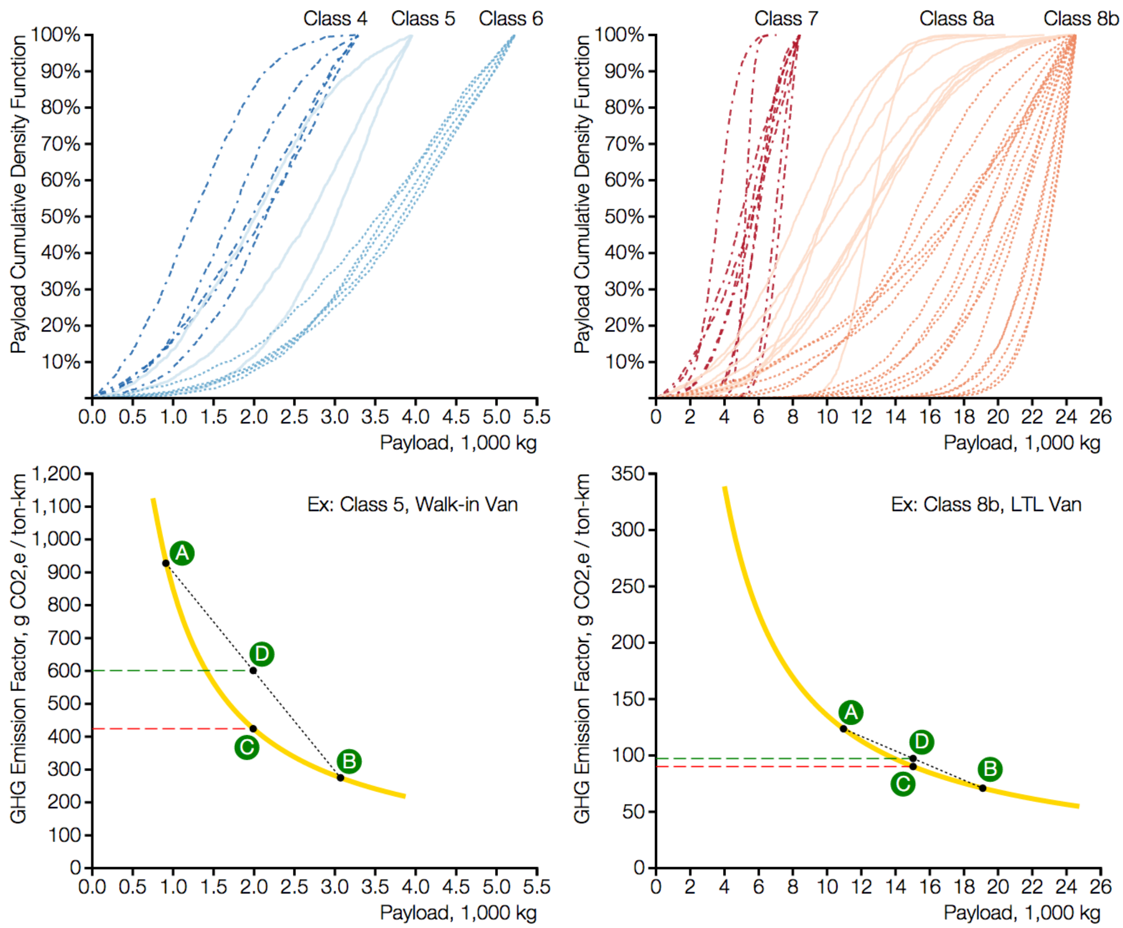

Figure 3.4: (TOP) Distributions formed from data collected through the EPA's clean trucking partnership [114] indicate that medium- and heavy-heavy duty truck payloads vary both across and within GVWR classes. This suggests that each truck class has a unique set of GHG emission factors. (BOTTOM) Illustratively, the secant line ADB represents the weighted means of the well-to-wheel GHG emission factor for diesel-powered trucks operating in California assuming constant W2W emission rates (Class 4-6: 840 g $CO_{2,e}$ / km; Class 7-8b: 1350 g $CO_{2,e}$ / km). The emission factors are not shown for less than 1 ton for class 5 and less than 4 tons for class 8b. Given equal weights to points A and B, the difference between points C and D represents the level of bias between the two estimations.

Each line in Figure 3.4 (top) represents the assumed cumulative distribution functions for all of the truck types provided by the EPA. Each GVWR truck class (labeled on top of the figure) shares a common maximum payload capacity, but has utilization rates that reflect the types of services they provide. For instance, less-than-truckload (LTL) class 8 tractors move goods from many different customers at a time and are more likely to see variable payloads, as compared to class 8 tractors with tanker trailer that perform primarily full-truckload services. As a result, we find that heavy-duty trucks span different portions of the $e_f - A$ graph. Payload variability in medium-heavy duty trucks may result in large fluctuations in the well-to-wheels GHG footprint since these vehicles fall within the super- or critically-marginal regions. In contrast, heavy-heavy duty truck emission factors are less sensitive to payload variability because payloads generally fall within the sub-marginal region. Overall, short-haul trucks (class 4-7) are located within the super- or critically-marginal regions, while long-haul trucks (class 8a and 8b) are within the sub-marginal region.

Figure 3.4 (bottom) shows an illustrative example of the level of bias (e.g., the distance along the y-axis between points C and D) associated with W2W GHG emission factors for two classes of trucks when average payload statistics are used. For each truck class, half of its trips contain payloads one standard deviation below their average and the other half one standard deviation above. For context, a class 5 walk-in van (left) provides services such as parcel deliveries in cities, and an LTL class 8 tractor provides services such as linehaul between freight terminals (right). Points A and B represent the upper and lower emissions factor estimate for each truck, respectively. The expected emission factor (g $CO_{2,e}$/t-km), represented by the dashed secant line ADB, lies above the graph of the function. Since $e_f(A)$ is a convex function when fuel economy is assumed to be constant over a range of A, $\mathbb{E}_A[e_f(a)]$ (point D) will always be greater than $e_f(\mathbb{E}_A[A])$ (point C). The degree of bias associated with estimating W2W emission factors based on average payload statistics will depend on where trucks operate on the $e_f - A$ graph. In this example, the walk-in van has larger estimation errors than the dry van because its payloads fall within the super-critical region. The errors for the dry van are less than 10 percent, which indicates that the use of emission factors based on average payloads may be appropriate for these truck types.

Table 3.1 summarizes the results of analyzing the W2W GHG footprint of various GWVR truck classes. Both medium- and heavy-heavy duty trucks have a range of expected GHG footprints and cannot be described based on a single central tendency. The corrected W2W GHG emission factors for medium-heavy duty trucks can range from 390 g $CO_{2,e}$ /t-km to 1,500 g $CO_{2,e}$ /t-km, which is 2-5 times greater than what was reported by Facanha and Horvath (2007) [8] and Meyer et al. (2011) [20]. Over a 50-km trip, these errors would result in 36-150 kg $CO_{2,e}$ of underestimated, unallocated emissions. For the larger heavy-heavy trucks, corrected W2W GHG emissions range from 87 g $CO_{2,e}$/t-km to 700 g $CO_{2,e}$/t-km. The unallocated emissions over a 50-km trip would be 10,190 kg $CO_{2,e}$. Truck types that are often associated with load consolidation freight operations (e.g., dry vans, reefers) have typically smaller P_{avg} and more variable P_{std} payloads than those dedicated to specific truck services (e.g., tanker, beverage, bulk, etc.). Accordingly, these truck types have a higher W2W GHG footprint.

Table 3.1 also shows that emissions estimates based on average payloads significantly underestimate the marginal influence of underproductive trucks. For most truck types analyzed, the magnitude of bias δ is greater in both net GHG emissions and as a percentage of expected GHG emissions than for smaller GVWR truck classes. These errors could be as high as 1,100 g $CO_{2,e}$/tkm or 240% larger than estimates based on average payload statistics. The bias δ would likely be smaller if W2W emission rates depended upon the levels

Table 3.1: Scenario results for levels of bias along with summary statistics for medium-heavy duty (top three) and heavy-heavy duty (bottom three) truck classes by truck-body/trailer configuration.

Class	**Truck Type**	P_{avg}, (mt)	P_{std}, (mt)	$\mathbb{E}_A[e_f(a)]$, (g/tkm)	δ, (g/tkm)	δ, (%)
Class 4	Flatbed	2.7	1.5	1500	1100	240%
	Step Van	2.2	1.2	1400	900	170%
	Walk-In Van	1.7	0.8	1800	1100	170%
	Conventional Van	2.3	0.9	850	330	60%
Class 5	Walk-In Van	2.0	1.1	1100	500	85%
	Conventional Van	3.4	1.0	450	100	30%
Class 6	Flatbed	4.7	1.7	410	160	62%
	Refrigerated (Reefer)	4.8	1.8	390	150	61%
	Walk-In Van	4.0	1.7	840	550	190%
Class 7	Beverage	6.1	2.2	450	130	42%
	Flatbed	7.1	0.9	280	8	3%
	Refrigerated (Reefer)	6.0	1.3	340	20	6%
	Tanker	7.5	0.9	270	12	5%
	Single-Axle Van	5.5	1.8	470	120	35%
Class 8a	Flatbed	10.0	5.9	410	220	120%
	Tanker	12.1	5.4	360	210	130%
	Single-Axle Van	8.1	3.8	700	470	200%
	Beverage	12.3	4.4	190	35	23%
Class 8b	Dry Van - Single (LTL-Moving-Package)	15.0	4.1	140	13	10%
	Dry Van - Single (Heavy-Bulk)	24.1	3.0	87	8	10%
	Specialty (Auto bin)	16.2	5.2	140	23	19%
	Dry Van - Double (Tanker)	24.1	3.0	88	8	11%
	Combination Flatbed	22.5	4.2	100	12	14%

of service provided [53]. Nonetheless, estimates of bias for medium heavy-duty trucks are up to an order of magnitude greater than heavy-heavy duty trucks because the maximum payloads for these truck classes limit them to within the super- or critically-marginal regions where errors tend to be the greatest.

The large errors for medium-heavy duty trucks could have major implications on the carbon footprint of goods shipped during the "first- and last-miles" of freight distribution networks [118] since these vehicles are often associated with this portion of many product supply chains (e.g., food stuffs, retail products, mail, etc.). Though representing a small proportion of total freight turnover in California (≈10%) [50], medium-heavy duty trucks emit CO_2 on the same order of magnitude as the larger heavy-heavy-duty trucks in the state. In 2014, the ARB estimates that medium- and heavy-heavy duty trucks will release

21 mmtCO_2 and 28 mmtCO_2 (tailpipe only), respectively [50]. Improving the productivity (e.g., preventing small payload size) for these smaller vehicles would be the best strategy for reducing their GHG footprint.

3.3.2 San Francisco Bus Case Study

The goal of the bus case study is to measure the level of bias associated with emission factors that are based on average passenger ridership statistics. The scope of our study is limited to the San Francisco Muni bus system, which supports the sixth largest average weekday ridership (approximately 312,400 persons) in the United States [73], but the analysis framework is applicable to any bus network. We rely on a robust dataset [117] that contains nearly complete information on bus ridership from the first week of October 2012. In total, over 27,000 bus trips and 9.3 million total riders are represented across 72 bus routes. With this information, we were able to measure ridership at each bus stop in the city and then use this information to estimate δ over the course of the week. As a point of reference, Chester and Horvath (2009) have reported the W2W GHG footprint of an urban diesel bus to be 80 g $CO_{2,e}$ per passenger-km [10].

Bus ridership in San Francisco, like in many cities, varies by both time of day and day of the week (Figure 3.5, top). Figure 3.5 (middle) shows that buses transport between 8 (10th percentile) and 24 (90th percentile) passengers on average (i.e., 8-30% of capacity). Daily peak average ridership corresponds to morning (inbound toward the city center) and evening (outbound toward residential neighborhoods) commutes. The choropleth graph also indicates that the greatest average ridership occurs during the weekends, but total hourly ridership is the highest during weekday commute hours (8-10 AM and 5-7 PM). Across the city the median value for average ridership at bus stops is 14 riders. This is an interesting result because it suggests that half of the bus stops in the city fall within the sub-marginal region of the $e_f - A$ graph while the other half fall within the super-marginal region.

Figure 3.5 (bottom) shows δ as a percentage of $e_f(\mathbb{E}_A[A])$, which allows us to compare levels of bias across both diesel- and electric-powered buses without needing to prescribe bus-specific E_f. The bias δ, based on hourly averages, ranges between 90% (10th percentile) and 157% (90th percentile) across the city. The greatest estimation errors occur on the weekend when average ridership is the highest. The reason for these high errors is that the distribution of ridership at bus stops across the city exhibits large skewness, meaning that buses can be either very full or practically empty. Thus, emission factors based on average ridership predict values that are between these extremes, which in this case fall within the sub-marginal region. However, since ridership spans across both super- and sub-marginal regions, we see higher expected e_f values and large levels of bias.

The number of riders also varies depending on the stop location. To simplify the reporting of results, in Figure 3.6 we show values for the top five routes based on total weekly ridership. Stops located within the downtown and its surrounding districts yield more riders than stops along the bus route termini. Overall, these routes average 18-25 passengers or operate 23-31% full. Figure 6 shows that the inner quartile values for bias δ vary depending on the

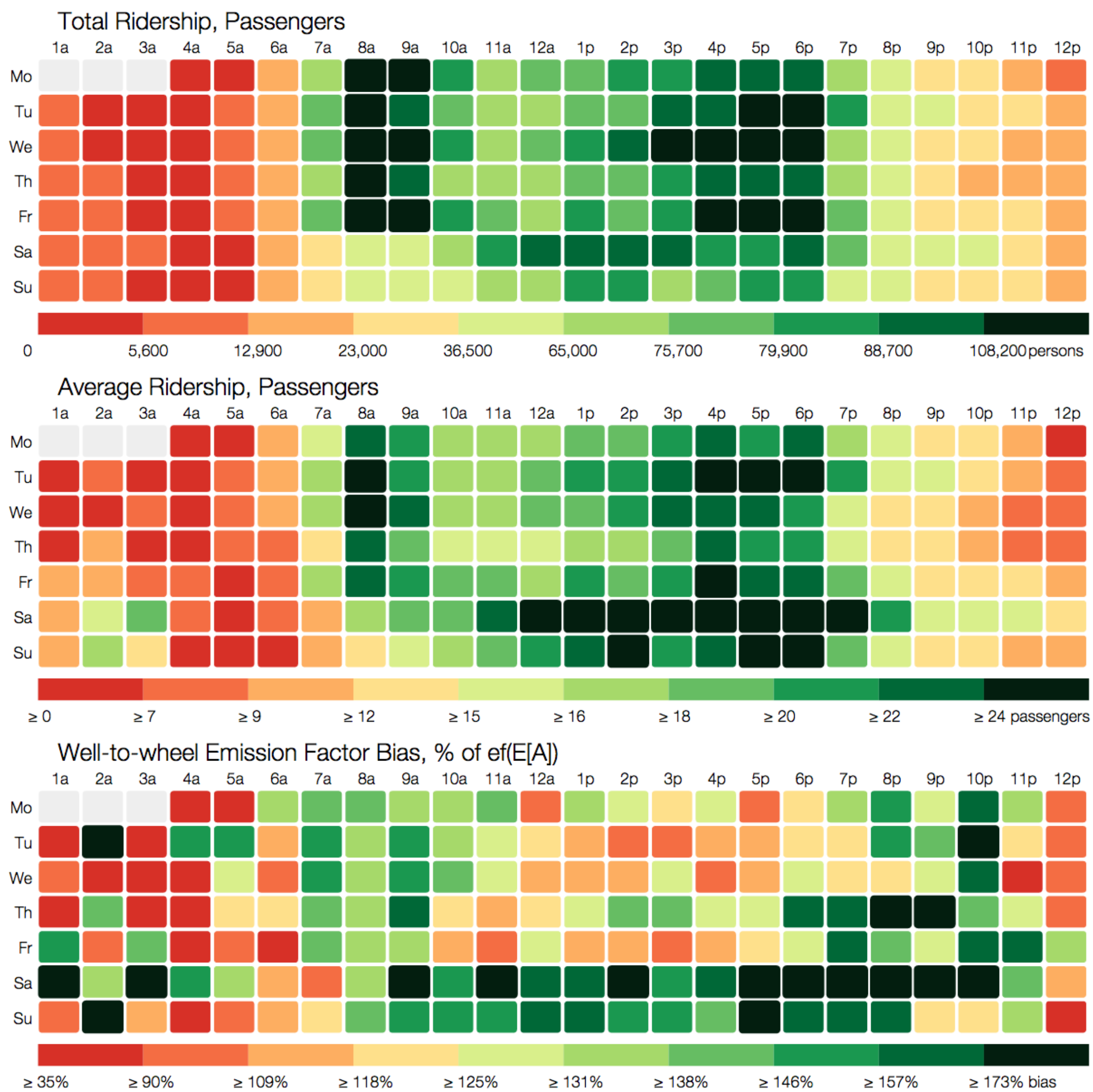

Figure 3.5: (TOP) Total hourly ridership by days of the week for San Francisco (binned by percentile ridership). (MIDDLE) Average hourly bus ridership by days of the week for San Francisco (binned by percentile ridership). Maximum capacity for most Muni buses is 80 passengers, which accounts for both sitting and standing room. (BOTTOM) The bias δ for well-to-wheel bus emission factors for San Francisco is reported as a percentage of $e_f(\mathbb{E}_A[A])$ (e.g., emission factor based on average hourly ridership) and are binned by percentile bias. In each, the 90th percentile is highlighted by yellow borders.

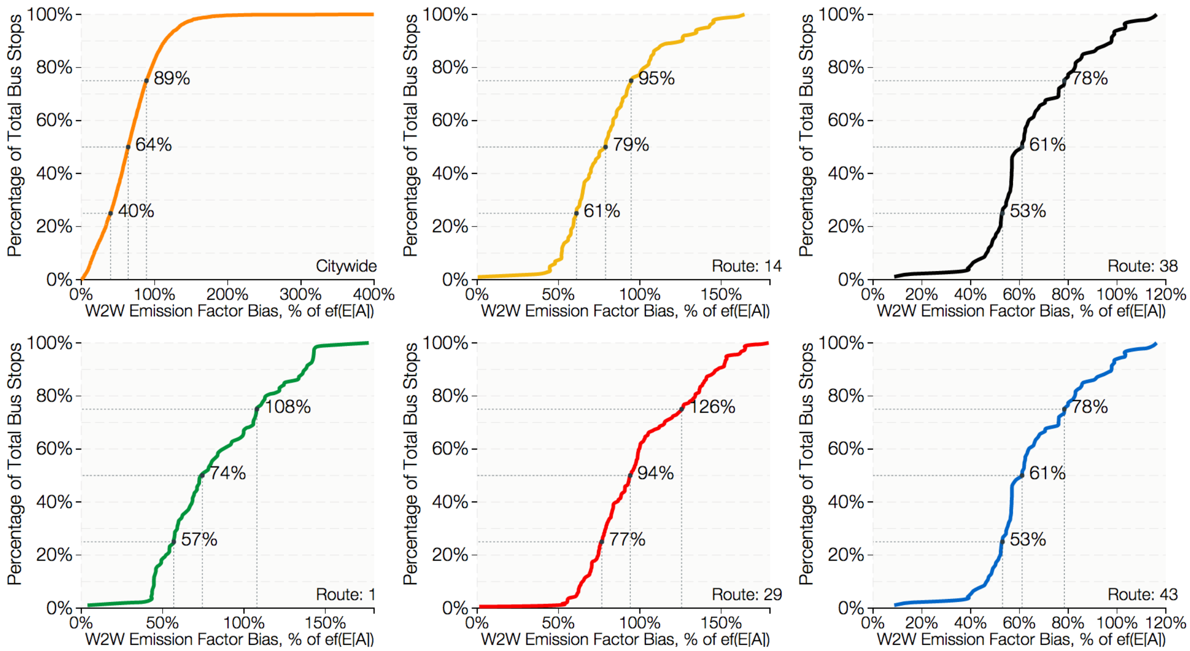

Figure 3.6: In each graph, the inner quartile values for bias δ are shown. These results reflect a local level of specificity.

route. The results indicate that bus emission factors based on average ridership underallocate emissions by 40-89% across the city, but the bias δ could be as great as 400%. When large portions of a route fall into the low-occupancy ranges (<15% capacity), W2W GHG emission factor estimates based on average ridership have higher levels of bias. Less than 5% of the bus stops in San Francisco had bias estimates smaller than 10%, which suggests that average weekly ridership data do not properly characterize the expected environmental implications of this system. Instead, analyses must include the distribution of ridership at more refined temporal scales or correct for these biases otherwise.

For a more specific example, we calculated the W2W GHG emission factors along route 38 (Geary Street), which extends east to west for 12 km across the city and services 6% of the weekly bus ridership. Figure 3.7 illustrates how bus ridership changes throughout the day for both inbound and outbound routes. Only diesel buses are used along this route. Average bus traveling speeds throughout the day were calculated to be 17 kilometers per hour ($\approx$10 miles per hour) [75]. On a weekly basis, buses along this route have an average GHG footprint of 220 g $CO_{2,e}$ per passenger-km (bus stop minimum: 53 g $CO_{2,e}$ per passenger-km, bus stop maximum: 810 g $CO_{2,e}$ per passenger-km). As expected, buses are more environmentally efficient during peak hours and less during off-peak hours, such as at night.

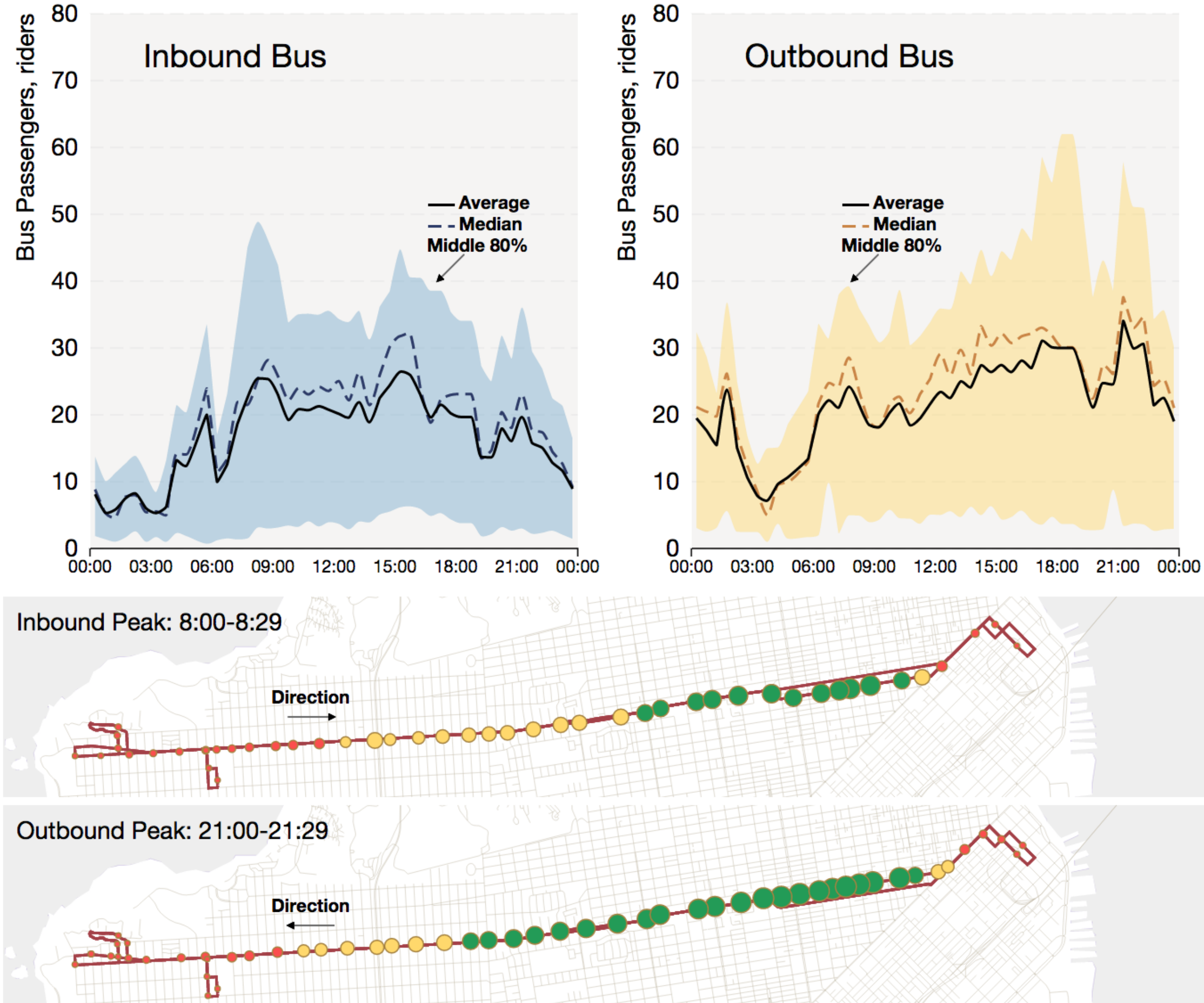

Figure 3.7: Weekday ridership along the bus route 38 (Geary St.) inbound and outbound in San Francisco (Fall 2012). Peak occupancy periods are depicted in the maps below in order to provide spatial context. Each circle represents average number of passengers at bus stops during peak ridership and indicate high (green, >50%), medium (yellow, 25-50 %), and low (red, <25%) occupancy levels.

3.4 Chapter Summary

The life-cycle output (e.g., level of service) of infrastructure systems heavily influences their normalized environmental footprint. Many studies and tools calculate emission factors based on average productivity, however, the performance of these systems varies over time and space. We evaluate the appropriate use of emission factors based on average levels of service by comparing them to those reflecting a distribution of system outputs. For the provision of truck and bus services where fuel economy is assumed constant over levels of service, emission factor estimation biases, described by Jensen's inequality, always result in larger-than-expected environmental impacts (3% - 400%) and depend strongly on the variability and skew of truck payloads and bus ridership. Well-to-wheel greenhouse gas emission factors for diesel trucks in California range from 87 to 1,500 grams of CO2 equivalents per ton-km, depending on the size and type of trucks and the services performed. Along a bus route in San Francisco, well-to-wheel emission factors ranged between 53 and 940 grams of CO2 equivalents per passenger-km. The use of biased emission factors can have profound effects on various policy decisions. If average emission rates must be used, reflecting a distribution of productivity can reduce emission factor biases.

3.5 Discussion

When emission rates are held constant over a range of services, the expected environmental impacts associated with transporting goods and people cannot be correctly predicted using average values for truck payloads or bus ridership. We show that the bias in GHG emission factors for heavy-duty trucks and buses always results in errors, i.e., larger-than expected environmental impacts. The levels of bias depend strongly on the variability and skew of truck payload and bus ridership distributions.

For many applications, using emission factors that are based on average productivity may suffice. For example, a concrete truck may always run at nearly full payloads, thus consistently operating within the sub-marginal region. In all other cases, emission factors based on average productivity significantly underestimate the environmental burdens. This is especially important for product environmental assessments that use trucking as a delivery option, which in effect includes all products in the economy, at least in the first and the last mile of a trip.

Addressing the levels of bias requires an understanding of the extent and distribution of system productivity as well as its impact on W2W emission rates. More resolved emission factors can help policy makers better understand how infrastructure systems are performing from an environmental perspective, which could lead to lower environmental burdens through more effective resource allocation. For smaller trucks and buses with low ridership, focusing on improving productivity can provide opportunities to lower their overall carbon intensity, without necessarily lowering the W2W emission rates.

Future work should focus on the relationship shared between productivity and emission rates for vehicles and other infrastructure systems. While we show the biases in GHG emission factors when emission rates are assumed independent of levels of service, these biases would be smaller if this assumption were relaxed. For heavy-duty vehicles, studies have shown that fuel consumption and GHG emission rates are linearly proportional to vehicle mass [53], and emissions from road infrastructure maintenance grow by a fourth-power law with mass (21). Similar feedbacks to emission rates may be found in other infrastructure systems. In cases where $e_f(A)$ is linear (i.e., emission rates exponentially grow with levels of service), there is no bias associated with $e_f(\mathbb{E}_A[A])$.

There are also other forms of bias associated with W2W emission factors for heavy-duty vehicles. Most notably is the assumption that emission factors scale emissions and impacts linearly with distance, irrespective of when, where, or how a truck is driven. This assumption of linearity significantly impedes comparisons between different trucks on a micro scale, since each road segment is treated as being one and the same. In reality, traveling speed [119, 47], terrain, vehicle payload [44], driver behavior [120], road conditions [24], extended periods of idling associated with frequent stops, among other factors [56], all have impacts on fuel economy and GHG emissions.

Chapter 4

Aggregation Errors in LCAs of Heavy-Duty Trucks: Infrastructure Topology Variability

4.1 Introduction

[1] The potential for exchanges between producers and consumers with minimal environmental impacts is important for sustainable development. Freight modes (trucks, trains, ships, airplanes) have varying life-cycle environmental impacts per ton-km of transport [8, 20, 12, 9, 29], depending on fuel consumption rates, pollution control technologies, consignment sizes, and lifetime productivity [41]. These differences result in varying levels of access potential [121], as modes with lower emissions footprints can travel larger distances per unit emissions [122, 123]. Ideally, total 'localization' of the supply of goods would completely minimize the environmental impacts stemming from exchanges between producers and consumers by eliminating the need for freight transportation. This is unrealistic in practice, however.

Measuring market accessibility from an environmental perspective takes into account many location-specific factors, such as levels of producer outputs, critical infrastructure availability, etc . Accessibility, broadly defined, is the potential of opportunities for interaction about a point, given a discrete spatial limit or impedance over a distance [124]. Generally, consumers have good access to a supply of a commodity if there exists a large quantity of this supply that can be attained through some form of logistics at minimum environmental cost. In the United States, like other areas of the world, the production centers for different commodities are regionally dependent [2, 125]. The dispersed nature of industries has major implications on how supply chains form, freight infrastructure networks develop, and

[1]Reproduced in part with permission from Taptich, MN. Horvath, A. Freight on a Low-Carbon Diet: Accessibility, Freightsheds, and Commodities. *Environmental Science & Technology*, 2015, 49 (19), pp 11321—11328. Copyright 2015 American Chemical Society. Weblink to Article: `http://pubs.acs.org/doi/full/10.1021/acs.est.5b01697`

shippers operate. Thus, the geographic area in which trade is possible given some external environmental goal (e.g., energy, emissions, or impacts budget) will likely differ across the United States. In this paper, we refer to this area as a location's environmental freightshed.

We evaluate how transportation mode choice influences the spatial extent of freightsheds in terms of the amount of production that is attainable under a transportation emissions budget for different commodities. We seek to identify which counties in the United States have the best accessibility to goods. We also seek to assess how county-level emissions inventories are affected by infrastructure topology, e.g., the manner in which freight infrastructure components are interrelated or arranged. We consider greenhouse gases (GHG) emissions as the guiding decision-making metric, though other environmental metrics are also important, and may be explored in future work. To showcase how the extent of freightsheds is also tied to commodity-specific mode choice, we consider only shifting truck demand to intermodal rail, which is a combination of rail transport and truck drayage (e.g., short truck trips required to and from the rail network) between producers and consumers [121]. Truck and rail freight modes represent the majority of goods moved in the United States [2] and have the greatest combined infrastructure network [126, 127]. We do not considered waterway freight primarily because these modes represent only a small percentage of the total goods movement in the United States (8% of ton-km) [2] and are limited to only select transportation corridors. However, we could consider these alternatives in future studies.

In order to determine low-GHG accessibility across the United States, we first estimate the number of tons of goods shipped by truck (e.g., production volumes) a consumer could reach across the US given some carbon budget or preference for low-carbon goods, using a combination of disaggregation methods and network flow optimization techniques. Given variations in statistical significance [128, 129, 130], we select only two commodity classes listed in the US Census Bureau's Commodity Flow Survey (CFS) [125]: "Meat/Seafood" and "Paper Articles." Meat/seafood includes fresh, frozen, and chilled beef, pork, poultry, fish and aquatic invertebrates. Paper articles include toilet paper, towel, tissue, personal hygiene, paperboard, and other paper packaging items [131]. It is important to note, however, that many other commodities could be assessed in the future. We then model how upgrading current intermodal terminals to allow the exchange of all types of goods could increase overall accessibility as well as expected GHG savings of mode-switching policies.

4.1.1 Background and Further Motivation

The demand for freight transportation is projected to increase in the coming decades across the United States [2, 1], which has many implications for the nation's total annual GHG emissions. The transportation sector is the second greatest source of GHG emissions in the U.S. after electric power systems [1], while freight transportation represents about a quarter of these emissions. Of all the domestic freight modes (e.g., road, rail, waterway, air), heavy-duty trucks move the greatest amount of goods [2], have the highest GHG footprint among land-based freight modes [125], and thus emit the most GHGs annually [8]. Hence shifting demand from trucks to modes that emit less is one pathway to reducing overall GHG emissions.

Studies have shown that stakeholders can reduce GHG emissions by promoting intermodal freight activities, e.g., augmenting portions of freight flows by Class 8b trucks (on average 120 g CO_{2e}/tkm) to rail (on average 19 g CO_{2e}/tkm) or water vessel (on average 33 g CO_{2e}/tkm) [88]. In a case study of a major logistics company, Craig et al. (2012) found that the GHG footprint of intermodal rail is less than trucking, though the benefits of mode-switching policies are location dependent [121]. In addition, the researchers note that access to intermodal terminals is a key contributor to the overall carbon footprint of this mode. These researchers did not explore the effects of specific commodities or locations, however. Corbett et al. (2010) developed a comprehensive and GIS-based intermodal freight model that estimates the shortest environmental path — along with other measures of costs (e.g., time and dollars) — between origin-destination (OD) pairs in the United States [132]. Their research shows that shifting West Coast port-generated truck demand to intermodal freight could reduce GHG emissions by 1.7 million metric tons of CO_2 per year. The researchers also showcase the value of coupling national commodity flows with GIS-based informational tools [133] and suggest that these tools could be used to measure mode accessibility. Using input-output analysis (i.e., a top-down model), Nealer et al. (2012) examined the energy and emissions benefits of mode-switching policies across different sectors of the US economy in 2002 [88]. Their scenarios suggest that improving the fuel efficiency of trucks may be a more prudent way to reduce GHG emissions within the freight sector, as historically unprecedented sums of mode switching would need to occur in order amount to the same levels of GHG reductions. However, these findings are highly uncertain [88], are based on shifting modes in the top 20% of all sectors, and ignore all added emissions required for mode switching to occur (e.g., truck drayage).

Transportation is only one part of a good's life cycle. Weber and Matthews (2008), who focused only on food products, assert that product selection has greater influence on environmental impacts as opposed to localism, or the preference for locally or regionally sourced goods, because transportation accounts for only a small portion of many products' total environmental footprint [134]. While that may be true on average across a national economy, the intent of this paper is to evaluate and put into use the environmental performance of freight transportation for different, specific commodities and locations.

Each of these previous studies evaluate the environmental impacts associated with intermodal freight policies and, in parts, low-carbon accessibility; however, they do not fully address the questions of where to incentivize mode-shifts and how proximity to infrastructure may influence the access between producers and consumers for different commodities. By best locations, we mean the 3,109 counties in the lower 48 states. By incentivizing, we denote our efforts to provide complete information to stakeholders in order for them to make more informed decisions.

Moreover, to address these concerns, we need to understand how these benefits may change across different product supply chains and between specific locations across the United States. In a study on whether locally or regionally sourced goods reduce GHG emissions, Edwards-Jones et al. (2008) concluded that "spatially explicit life-cycle assessment[s]" are needed in order to fully address this question [123]. Thus, to model the environmental impacts of different product supply chains and between specific locations across the United States requires a bottom-up modeling approach [123, 132, 135, 136] that accounts for freight infrastructure networks, commodity flows, and commodity-specific freight characteristics and life-cycle environmental impacts.

4.2 Methods

4.2.1 Measures of Accessibility

To identify which areas of the country have the greatest opportunities for low-carbon exchanges between producers and consumers, we rely on both discrete and continuous measures of accessibility. We define accessibility, A_i, as the potential amount of production (T_j, tons) a consumer could reach for a respective commodity at a particular location i. For discrete measures of accessibility, the spatial extent of GHG freightsheds is limited such that the GHG emissions produced in transport between producers and consumer, E_j, is within a set GHG budget, B. E_j is a function of both distance travelled as well as the GHG emission rates associated with a particular freight mode:

$$A_i = \sum_{j \in n \text{ such that } E_j \leq B_j} T_j \tag{4.1}$$

Generally, the discrete accessibility measure is effective at comparing system performance against external goals and targets as well as communicating results to stakeholders. However, discrete measures of accessibility require an a priori limit or budget and treat all accessible tonnage the same, which is a limitation of the model. In contrast, the results of a continuous accessibility model could be viewed as more ambiguous from a policy implementation standpoint, but are the best for comparing against itself as it accounts for all possible destinations. Low-carbon accessibility, when evaluated over a continuum, is measured using an exponential decay-type potential accessibility model:

$$A_i = \sum_{j \in n} T_j e^{-\beta E_J} \tag{4.2}$$

The impedance function, $e^{-\beta E_J}$, reflects the severity of higher emissions deterrence. This discounting factor, β, captures a consumer's preference for low-carbon transportation emissions. Lim and Thill 2008 point out that there is these constants are usually estimated empirically rather than ex-ante. In their study, the authors assign parameters based on a shippers cost preference under three scenarios: large cost decays (e.g., shippers have a larger preference for local goods), medium cost decays, and low cost decays (e.g., shippers have a smaller preference for local goods). We follow the reasoning presented by these researchers [135, 136] and assume that environmentally conscious shippers discount GHG emissions by

95% (large), 90% (medium), and 75% (low) at a location whose shipping distances would be 1,600 kilometers (1,000 miles) or 190 kg $CO_{2,e}$ by truck away. Our resulting values for β are 0.0158, 0.0121, and 0.0073, respectively.

4.2.2 National Intermodal Assessment

The scenarios presented in this chapter compare the potential benefits of shifting demand from heavy-duty trucks to intermodal rail across all counties in the United States. To assess these benefits at a county level for specific commodities, we had to develop a bottom-up model that incorporates the locations of commodity producers within the national highway and freight rail networks [126, 127]. For each county, origin and destination locations were established by snapping county centroids to the closest highway network nodes. Then, we joined both networks at road-to-rail intermodal terminals, or ramps that allow cargo to be exchanged unilaterally between modes. All other terminal types were excluded from the national network. Road-to-rail intermodal terminals vary by cargo (e.g., containerized, breakbulk, dry bulk, liquid bulk) and transfer type (e.g., direct, short-term, long-term), which results in each commodity class having a unique set of possible exchange points along the network [126]. In this study, commodities were assigned to terminals based on information provided in the US National Transportation Atlas [126]. Table 4.1 summarizes the distribution of road-rail intermodal terminals for the commodities explored in this study and others listed in the Commodity Flow Survey. The final intermodal networks were adapted to allow goods to flow between their respective intermodal terminals. For truck flows, only the national highway network was used.

Based on methods developed in prior freight studies [128, 129, 130] we compiled a subnational commodity dataset that reflects county-level truck freight flow patterns between producers and consumers. This involved a four-step process, which disaggregated national freight flows using scaling factors based on county-level industry employment [137]. First, we determined employment at the three-digit North American Industry Classification System (NAICS) [138] for each county, using mid-point imputing to account for flagged data entries [128].

Next, we created a bridge between the three-digit NAICS employment data and freight flows listed at the two-digit Standard Classification of Transported Goods (SCTG) [131] within the Freight Analytic Framework 3 (FAF) database [2]. The FAF database provides information regarding the flow of goods (tons) between states and major metropolitan areas (123 FAF zones) in the United States (Figure 4.1). The SCTG to NAICS pairing was guided by an unpublished Federal Highway Administration study [128].

To estimate the level of production and attraction (e.g., demand) at a county-level, we rely on regressions of commodity-specific employment and population data with commodity flows found in the within the Freight Analytic Framework 3 (FAF) database [2]. We referred to Cambridge Systematics (2009)[128] for commodity class to North American Industry Classification System (NAICS) industrial pairs, while only including employment categories

Table 4.1: Summary of Road-Rail Intermodal Terminal Availability

Commodity Description	SCTG Code	Road-Rail Terminals (total)	Fraction of Total
Live Animals And Fish	1	8	0.1%
Cereal Grains	2	261	4.2%
Other Crops	3	157	2.5%
Animal Feed, Pet Food, And Products Of Animal Orig	4	71	1.1%
Meat, Fish, And Preparations	5	129	2.1%
Milled Grain Products And Preparations And Bakery	6	211	3.4%
Other Prepared Food Stuffs	7	422	6.8%
Alcoholic Beverages	8	109	1.8%
Tobacco And Manufactured Tobacco Substitutes	9	13	0.2%
Monumental Or Building Stone	10	31	0.5%
Gravel And Crushed Stone	11	82	1.3%
Natural Sands Except Metal-Bearing	12	91	1.5%
Non-Metallic Mineral Products N.E.C.	13	225	3.6%
Metallic Ores	14	82	1.3%
Coal	15	97	1.6%
Crude Petroleum	16	47	0.8%
Gasoline	17	11	0.2%
Fuel Oils Including Aviation Turbine	18	28	0.5%
Refined Petroleum Products N.E.C.	19	193	3.1%
Basic Chemicals	20	274	4.4%
Pharmaceutical Products	21	19	0.3%
Fertilizers	22	78	1.3%
Chemical Preparations N.E.C.	23	352	5.7%
Plastics And Rubber	24	271	4.4%
Forest Products	25	204	3.3%
Wood Products	26	357	5.8%
Pulp, Newsprint, Paper, And Paperboard	27	328	5.3%
Converted Paper And Converted Paper Products	28	19	0.3%
Printed Products	29	4	0.1%
Textiles, Leather, And Articles	30	25	0.4%
Articles Of Stone, Ceramic, Or Glass	31	388	6.3%
Iron And Steel In Primary Forms And Basic Shapes	32	315	5.1%
Other Metal, And Articles Of Metal	33	297	4.8%
Mechanical Machinery	34	407	6.6%
Computers, Components, Peripherals, And Software	35	9	0.1%
Electrical Machinery And Equipment	36	103	1.7%
Motor Vehicles	37	56	0.9%
Engines, Parts, And Accessories For Motor Vehicles	38	36	0.6%
Transportation Equipment N.E.C.	39	7	0.1%
Precision Instruments And Apparatus	40	54	0.9%
Furniture And Furnishings	41	127	2.1%
Miscellaneous Manufactured Products	42	37	0.6%
Waste And Scrap	43	147	2.4%

that were statistically significant at the 95 percent confidence level (e.g., $P>|t| <0.05$) as explanatory variables (X_i) in the regression (Eq 4.3 and 4.4).

$$P(\text{Production}) = \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 \tag{4.3}$$

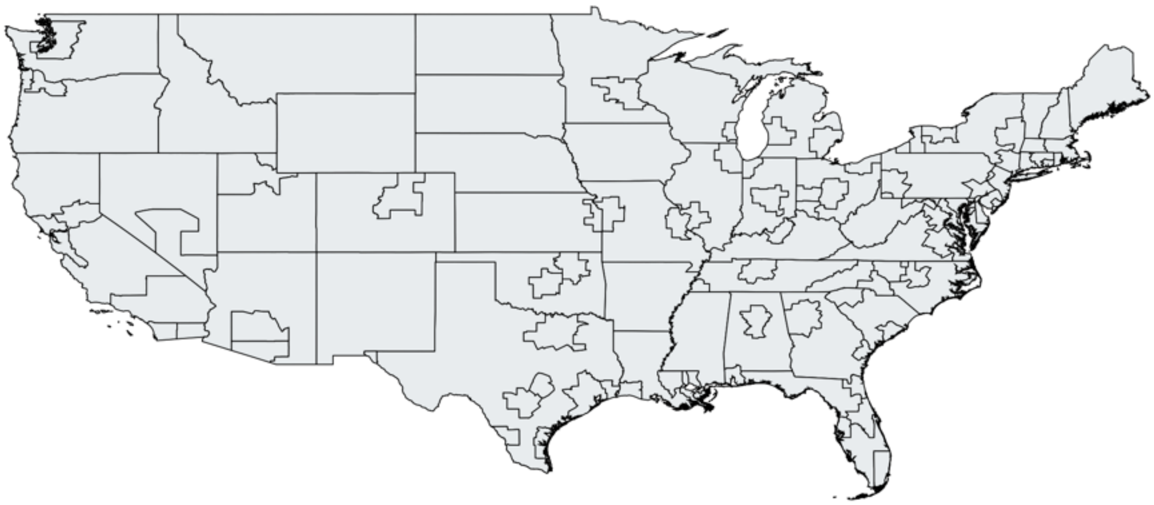

Figure 4.1: Zones listed within the Freight Analytic Framework 3 (FAF) database for the lower 48 states.

Table 4.2: SCTG-NAIC Pairs and Regression Summaries (Production)

NAICS Code	Description	Coefficient	t-stat
Meat and Seafood			
311	Food Manufacturing	0.0698	24.8
Paper Articles			
322	Paper Manufacturing	0.1139	6.0
323	Printing and Related Activities	0.0813	5.4

$$P(\text{Attraction}) = \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 \tag{4.4}$$

For each data point, data for our explanatory variables were aggregated to match the geographic scope of the parent FAF zone. For example, a single data point for the FAF zone representing the state of Kansas (Figure 4.1) would include the summation of all the relevant data from the counties falling within this zone, which would then be compared against the commodity data listed in the FAF database for this zone. Tables 4.2 and 4.3 represent a summary of the results for our regression coefficients.

Then we estimated allocation coefficients based on regressions for both the production and attraction of goods at a FAF zone resolution for the year 2012 [128, 129, 130]. Lastly, the allocation coefficients were used to estimate county-level production and attraction (e.g., demand) for all commodities and subsequently county-to-county flows [128, 132]:

Table 4.3: SCTG-NAIC Pairs and Regression Summaries (Attraction)

NAICS Code	Description	Coefficient	t-stat
Meat and Seafood			
311	Food Manufacturing	0.0285	8.0
722	Food Services and Drinking Places	0.0068	12.0
Paper Articles			
322	Paper Manufacturing	0.0699	5.4
323	Printing and Related Activities	0.0297	2.0
-	Population, 2012	0.0001	6.6

$$CF_{i,j} = T_{k,l}\left(\frac{\hat{p}_i}{\sum_{m\in k}\hat{p}_m}\right)\left(\frac{\hat{a}_i}{\sum_{n\in l}\hat{a}_n}\right) \tag{4.5}$$

where

$CF_{i,j}$ = The flow of tons by truck from county i to county j
$T_{k,l}$ = The flow of tons by truck from parent FAF zones k and l
$\left(\frac{\hat{p}_i}{\sum_{m\in k}\hat{p}_m}\right)$ = The ratio of estimated production in county, i, relative to the total estimated production in parent FAF zone, k
$\left(\frac{\hat{a}_i}{\sum_{n\in l}\hat{a}_n}\right)$ = The ratio of estimated attraction in county, j relative to the total estimated attraction in parent FAF zone, l

Table 4.4 shows a detailed calculation for the flow of Meat/Seafood productions from the San Francisco Bay Area to Los Angeles metropolitan area using data from the 2007 Commodity Flow Survey. The column labeled “Meat tons (2007)” represents the total amount of goods being shipped from the Bay Area to Los Angeles.

As was noted in ref. [128], only a small subset of commodities can be appropriately disaggregated to the counties using employment data. Accordingly, we limited the scope of our study to two commodity types that have strong correlations between these variables: meat/seafood (production r-squared: 0.84, attraction r-squared: 0.90) and paper articles (production r-squared: 0.77, attraction r-squared: 0.87). Through well correlated, using employment data to disaggregate national-commodity flows is subject to uncertainty. Other commodities types had strong correlations, however, but were excluded. Information regarding the FAF’s geospatial boundaries, the SCTG to NAICS pairing, and regression analysis is provided in the Supporting Information section of this paper.

Once county-level commodity flows were estimated, we then constructed truck life-cycle emission factors for each of the commodity types based on the methodologies established

Table 4.4: County-Level Freight Flow Allocation (Meat /Seafood, SF to Los Angeles)

County Source FIPS	County Sink FIPS	Parent FAF ID, Source	Parent FAF ID, Sink	Meat tons (2007), 1000 tons	Source County Allocation Factor	Sink County Allocation Factor	Final County-Level Shipment, 1000 tons
6001	6037	64	61	32.018	0.321	0.596	6.126
6001	6059	64	61	32.018	0.321	0.186	1.908
6001	6065	64	61	32.018	0.321	0.085	0.873
6001	6071	64	61	32.018	0.321	0.092	0.946
6001	6111	64	61	32.018	0.321	0.041	0.419
6013	6037	64	61	32.018	0.070	0.596	1.331
6013	6059	64	61	32.018	0.070	0.186	0.415
6013	6065	64	61	32.018	0.070	0.085	0.190
6013	6071	64	61	32.018	0.070	0.092	0.206
6013	6111	64	61	32.018	0.070	0.041	0.091
6041	6037	64	61	32.018	0.011	0.596	0.206
6041	6059	64	61	32.018	0.011	0.186	0.064
6041	6065	64	61	32.018	0.011	0.085	0.029
6041	6071	64	61	32.018	0.011	0.092	0.032
6041	6111	64	61	32.018	0.011	0.041	0.014
6055	6037	64	61	32.018	0.028	0.596	0.543
6055	6059	64	61	32.018	0.028	0.186	0.169
6055	6065	64	61	32.018	0.028	0.085	0.077
6055	6071	64	61	32.018	0.028	0.092	0.084
6055	6111	64	61	32.018	0.028	0.041	0.037
6069	6037	64	61	32.018	0.019	0.596	0.367
6069	6059	64	61	32.018	0.019	0.186	0.114
6069	6065	64	61	32.018	0.019	0.085	0.052
6069	6071	64	61	32.018	0.019	0.092	0.057
6069	6111	64	61	32.018	0.019	0.041	0.025
6075	6037	64	61	32.018	0.064	0.596	1.223
6075	6059	64	61	32.018	0.064	0.186	0.381
6075	6065	64	61	32.018	0.064	0.085	0.174
6075	6071	64	61	32.018	0.064	0.092	0.189
6075	6111	64	61	32.018	0.064	0.041	0.084
6081	6037	64	61	32.018	0.131	0.596	2.495
6081	6059	64	61	32.018	0.131	0.186	0.777
6081	6065	64	61	32.018	0.131	0.085	0.356
6081	6071	64	61	32.018	0.131	0.092	0.385
6081	6111	64	61	32.018	0.131	0.041	0.170
6085	6059	64	61	32.018	0.107	0.186	0.639
6085	6065	64	61	32.018	0.107	0.085	0.292
6085	6071	64	61	32.018	0.107	0.092	0.317
6085	6111	64	61	32.018	0.107	0.041	0.140
6085	6037	64	61	32.018	0.107	0.596	2.051
6087	6037	64	61	32.018	0.052	0.596	0.989
6087	6059	64	61	32.018	0.052	0.186	0.308
6087	6065	64	61	32.018	0.052	0.085	0.141
6087	6071	64	61	32.018	0.052	0.092	0.153
6087	6111	64	61	32.018	0.052	0.041	0.068
6095	6037	64	61	32.018	0.056	0.596	1.064
6095	6059	64	61	32.018	0.056	0.186	0.331
6095	6065	64	61	32.018	0.056	0.085	0.152
6095	6071	64	61	32.018	0.056	0.092	0.164
6095	6111	64	61	32.018	0.056	0.041	0.073
6097	6037	64	61	32.018	0.141	0.596	2.700
6097	6059	64	61	32.018	0.141	0.186	0.841
6097	6065	64	61	32.018	0.141	0.085	0.385
6097	6071	64	61	32.018	0.141	0.092	0.417
6097	6111	64	61	32.018	0.141	0.041	0.184

by Facanha and Horvath (2007). Data driving these estimates is based on average truck manufacturing and maintenance costs [139, 8], national average fuel consumption rates [1, 88, 140], commodity-specific payloads [116], and commodity-specific empty driving statistics [116].

The scope of this assessment includes GHG emissions from truck operation, fuel production and distribution, truck manufacturing, and maintenance. Fuel economy estimates for diesel-powered engines were taken from Argonne National Laboratory's VISION model, which was developed to quantify and forecast the energy, oil, and carbon emissions associated from the U.S. transportation sector [1]. Tailpipe GHG emission rates are assumed to be proportional to fuel rates. The GREET model (2013) was used to model the GHG emissions generated along the fuel production pathways for ultra-low sulfur diesel fuels [140]. Heavy-duty trucks (class 7-8) are modeled assuming the trailer type is dry van that drives empty for 20% for Meat/Seafood and 23% for Paper Articles over its lifetime usage [116]. Infrastructure-related emissions are based on Sathaye et al. (2009) (46). In this study, it is assumed that trucks remain in operation for on average 20 years. This corresponds to a scrappage odometer reading of 1.8 million vehicle kilometers traveled (VKT). Manufacturing and maintenance GHG emissions were estimated using EIO-LCA [8].

The functional unit of comparison used to characterize the emissions generated by the freight industry is the ton-km. This approach facilitates intermodal comparisons because it describes the efficiency in which goods are moved through infrastructure networks on a unit basis. In this study, we assume average payloads of 20 tons for Meat/Seafood and 18.9 tons for Paper Articles, which are based on the 2002 Vehicle Use Inventory Survey[116].

The total GHG emissions footprint per ton-km of a set of goods, e_f, is:

$$ef_t = ef_s + ef_f + ef_i \tag{4.6}$$

where ef_s represents supply-chain emissions,

$$ef_t = \frac{E_s}{VKT \times P \times (1-e)} \tag{4.7}$$

where ef_f represents well-to-wheel emissions,

$$ef_f = \frac{E_f}{P \times (1-e)} \tag{4.8}$$

where ef_i represents infrastructure emissions,

$$ef_i = \frac{E_i}{P \times (1-e)} \tag{4.9}$$

and the remaining variables:

E_s = Emissions from supply-chain process [g $CO_{2,e}$]
E_f = Emissions from well-to-wheel processes [g $CO_{2,e}$ / km]

Table 4.5: Commodity-resolved, Life-Cycle GHG Emission Factors for Heavy Heavy-duty Trucks (g $CO_{2,e}$/tkm)

Commodity	e_f, g/tkm	Commodity	e_f, g/tkm
Live animals/fish	104	Fertilizers	116
Cereal grains	110	Chemical prods.	119
Other ag prods.	84	Plastics/rubber	128
Animal feed	109	Logs	107
Meat/seafood	**101**	Wood prods.	114
Milled grain prods.	93	Newsprint/paper	91
Other foodstuffs	82	**Paper articles**	**97**
Alcoholic beverages	98	Printed prods.	182
Tobacco prods.	120	Textiles/leather	70
Building stone	128	Nonmetal min. prods.	89
Natural sands	111	Base metals	116
Gravel	117	Articles-base metal	137
Nonmetallic minerals	123	Machinery	109
Metallic ores	86	Electronics	151
Coal	73	Motorized vehicles	99
Crude petroleum	92	Transport equip.	86
Gasoline	101	Precision instruments	105
Fuel oils	113	Furniture	137
Coal-n.e.c.	123	Misc. mfg. prods.	122
Basic chemicals	139	Waste/scrap	197
Pharmaceuticals	178		

E_I = Emissions from infrastructure processes [g $CO_{2,e}$ / km]
VKT = Lifetime vehicle kilometers traveled [km]
P = Payload (mt)
e = Average lifetime empty driving (%)

The resulting GHG emission factors for diesel-powered trucks were 101 g $CO_{2,e}$/tkm and 97 $CO_{2,e}$/tkm for meat/seafood and paper articles, respectively (Table 4.5). Though the life-cycle emission factors for these two commodities are quite similar, we note that this will not be the case for all commodity types (Table 4.5) as truck payloads and empty driving are unique to each type of good moved [32]. Given the large payloads for diesel-powered trains (3,000 tons per train, US average)[41], we relied upon a single average emission factor of 19 g $CO_{2,e}$/tkm [88, 32]. The final intermodal rail GHG emissions were calculated by totaling the GHG emissions generated during truck drayage to and from intermodal terminals as well as the GHGs from the associated rail portion of a delivery [121]. Due to lack of data, we assume no emissions penalty for exchanging goods at intermodal terminals.

Lastly, we model the flow of goods through commodity-specific networks to be based on the lowest GHG pathway. For each commodity and mode type (i.e., truck-only and intermodal rail), we created travel cost matrices for pairwise county-to-county sets by solving for the shortest GHG emission paths using an open-sourced routing model that implements the Dijkstra algorithm [141]. We ignore alternative routing schemes that may often occur due to queuing at busy exchange terminals, which may increase the degree of uncertainty in our results. The expected county-level GHG benefits from mode-switching and average county-level truck drayage distances were estimated by assigning a weight to each pairwise county-to-county set based on a percentage of total county-to-county commodity flow (tons).

4.3 Results

To illustrate the effect mode choice has on the spatial extent of GHG freightsheds, we show the results for a single county (Cook County, IL, population 5.2 million, including Chicago), in Figure 4.2, which has access to a well-developed intermodal transportation system. The geographic extent of truck and intermodal rail freightsheds are compared. For each commodity, a GHG budget was set to 800 km or roughly 80 kg $CO_{2,e}$ per ton emitted by a Class 8b truck on average. The 800-km distance traveled represents a threshold in which a commodity is considered to be locally or regionally produced under the US Green Building Council's LEED program [142], though other spatial definitions of localism exist [61, 143, 144, 145]. This GHG budget was motivated by the increased attention being paid to the economic, environmental, etc. benefits of using locally-sourced goods, services, and resources [134, 146, 147, 148]. For perspective, one can also define a budget in the context of emission reduction goals. For instance, a budget could be set relative to current emission levels (20% from business-as-usual) or with specific end-points in mind (e.g., kg emissions per person-day)[149].

When only trucks are considered, freightsheds are of similar size and symmetry for two major reasons. First, trucks of equivalent size and payload have equal opportunities within the highway networks and can therefore choose similar paths between origin-destination (OD) pairs. Second, we chose two commodity types that have similar emission factors, causing the total GHG emissions (e.g., transport costs) between OD pairs to be of similar magnitude. However, as we noted earlier, this may not be the case for all commodities. Overall, trucks with larger payloads or lower well-to-wheel GHG emission rates can travel greater distances given a GHG budget since their normalized GHG footprint is smaller [41].

In contrast, despite sharing the same GHG budget, the geographic reach and symmetry of intermodal rail freightsheds are vastly different between the commodity types. Intermodal rail freightshed are significantly larger than truck freightsheds due to the differences in normalized emission rates between the modes. The major factors differentiating each freightshed are due to intermodal terminal availability. As noted earlier, intermodal terminals are not equipped to handle all types of goods, therefore, commodities are restricted in access to only a subset of the total number of terminals. Only a small fraction of road-rail terminals accommodate meat/seafood (127 or 4.9%) and paper articles (19 or 0.7%). For perspective, terminal availability for our case examples is less than the US average (μ =144) but more

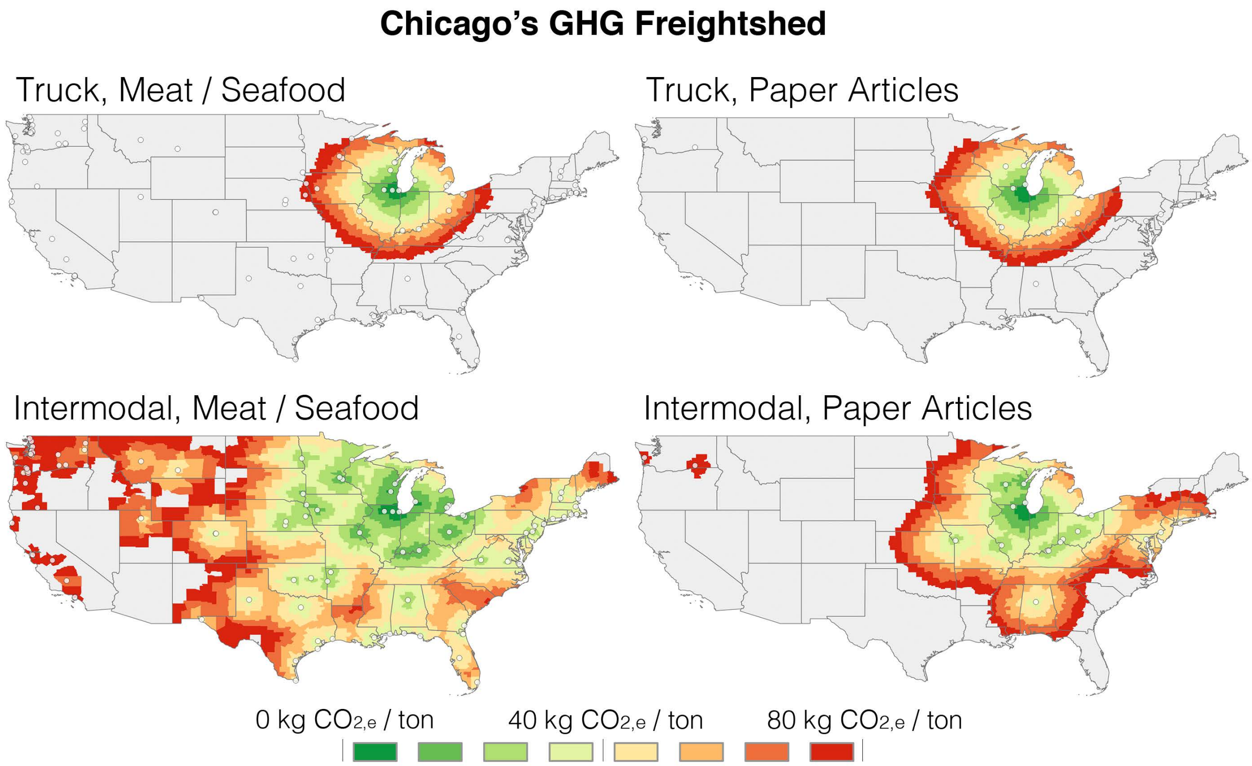

Figure 4.2: A commodity-focused comparison of the greenhouse gas emissions per ton, shipped from Cook County, IL by truck only (top) and intermodal freight (bottom). To illustrate the differences in spatial coverage, a carbon budget of 80 kg $CO_{2,e}$, or roughly equivalent to 800 km driven by truck is shown for each commodity. Intermodal terminals are shown as circles.

than the median ($\hat{x}$= 97) for the all of the commodities listed in the CFS. Overall, the added emissions from longer trips during truck drayage, which are the result of limited intermodal terminal availability, cause the extent of the paper articles freightshed to be less than the freightshed for meat/seafood.

As Craig et al. (2013) point out, when terminals are dispersed over great distances, isolated commercial markets may form [121]. To illustrate, we call the reader's attention to the market at the southwestern corner of the state of Washington (Figure 4.2, bottom right). Paper articles sourced from this location for Cook County using intermodal rail is equivalent to trucking in goods from Pittsburgh, PA. This finding reaffirms the position [134] that 'local' is a poor metric for defining the overall environmental impacts associated with the production and supply of a commodity, especially in the context of multimodal freight operations.

Overall, we find that consumers could increase their opportunities to supply a product by choosing intermodal rail over trucks, but the scale of this increase in access depends on

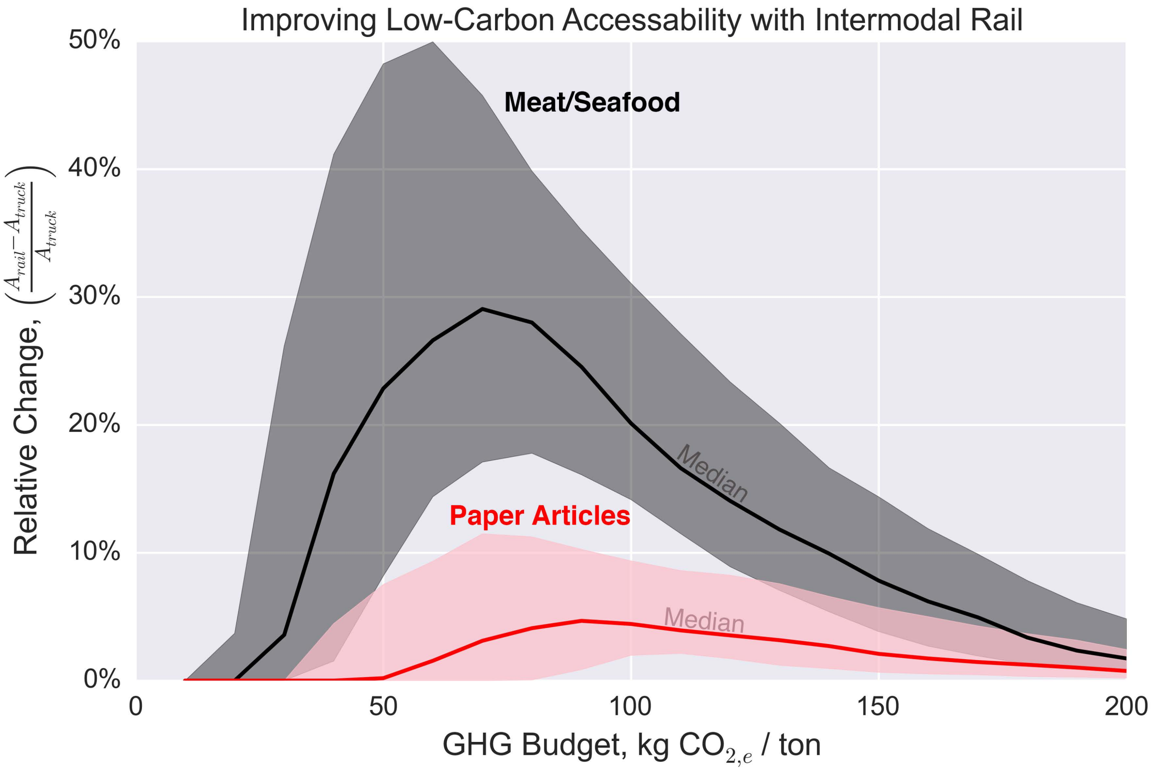

Figure 4.3: A summary of county-level differences in accessibility between intermodal rail and truck-only transport (baseline) under varying GHG budgets. Interquartile ranges are shown in the area and median estimates are shown as a line for each commodity, respectively. At low budgets, truck-only routes are possible; therefore, the relative change is zero. At high budgets, nearly all locations can be reached by each mode; therefore, the relative change is low. Overall, intermodal rail positively improves accessibility but this change is commodity dependent.

the commodity and GHG budget. Figure 4.3 compares the differences in consumer access to producers under varying GHG budgets for both commodity classes across the United States. Maps of the total tons shipped by truck (herein referred to as production) at a county and regional level are provided in the Supporting Information. For reference, regional [150] shares of production for meat/seafood and paper articles are 11% and 18% (Northeast), 30% and 25% (South), 45% and 38% (Midwest), and 14% and 19% (West), respectively.

The percentage change in total accessibility depends on the magnitude of the GHG budget. At very low budgets, trucking policies dominate intermodal rail policies, causing the differences in total access (tons by truck in 2012) between the two networks to be zero. Once GHG budgets breach a commodity-specific departure point (meat/seafood: 20 kg $CO_{2,e}$/ton, paper articles: 50 kg $CO_{2,e}$/ton), differences in accessibility quickly grow as goods could feasibly be transported by intermodal rail. At the point of greatest relative change between the two freightsheds (meat/seafood: 70 kg $CO_{2,e}$/ton, paper articles: 90 kg $CO_{2,e}$/ton), the percent change in access between intermodal and truck-only freightsheds begins to decline and converges to zero, as all locations can be reached by both modes within the budget. Additional analysis is provided in a later subsection to assess uncertainty of our freight flow disaggregation methods as well as life-cycle GHG emission factors.

In order to determine which areas of the country have greatest opportunities for low-carbon exchanges between producers and consumers, we measure intermodal rail accessibility over a continuum under two scenarios for each county in the United States. In our 2012 or baseline infrastructure scenario, we assume a medium rate of impedance over space (β = 0.0121) and that the movement of goods is constrained to commodity- specific intermodal terminals. In an alternative future scenario, we assume goods can be exchanged across all of terminals (n=2612). This scenario represents the best case for improving the low-GHG accessibility without increasing the number of terminals to the network. The scenario also provides insights as to how improving accessibly may increase GHG emissions savings associated with mode-switching policies.

The scenario results (4.4, top) show that the counties with the greatest access in terms of percentage of total production share two common characteristics. First, these counties are collocated near intermodal freight terminals, which reduces the truck trip distances required to move goods onto the rail network and ultimately complete a delivery (e.g., drayage). Overall, we estimate the average county-level drayage distances to be 220 km ± 79 km (standard deviation, sd) for meat/seafood and 397 km ± 175 km (sd) for paper articles in our baseline scenario. Second, counties with the best low-GHG accessibility are also located near major regions of production. For meat/seafood and paper articles, we find average regional accessibility estimates as a percentage of total commodity production to be 46% and 38% (Northeast), 48% and 34% (South), 49% and 36% (Midwest), and 35% and 17% (West), respectively. It is important to note that counties with nearby intermodal access do not always have high accessibility (see Figure 4.4 top left, California). In these cases, a large share of total US production occurs at distant locations, which worsens the accessibility score. Overall, more counties in the United States have better access to meat/seafood than paper articles.

In an alternative future scenario, upgrading current terminals to allow the exchange of all types of goods will allow consumers the same level of access to both commodities reviewed in the study. Across the country, average drayage distances were reduced by 75% for meat/seafood and 86% for paper articles, causing accessibility scores to significantly improve (Figure 4.4, bottom). The results of this scenario for meat/seafood and paper articles, respectively, show that 60% and 62% (Northeast), 64% and 63% (South), 65% and 64% (Midwest), and 46% and 46% (West) of total commodity production is accessible to consumers. Overall, we find that states in the eastern half of the United States have better access to meat/seafood and paper articles than the western United States. In the following subsection, we provide a summary chart that explores the sensitivity of our accessibility results under varying assumptions for the discounting factor, β.

Increasing the availability of intermodal terminals will increase low-GHG accessibility na-

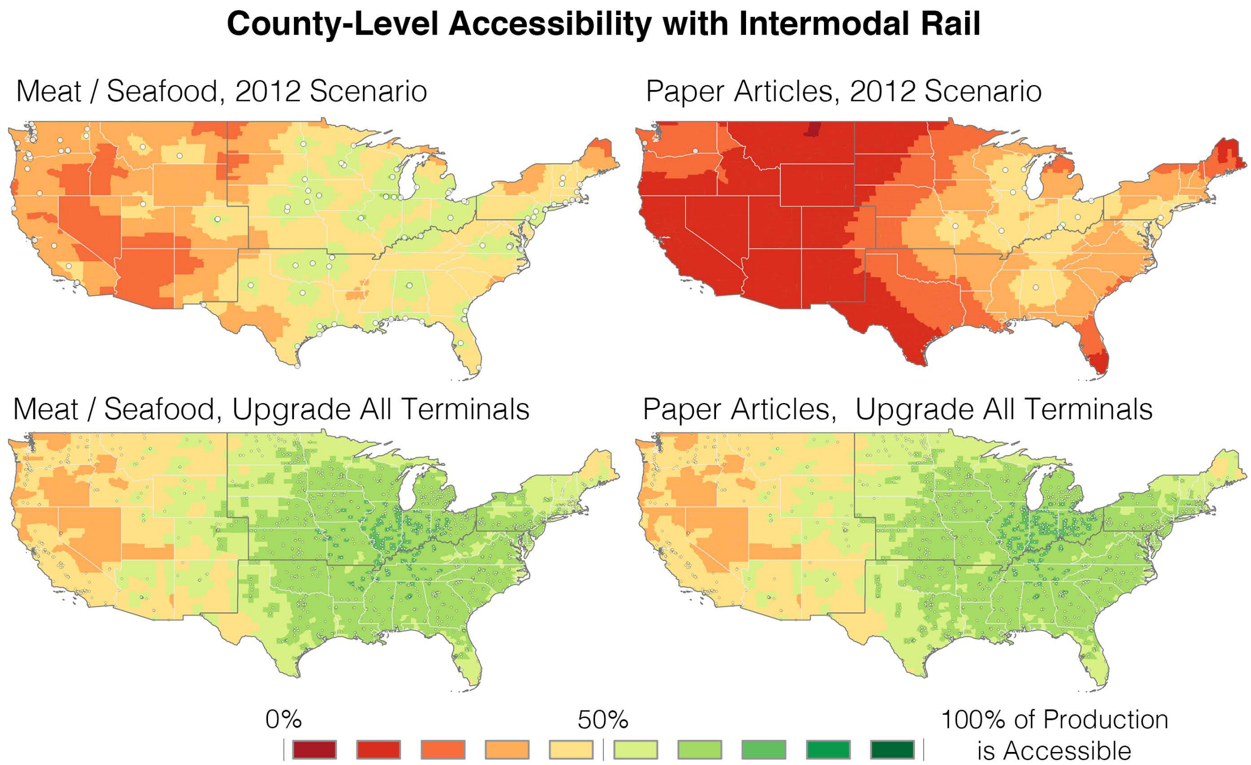

Figure 4.4: A comparison of county-level accessibility using intermodal rail under current infrastructure availability (top) and a scenario where all road-rail terminals can transfer all types of goods (bottom). The results were derived using a continuous approximation model for accessibility (Eq. 2) and are reported as the fraction of total US production (tons shipped by truck) attainable given a medium rate of impedance over space ($\beta = 0.0121$).

tionwide, but it also has beneficial impacts on GHG reduction potentials of mode-switching policies. Figure 4.5 shows the average county-level GHG savings from mode-switching policies, weighted by county-level commodity flows (2012). On average, the split of kilometers traveled for our baseline scenario was estimated to be 43% rail to 57% truck for meat/seafood and 17% rail to 83% truck for paper articles. We find that the amount of GHG emissions reduced through mode-shifting policies is commodity dependent. In our baseline scenario, median GHG savings for meat/seafood and paper articles were estimated at 23 kg $CO_{2,e}$/ton and 8 kg $CO_{2,e}$/ton, respectively. By comparison, upgrading current intermodal terminals to allow the exchange of all commodity types may increase the median GHG savings for meat/seafood and paper articles to 40 kg $CO_{2,e}$/ton and 33 kg $CO_{2,e}$/ton. This improvement can be attributed to the reduction in truck drayage needed as intermodal availability increases. For this alternative future scenario, we find that the national average split of kilometers travelled was estimated to be 82% rail to 18% truck for meat/seafood and paper articles, respectively.

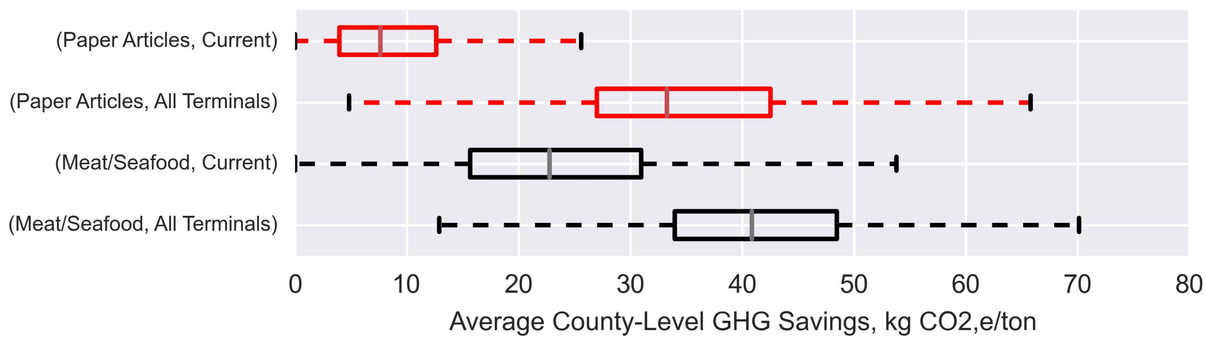

Figure 4.5: Average county-level GHG savings associated with switching from truck-only to intermodal freight rail under current and all terminals available scenarios. By upgrading all of its current intermodal terminals, the United States could improve its median GHG savings associated with truck-to-rail mode-switching policies by 70% and 310% for Meat/Seafood and Paper Articles, respectively.

4.3.1 Accessibility Sensitivity Analysis for Discrete GHG budget

To assess the sensitivity our results, we provide four additional cases for comparison. Figure 4.6 shows a summary of our results for discrete accessibility under varying GHG budgets. In the first case, we allocated goods flowing between FAF zones to counties uniformly, meaning each county within a parent FAF zone produces and attracts an equal amount of goods. We find that the results for this assumption and those presented in our base case are similar. Future work should be dedicated to see if this finding holds for other commodities. Our second case disaggregates goods proportionately to county level populations. We find that this results in a lower relative change in the accessibly between intermodal rail and truck-only freightsheds. This finding could be due locating major production areas closer to populations, which would increase the extent of truck-only freightsheds and thus decrease the intermodal differences in accessibility. The final two cases look at the sensitivity of our results to trucking GHG emission factors. We find that increasing truck emission factors will decrease overall accessibility to goods. However, increasing truck emission rates will increase the relative change in accessibility between intermodal rail and truck-only freightsheds. These results indicate that higher trucking emissions reduce the extent of truck-only freightsheds at a greater rate than intermodal rail, which only utilizes trucks for a small portion of the complete exchange of goods.

The impacts on the GHG reduction potentials of mode-switching policies for each of these scenarios are shown in Figure 4.7. The results of our scenario analysis under varying assumptions for β coefficient are shown in Figure 4.8. Overall, a greater preference for low-GHG transport emission (e.g., higher β) results in less accessibility to goods.

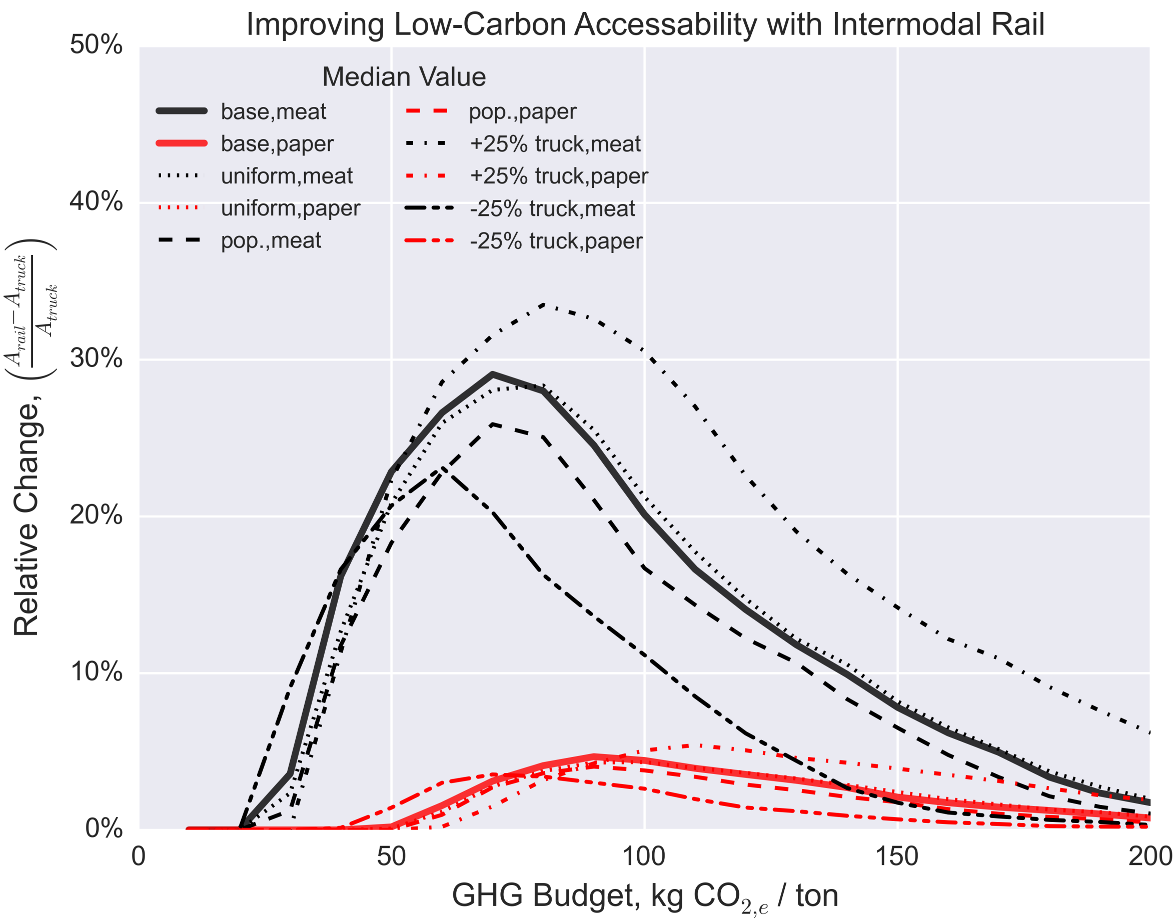

Figure 4.6: A summary of county-level differences in accessibility between intermodal rail and truck-only transport (baseline) under varying GHG budgets under different modeling assumptions (Base: Originally reported data; Uniform: Freight flows disaggregated uniformly to counties; Pop.: Freight flows disaggregated based on population to counties; +25%: Trucking emission factors were increased by 25%; -25% Trucking emission factors are reduced by 25%). The estimated median values are shown for each scenario.

4.3.2 Limitations and Uncertainties

Scenario analysis reveals that investments into freight infrastructure can improve the accessibility to commodities and lower the GHG footprint of intermodal freight operations. These results are based on emission factors that reflect life-cycle GHG emission rates that coincide with estimates from previous research [8, 20, 41, 88]. Given that commodity flow estimates for the two commodities considered are well correlated with industry employment and that the transportation network is well defined, our low-GHG accessibility scores for the considered modes are robust on a county basis. For other commodities, the disaggregation method implemented in this research [128, 129, 130], which assigns national freight flows

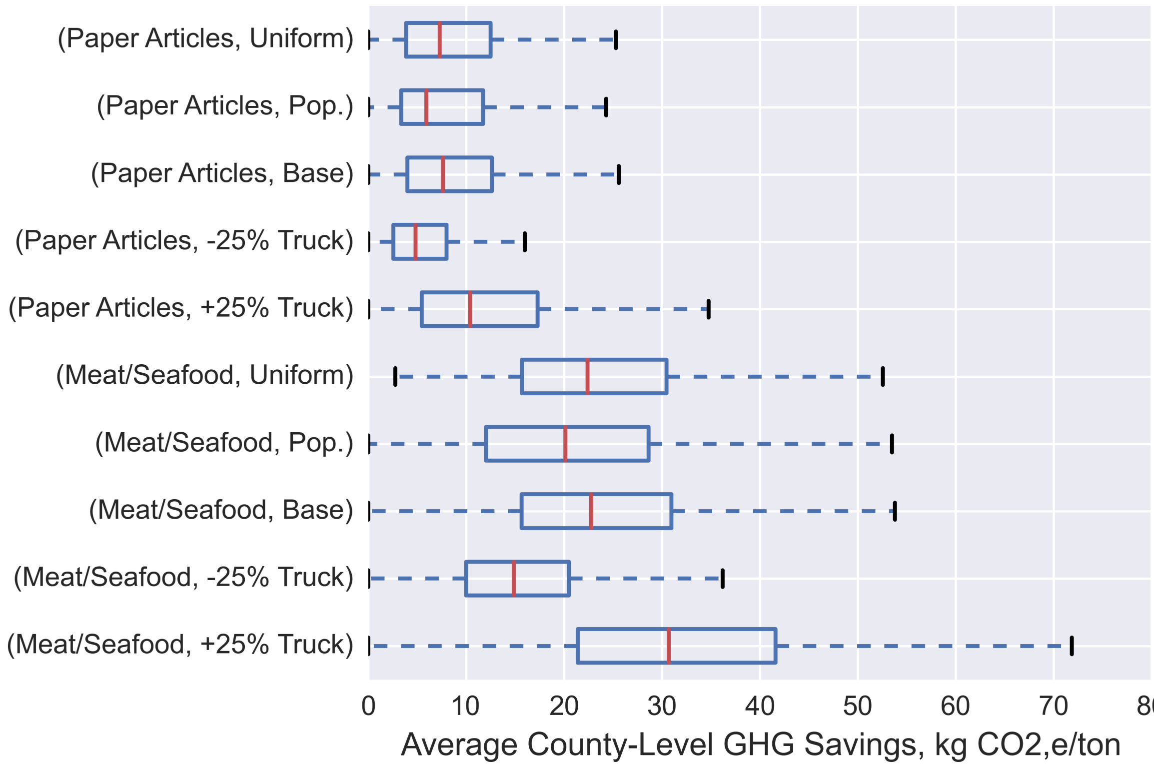

Figure 4.7: Average county-level GHG savings associated with switching from truck-only to intermodal freight rail under current and all terminals available scenarios budgets under different modeling assumptions. In the parenthesis, the left term refers to the commodity while the right term refers to the scenario.

to counties, may bias results for goods produced in industrial sectors where operations are capital intensive or where SCTG and NAICS classification groups are jointly inconsistent.

In terms of generalizing our results, this research?s largest uncertainties stem from analyzing only a portion of the US freight distribution network and vehicle routing decision-making process. We compare only truck and intermodal freight services, though other low-GHG modes should be considered in the future. For instance, if freight transport along inland waterways were considered, counties within proximity to intermodal terminals that serve waterways would likely have higher accessibility scores.

As well, emissions generated during intermodal exchanges between truck and rail networks have not been accounted for as they have not been thoroughly researched. Including these emissions would increase the 'fixed' emissions associated with intermodal rail services and decrease to an extent the accessibility of counties that utilize these services. We also assume that carriers traverse the highway and rail network along the lowest GHG emissions pathways. However, this policy choice comes at time, financial, and external costs (e.g., safety, human health, etc.) [151, 103, 24] and considerations of scale (e.g., production, link,

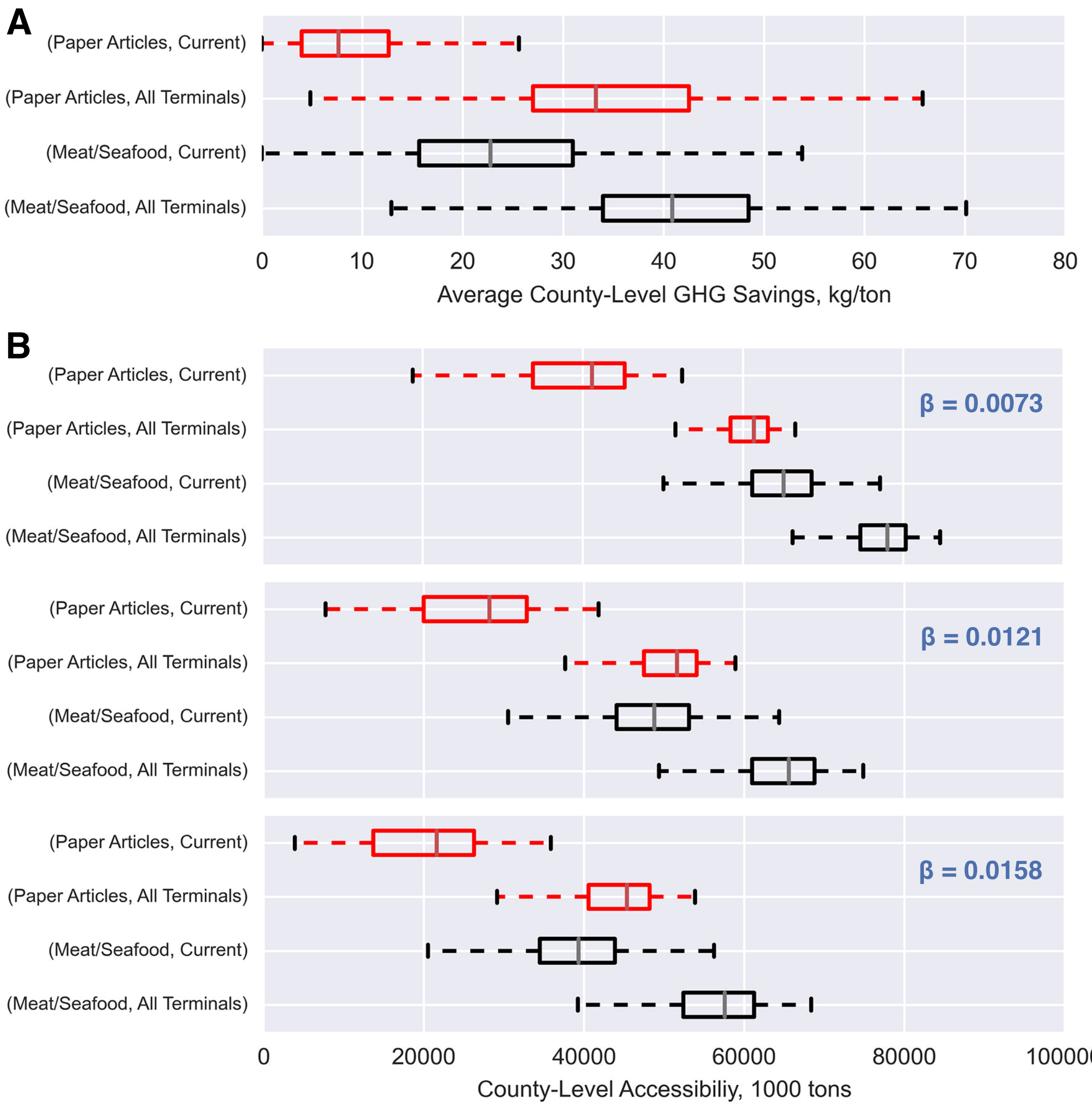

Figure 4.8: (A) Average county-level GHG savings associated with switching from truck-only to intermodal freight rail under current and all terminals available scenarios. (B) Sensitivity analysis of β coefficient on accessibility scores across the United States.

and node capacities) were not included in this analysis but could have been implemented [132]. Ultimately, each of these factors is an important consideration that influences consumer choice. Future research should evaluate the tradeoffs related to mode-switching policies at a county level while considering these factors as well as including other environmental measures.

4.4 Chapter Summary

The freight infrastructure network (e.g., roads, railways, waterways, etc.) is the backbone of nearly all trade partnerships in the United States and abroad. The manner in which each portion of its constituent parts are interrelated or arranged plays an important role for determining the environmental footprint of goods moved within its network. In this study, we compared the spatial distribution of potential consumer-producer exchanges (i.e., accessibility) under varying greenhouse gas (GHG) budgets or preferences for minimal transportation-related GHG emissions. We conducted case studies using two freight modes (truck and intermodal rail) for two representative commodities listed in the US Commodity Flow Survey: meat/seafood and paper articles. Results across all counties in the United States indicate that the geographic area in which trade is possible given a GHG budget varies by transportation mode, location, and commodity. Our results suggest that intermodal terminal availability is an important determinant of low-GHG accessibility. Since only a fraction of road-to-rail terminals accommodate meat/seafood (4.9%) and paper (0.7%), the U.S could increase its expected GHG savings associated with truck-to-rail mode-switching policies by 70% (+20 kg $CO_{2,e}$/ton, meat/seafood) and 310% (+30 kg $CO_{2,e}$/ton, paper) by upgrading current terminals to allow the exchange of all types of goods.

4.5 Discussion

Our results show that counties with the best accessibility to resources from a GHG perspective are not necessarily collocated in major regions of production. We show that proximity to critical supply-chain infrastructure, e.g., intermodal terminals, is an equally important consideration when evaluating the environmental performance of freight transportation for different locations. Overall, improving the availability of intermodal terminals effectively expands GHG freightsheds, which can lead to overall reductions in emissions. While we show a case for only two commodity types, one environmental indicator, and two modes, evidence suggests that the spatial extent of environmental freightsheds at any particular location in the United States is commodity dependent.

From a policy perspective, environmental freightsheds may take on a different meaning based on whether someone is shipping a good or receiving it. Shippers could use this approach for defining a freightshed in order to evaluate the environmental footprint of their downstream supply chain logistics, to choose modes that maximize their coverage areas while minimizing their environmental impacts, or to expand production in regions where the potential for low energy and emissions trade is greatest. Receivers may want to know their freightsheds to maximize the quality of their goods in terms of utility and environmental impacts [134] and to choose freight mode combinations that minimize their total environmental footprint.

Chapter 5

Conclusions and Future Work

5.1 Summary of Contributions

In Chapters 2, 3, and 4, we develop GHGn factors for heavy-duty trucks and/or buses.

In Chapter 2, we assessed whether it is appropriate to use generic, aggregated LCA emission factors available in the literature and LCA databases within regional, local, and discrete analyses in leu of emission factors that change with respect to speed. To complete this task, we calculated GHG emission factors for 34 categories of heavy-duty vehicles operating in California, comprising both medium and heavy heavy-duty trucks as well as buses (e.g., transit, school, charter). One set of these emission factors was based on fuel economy data reflective of the state-wide fleet of vehicles (Table 2.1). The second set of GHG emission factors was based on speed-corrected fuel economy (Figure 2.2), which could be used to differentiate the GHG footprint of trucks and buses based on their traveling speeds.

In Chapter 3, we assessed the extent to which the life-cycle output (level of service) of infrastructure systems influences their normalized environmental footprint. In two case studies, we quantified the well-to-wheels GHG emissions associated with on-road goods movement by medium- and heavy-heavy-duty trucks and buses that travel under varying loading factors (i.e., truck payloads and bus ridership). For heavy-duty trucks, we calculated GHG emission factors for six gross vehicle weight rating classifications and their respective truck types operating in California (Table 3.1). We also quantified GHG emission factors for buses operated by the San Francisco Municipal Transportation Agency based on minute-by-minute bus ridership data (Figure 3.5).

In Chapter 4, we evaluated how the GHG emissions rates for heavy-duty trucks and intermodal rail (e.g., the combination of heavy-duty trucks and freight rail) change across different product supply chains (i.e., commodity types) and between specific counties across the United States. In our case study, we provide life-cycle GHG emission factors for class 8 heavy-duty trucks based on commodity-specific data (payloads and empty driving) (Table

4.5).

This dissertation quantifies the level of estimation errors in GHG inventories resulting from the use of generic emission factors for trucks and buses across different levels of specificity or aggregation, which ultimately leads to more informed decisions and actions related to climate change mitigation.

We presented new knowledge on the uncertainties surrounding the use of generic data, specifically generic fuel economy, vehicle productivity, and infrastructure topologic data, to generate GHG emission inventories for heavy-duty vehicles. By assessing these uncertainties and improving the accuracy of GHG emission factors, decision-makers now have better and more reliable information to assess the environmental performance of heavy-duty trucks and buses on more resolved levels of specificity.

In Chapter 2, we conducted original case studies for trucks monitored in the Caltrans Performance Measurement System and real-time operations of buses in nine agencies in California. In each of the case studies, we measured the relative difference, δ, between GHG emission factors based on fleet-scale fuel economy data, $E_{f,avg}$, and GHG emission factors based on speed-corrected estimates for fuel economy, $E_{f,s}$. Our results indicate that the level of emission deviation, δ, varies across traveling speeds, with large deviations occurring at reduced and elevated traveling speeds (Figure 2.3). We show that there is more variability in speeds along urban arterial road networks than on highways. Hence, emissions deviation is greater for buses operating in cities than heavy-duty trucks operating along highways (Figure 2.6 and Figure 2.20). For buses in particular, we estimate that the expected route-level emissions deviation varies from -13% — 62% across the 9 agencies considered in the case study. These errors have significant implications on local GHG emission inventories (Figure 2.24). We conclude the chapter with summary decision-making directives that guide LCA modelers as to when it is appropriate to use generic, fleet-scale GHG emission factors to calculate the carbon footprint of heavy-duty vehicles (Table 2.3).

In Chapter 3, we evaluated the appropriate use of emission factors based on average levels of productivity (e.g., truck payloads and bus ridership) by comparing them to those reflecting a distribution of system outputs. This work identified a systematic bias associate with the use of average productivity data (e.g., freight tonnage and bus ridership) in fleet-scale LCAs [41]. For the provision of truck and bus services where fuel economy is assumed constant over levels of service, we found that emission factor estimation error resulting from the use of average loading factors, e.g., $\mathbb{E}_A[e_f(a)] - e_f(\mathbb{E}_A[A])$, always result in larger-than-expected environmental impacts. The magnitude of this emissions error depends on the truck vehicle classification and truck type (see, Table 3.1) as well as the utilization rates of buses within public transit networks (see, Figure 3.6). Overall, well-to-wheel greenhouse gas emission factors for diesel trucks in California range from 87 to 1,500 grams of CO_2 equivalents per ton-km, depending on the size and type of trucks and the services performed. Along a bus route in San Francisco, well-to-wheel emission factors ranged between 53 and 940 grams of CO_2 equivalents per passenger-km.

In Chapter 4, we estimate the expected county-level GHG reduction potential from mode-switching policies in the United States [42]. We conduct case studies using two freight modes (truck and intermodal rail) for two representative commodities listed in the US Commodity Flow Survey: meat/seafood and paper articles. Our results across all counties in the United States indicate that effectiveness of mode-switching policies varies by both location and commodity type. We find that intermodal terminal availability is an important determinant of both low-GHG accessibility as well as low-GHG mobility when intermodal activities are considered. Through a scenario analysis, we show that the U.S could increase its expected GHG savings associated with truck-to-rail mode-switching policies by 70% (+20 kg $CO_{2,e}$/ton, meat/seafood) and 310% (+30 kg $CO_{2,e}$/ton, paper) by upgrading current terminals to allow the exchange of all types of goods.

In Chapter 4, we developed a national freight logistics model, which routes trucks and trains along the 'lowest impact' pathway.

To assess the potential GHG reduction benefits of shifting demand from heavy-duty trucks to intermodal rail at a county level for specific commodities, we developed a bottom-up vehicle routing model that incorporates the locations of commodity producers within the national highway and freight rail networks. This model is unique from other models found in the literature in that it differentiates the movement of goods based on their respective commodity classes. The reason that this distinction is important is because road-rail intermodal terminal availability varies across the United States. Hence, we show that proximity to critical supply chain infrastructure, e.g., intermodal terminals, is an important consideration when comparing the environmental performance of trucks and intermodal rail.

5.2 Future Work

5.2.1 Greenhouse Gas Marginal Abatement Cost Curves

Speed-specific GHG emission factors can be integrated into current transportation network models to provide valuable information about how the GHG footprint of trucks may change within specific settings. Until now, transportation LCAs have primarily been a way of modeling the footprint of goods from an average perspective. This new dynamic LCA modeling approach allows scientists and engineers to manage the GHG footprint of goods in a more localize context, using route-based modeling techniques. Removing the constraint of utilizing average data, new statistics can be formed given additional information that is readily available today.

Targeting "high emitter" trucks is an effective way to reduce GHG emissions. Research has shown that a small number of trucks may represent a substantial portion of total emissions in certain areas of the country. Ideally, stakeholders that are looking to reduce emissions at the lowest cost would prescribe targeted vehicle substitution policies to either remove these trucks, subsidize the adoption of cleaner technologies within these fleets, or incentivize complete mode switches. Before these policies can be developed, there needs to be an understanding of how GHG emissions vary along the different points in the supply chain that are serviced by heavy-duty trucks.

Cost effective GHG mitigation strategies should target heavy-duty trucks that have the greatest GHG reduction potentials at the lost marginal costs. Marginal abatement cost curves (MACC) are used to make comparisons of the cost-effectiveness of mitigation options between different technologies, and are often utilized in climate science to identify efficient reductions of greenhouse gases. MACCs plot the marginal unit cost of an action against its abatement potential. Different mitigation options will occupy different positions on the curve, but are ranked from most to least effective at reducing customer demand. These curves are powerful tools due to their simple and effective display of information. MACCs for GHGs can benefit shippers, carriers, and other stakeholders by helping them prioritize GHG saving options.

5.2.2 "First- and Last-Miles" of Freight Networks

This research outlines the methods and tools needed to quantify the change in the GHG footprint of goods during the "first- and last-miles" of a freight distribution network. It is well known that the unit costs of moving goods during the"first- and last-miles" are disproportionately larger, but little is known from about the change in the total environmental costs. I would expect to see emissions increase along these sections due to increases in congestion and lowered payloads. The key insight from this research would then be to relate the emissions along "first- and last-miles" to other portions of freight distribution network, which may include rail, shipping, or air freight modes, as well.

5.2.3 Criteria Air Pollutant and Short-Lived GHG Emission Factors

The modeling tools and allocation methods presented in this proposed research can be adapted to capture life-cycle criteria air pollutant and short-lived GHG emissions, too. These emissions have significant impacts to local air quality and human health and may varying in magnitude over time, location, or scale. I hope to one day explore the non-linear nature of human exposure to these pollutants with the goal of evaluating the tradeoffs or co-benefits associated with improving long-lived GHG emission factors.

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Appendix A

Emission Deviation Due to Variability in Vehicle Speeds

Table A.1: Expected Emissions Deviation by Agency and Bus Route.

Agency	Route	$\mathbb{E}(deviation)$
actransit	1	0.686709
actransit	11	0.944221
actransit	12	1.056222
actransit	14	0.426420
actransit	18	1.013350
actransit	1R	1.006335
actransit	20	0.717343
actransit	200	0.567699
actransit	21	0.613425
actransit	210	0.580033
actransit	212	0.902881
actransit	215	0.851077
actransit	216	0.961562
actransit	217	0.547420
actransit	22	0.712504
actransit	232	0.857393
actransit	239	0.556654
actransit	25	1.061973
actransit	251	0.796964
actransit	26	1.025433
actransit	275	0.902566
actransit	31	1.018741
actransit	314	0.509333
actransit	32	1.027286
actransit	339	0.568914
actransit	356	0.332195
actransit	37	1.009302

actransit	376	0.521908
actransit	386	0.982649
actransit	39	0.942515
actransit	40	0.470107
actransit	45	0.375888
actransit	46	-0.105565
actransit	47	0.441421
actransit	48	1.033030
actransit	49	1.081035
actransit	51A	0.601839
actransit	51B	1.069492
actransit	52	1.094614
actransit	54	0.298776
actransit	57	0.341667
actransit	58L	0.291286
actransit	60	0.514376
actransit	62	0.545488
actransit	65	1.013406
actransit	67	1.044198
actransit	687	0.054286
actransit	7	1.000854
actransit	70	1.069971
actransit	71	0.934051
actransit	72	0.923336
actransit	72M	0.954828
actransit	72R	1.074100
actransit	73	0.285305
actransit	74	0.999032
actransit	75	0.974747
actransit	76	0.822577
actransit	800	0.889491
actransit	801	0.773173
actransit	802	1.026728
actransit	805	0.077643
actransit	822	0.043969
actransit	83	0.993062
actransit	840	0.023610
actransit	85	1.017606
actransit	851	1.046843
actransit	86	0.962466
actransit	88	1.060022
actransit	89	0.964730
actransit	93	0.995703
actransit	94	0.974218
actransit	95	0.994269
actransit	97	0.658962
actransit	98	0.501272

actransit	99	0.636125
actransit	B	0.169799
actransit	BSD	1.097294
actransit	BSN	1.094691
actransit	C	0.188630
actransit	CB	0.072710
actransit	E	-0.053894
actransit	F	0.844391
actransit	FS	0.577877
actransit	G	0.542360
actransit	H	0.520726
actransit	J	0.618278
actransit	L	0.468583
actransit	LA	0.293526
actransit	LC	0.392412
actransit	M	0.415360
actransit	NL	0.138665
actransit	NX	-0.071313
actransit	NX1	0.092857
actransit	NX2	-0.060980
actransit	NX3	0.068265
actransit	NX4	-0.224906
actransit	NXC	-0.089867
actransit	O	0.271160
actransit	OX	0.052937
actransit	P	0.027660
actransit	S	0.318141
actransit	SB	0.234239
actransit	U	0.497810
actransit	V	-0.154390
actransit	W	-0.030147
actransit	Z	0.636892
emery	Hollis	0.273761
emery	powell	0.223767
emery	south_hollis	0.294170
emery	wgexp_am	0.116312
emery	wgexp_pm	0.142220
lacmt	10	0.382449
lacmt	102	0.285483
lacmt	105	0.362038
lacmt	108	0.291740
lacmt	110	0.332676
lacmt	111	0.244334
lacmt	115	0.309324
lacmt	117	0.266573
lacmt	120	0.248205
lacmt	125	0.249246

lacmt	126	0.264295
lacmt	127	0.205346
lacmt	128	0.209889
lacmt	130	0.277512
lacmt	14	0.360711
lacmt	150	0.231384
lacmt	152	0.165122
lacmt	154	0.269174
lacmt	155	0.309409
lacmt	156	0.330245
lacmt	158	0.150515
lacmt	16	0.396094
lacmt	161	0.209685
lacmt	162	0.250008
lacmt	163	0.217021
lacmt	164	0.163428
lacmt	165	0.166317
lacmt	166	0.151704
lacmt	167	0.222281
lacmt	169	0.237121
lacmt	175	0.460841
lacmt	176	0.377502
lacmt	177	0.223439
lacmt	18	0.391580
lacmt	180	0.378344
lacmt	181	0.400401
lacmt	183	0.312353
lacmt	190	0.363045
lacmt	194	0.336843
lacmt	2	0.371746
lacmt	20	0.409090
lacmt	200	0.444122
lacmt	201	0.410302
lacmt	202	0.338793
lacmt	204	0.350129
lacmt	205	0.254726
lacmt	206	0.308458
lacmt	207	0.288706
lacmt	209	0.273376
lacmt	210	0.267205
lacmt	211	0.195186
lacmt	212	0.397142
lacmt	215	0.342480
lacmt	217	0.400571
lacmt	218	0.332577
lacmt	220	0.528689
lacmt	222	0.288617

lacmt	224	0.203879
lacmt	230	0.248748
lacmt	232	0.256479
lacmt	233	0.280089
lacmt	234	0.216413
lacmt	236	0.140986
lacmt	237	0.189512
lacmt	239	0.171832
lacmt	240	0.243526
lacmt	242	0.119222
lacmt	243	0.173779
lacmt	244	0.199038
lacmt	245	0.184002
lacmt	246	0.207242
lacmt	251	0.327048
lacmt	252	0.367999
lacmt	254	0.297831
lacmt	256	0.256506
lacmt	258	0.341637
lacmt	260	0.407222
lacmt	264	0.364360
lacmt	265	0.295603
lacmt	266	0.198726
lacmt	267	0.373105
lacmt	268	0.372357
lacmt	270	0.333612
lacmt	28	0.302956
lacmt	292	0.267770
lacmt	30	0.426513
lacmt	302	0.367235
lacmt	311	0.297838
lacmt	312	0.383717
lacmt	316	0.413225
lacmt	33	0.283505
lacmt	330	0.441994
lacmt	344	0.083146
lacmt	35	0.247781
lacmt	352	0.334844
lacmt	353	0.279846
lacmt	355	0.427964
lacmt	358	0.259437
lacmt	364	0.197594
lacmt	37	0.310172
lacmt	378	0.399859
lacmt	38	0.296915
lacmt	4	0.377497
lacmt	40	0.330681

lacmt	442	0.327324
lacmt	45	0.350817
lacmt	450	0.168679
lacmt	460	0.221464
lacmt	48	0.384941
lacmt	485	0.304973
lacmt	487	0.350075
lacmt	489	0.349497
lacmt	51	0.394490
lacmt	52	0.370827
lacmt	53	0.357324
lacmt	534	0.188453
lacmt	55	0.389516
lacmt	550	0.072922
lacmt	577	0.191162
lacmt	60	0.369311
lacmt	603	0.372177
lacmt	605	0.443172
lacmt	607	0.432135
lacmt	611	0.307906
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lacmt	62	0.288773
lacmt	620	0.428468
lacmt	625	0.124494
lacmt	656	0.167010
lacmt	66	0.380761
lacmt	665	0.409113
lacmt	68	0.371631
lacmt	685	0.206261
lacmt	686	0.415630
lacmt	687	0.453297
lacmt	70	0.432510
lacmt	704	0.381305
lacmt	705	0.361908
lacmt	71	0.457481
lacmt	710	0.295352
lacmt	720	0.325929
lacmt	728	0.438609
lacmt	733	0.342598
lacmt	734	0.228970
lacmt	740	0.291757
lacmt	744	0.218314
lacmt	745	0.366188
lacmt	750	0.252291
lacmt	751	0.314515
lacmt	754	0.290592
lacmt	757	0.325117

lacmt	76	0.394091
lacmt	760	0.379794
lacmt	762	0.260284
lacmt	770	0.360172
lacmt	78	0.369578
lacmt	780	0.369001
lacmt	788	0.284807
lacmt	79	0.354489
lacmt	794	0.256934
lacmt	81	0.308809
lacmt	83	0.331531
lacmt	90	0.230374
lacmt	901	0.075713
lacmt	91	0.273170
lacmt	910	0.125472
lacmt	92	0.439182
lacmt	94	0.256930
lacmt	96	0.304400
sfmuni	1	0.478555
sfmuni	10	0.524646
sfmuni	12	0.504764
sfmuni	14	0.488196
sfmuni	14R	0.409488
sfmuni	14X	0.148269
sfmuni	18	0.131833
sfmuni	19	0.448924
sfmuni	1AX	0.324118
sfmuni	1BX	0.416730
sfmuni	2	0.597838
sfmuni	21	0.590495
sfmuni	22	0.604632
sfmuni	23	0.227957
sfmuni	24	0.508053
sfmuni	25	0.036762
sfmuni	27	0.494581
sfmuni	28	0.150172
sfmuni	28R	0.256671
sfmuni	29	0.203588
sfmuni	3	0.623298
sfmuni	30	0.617227
sfmuni	30X	0.503569
sfmuni	31	0.464798
sfmuni	31AX	0.279967
sfmuni	31BX	0.355928
sfmuni	33	0.517982
sfmuni	35	0.424414
sfmuni	36	0.287972

sfmuni	37	0.397819
sfmuni	38	0.467060
sfmuni	38AX	0.282108
sfmuni	38BX	0.343671
sfmuni	38R	0.408186
sfmuni	39	0.568385
sfmuni	41	0.633844
sfmuni	43	0.400585
sfmuni	44	0.299041
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sfmuni	57	0.367083
sfmuni	5R	0.377125
sfmuni	6	0.471020
sfmuni	66	0.333691
sfmuni	67	0.428538
sfmuni	7	0.392998
sfmuni	76X	0.198855
sfmuni	7R	0.422365
sfmuni	7X	0.315026
sfmuni	8	0.372096
sfmuni	81X	0.481811
sfmuni	82X	0.444509
sfmuni	83X	0.401036
sfmuni	88	0.394866
sfmuni	8AX	0.251813
sfmuni	8BX	0.422030
sfmuni	9	0.332051
sfmuni	90	0.184416
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sfmuni	K_OWL	0.236656
sfmuni	L_OWL	0.160642
sfmuni	NX	0.229349
sfmuni	N_OWL	0.231616
south-coast	10	-0.003072
south-coast	11	0.024655

south-coast	15	0.123623
south-coast	16	-0.045533
south-coast	17	0.027805
south-coast	18a	0.171892
south-coast	18c	-0.029231
south-coast	18f	0.022249
south-coast	18g	0.111830
south-coast	19	-0.017823
south-coast	1a	0.111327
south-coast	1b	0.129953
south-coast	2	0.314372
south-coast	21	-0.006312
south-coast	22	-0.043963
south-coast	3	0.182933
south-coast	4b	0.157663
south-coast	5	0.095859
south-coast	6	0.122215
south-coast	8	0.083999
south-coast	9	0.154609
thousand-oaks	blue	0.088819
thousand-oaks	gold	-0.021106
thousand-oaks	green	-0.016862
thousand-oaks	metrolink_shuttle	-0.084314
ucsf	black	0.340990
ucsf	blue	0.343137
ucsf	bronze	0.633733
ucsf	gold	0.351769
ucsf	green	0.410948
ucsf	grey	0.308915
ucsf	lime	0.387242
ucsf	pink	0.609910
ucsf	purple	0.304282
ucsf	red	0.364246
ucsf	tan	0.314926
ucsf	va	0.258050
ucsf	yellow_am	0.406955
ucsf	yellow_midday_a	0.423434
ucsf	yellow_midday_b	0.437607
ucsf	yellow_pm	0.450784
unitrans	A	0.294779
unitrans	B	0.243348
unitrans	C	0.332087
unitrans	D	0.147882
unitrans	E	0.316759
unitrans	F	0.214777
unitrans	G	0.229320
unitrans	J	0.279507

unitrans	K	0.186893
unitrans	L	0.293503
unitrans	M	0.287656
unitrans	O	0.226275
unitrans	P	0.105776
unitrans	Q	0.115392
unitrans	S	0.114200
unitrans	T	0.288739
unitrans	V	0.346237
unitrans	W	0.358672
unitrans	Z	0.287170
vista	101	-0.145195
vista	126	-0.129202
vista	cc	-0.139731
vista	coast	-0.145970
vista	coastexp	-0.130639
vista	csucam	-0.122687
vista	csuox	-0.118053
vista	eastco	-0.115654