Methodology Report

FHWA

TOPR 33-01-18005: Developing a Statistically Valid and Practical Method to Compute Bus and Truck Occupancy Data

Technical and Program Support for Highway Policy Analysis

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16. Abstract

This project aims to assist the Federal Highway Administration (FHWA) in providing data to states and metropolitan areas in accordance with Title 23 of the US Code of Federal Regulations, Part 490 National Performance Management Measures. The specific task is to provide and implement a statistically valid and practical method to estimate bus and truck occupancy rates for each urbanized area (UZA) as defined by the U.S. Census Bureau, each state, and the District of Columbia (DC). All fifty states, DC, and 183 UZA's with a population higher than 200,000 are included in this project.

Bus occupancies were estimated separately for each of three categories: transit bus, school bus, and motorcoach. Average total bus occupancy was estimated by aggregating the average vehicle occupancies (AVO) for the above three categories weighted by annual vehicle miles traveled (VMT). Specifically, the Federal Transit Administration (FTA) National Transit Database (NTD) was used to calculate transit bus occupancy; "U.S. State by State Transportation Statistics 2015-16," reported by SchoolBusFleet.com were used to calculate average school bus occupancy for each state; and data provided by the Port Authority of New York and New Jersey (PANYNJ) for the Port Authority Bus Terminal (PABT) in New York City, the largest bus terminal in the US, were used to calculate motorcoach occupancy rates. For trucks, an overall average truck occupancy rate was calculated for all truck types based on National Highway Traffic Safety Administration (NHTSA) Trucks in Fatal Accidents (TIFA) data.

Results show that the mean state-level bus occupancy rate is 20.29, with a standard deviation of 5.24; and the mean state-level truck occupancy rate is 1.19, with a standard deviation of 0.07. Recommendations for future work include (1) work with providers of the various relevant data sources to ensure access to regularly updated new data; (2) initiate a training program for the software code to ensure the results can be easily updated in the future; and (3) make further use of the proposed alternative methods to validate results.

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Contents

General Background

Problem Statement

Many urban areas have introduced varieties of transportation management strategies which are designed to reduce the number of vehicles on the road. Some of these methods are aiming to encourage more high-occupancy-vehicle (HOVs) on the road to avoid severe congestion. Thus, monitoring and estimating average vehicle occupancy (AVO) has become a key prerequisite before implementing these strategies. Often, AVO rates are acquired via road-side video-recording and carousel methods. Heidtman et al. (1997) set up an observation team along the side of the roadway to count the passengers in the vehicles passing by, and they concluded that the method was most effective for collecting data for corridors and roadways of low functional classification, but less effective on multilane freeways. Hao et al. (2011) developed an imaging technique to make the occupants more visible in the vehicle, by use of infrared, while simultaneously using a video recording system. A study of vehicle occupancy conducted in Arizona used the carousel method as a supplement to roadside observations for AVO estimation, and applied a carousel method usually that used more than one vehicle with several observers in the traffic stream to observe occupants in other vehicles (MAG, 2013).

In addition to technical methodologies, researchers have also used survey and crash datasets to estimate vehicle occupancy. Gan et al. (2005) developed a user-friendly software system which could be used to estimate occupancy rates in Florida from multiple years of crash data; the system also included a stand-alone GIS interface to facilitate the selection of geographic features and display of occupancy rate estimates. Gan et al. (2008) also carried out a thorough AVO estimation study using existing traffic crash data co-modeled with other variables such as district, county, hour, week etc. However, in their paper, they admitted that the results are highly susceptible to potential bias resulting from issues related to traffic crash reports. Jung et al. (2010) provided a detailed process for estimating AVOs at the individual location, facility type, and county levels, along with a detailed sampling process designed to select data collection locations and dates on different facility types.

While aforementioned studies have implemented AVO estimation methods that have proven to work well, they are limited in their scope and often focused on a geographic area no larger than a state. Additionally, methods that involve manual counts are too time and resource intensive to be used to estimate AVO of each urban area nationwide. More importantly, most of the methods mentioned does not include a special consideration for AVO rates of buses and trucks. As such, methods are needed that can be applied nationally and only rely on data that are easily available nationwide, and are updated regularly. For this project, in order to estimate vehicle occupancy for urbanized areas nationwide, a combination of national-wide, local, and survey data will be used for large-scale sampling and modeling work.

Goals and Scope of Work

The goal of this task order is to provide and implement a statistically valid and practical method to estimate 1) bus occupancy rate for each of the urbanized areas as defined by the U.S. Census Bureau and each of the states and the District of Columbia and 2) truck occupancy rate for each of the urbanized areas as defined by the U.S. Census Bureau and each of the states and the District of Columbia. There are 497 urbanized areas defined by the U.S. Census Bureau as shown in Figure 1. Note that this project will only include the urbanized area with a population higher than 200,000. After filtering the urbanized area based on the population information obtained from the U.S. Census Bureau (U.S. Census Bureau, 2012), 183 urbanized areas are considered in this project. Table 1 summarizes top 20 urbanized areas in terms of population. To map different data into the urbanized areas, the U.S. Census Bureau website also provides a set of files that contains the relationships between the urbanized areas and other geospatial regions (e.g., county, city, and zip code) (U.S. Census Bureau, 2010).

The tasks are to develop statistically valid and practical methods to estimate a) bus occupancy rate each of the urbanized areas as defined by the U.S. Census Bureau and each of the states and the District of Columbia and b) truck occupancy rate for each of the urbanized areas as defined by the U.S. Census Bureau and each of the states and the District of Columbia.

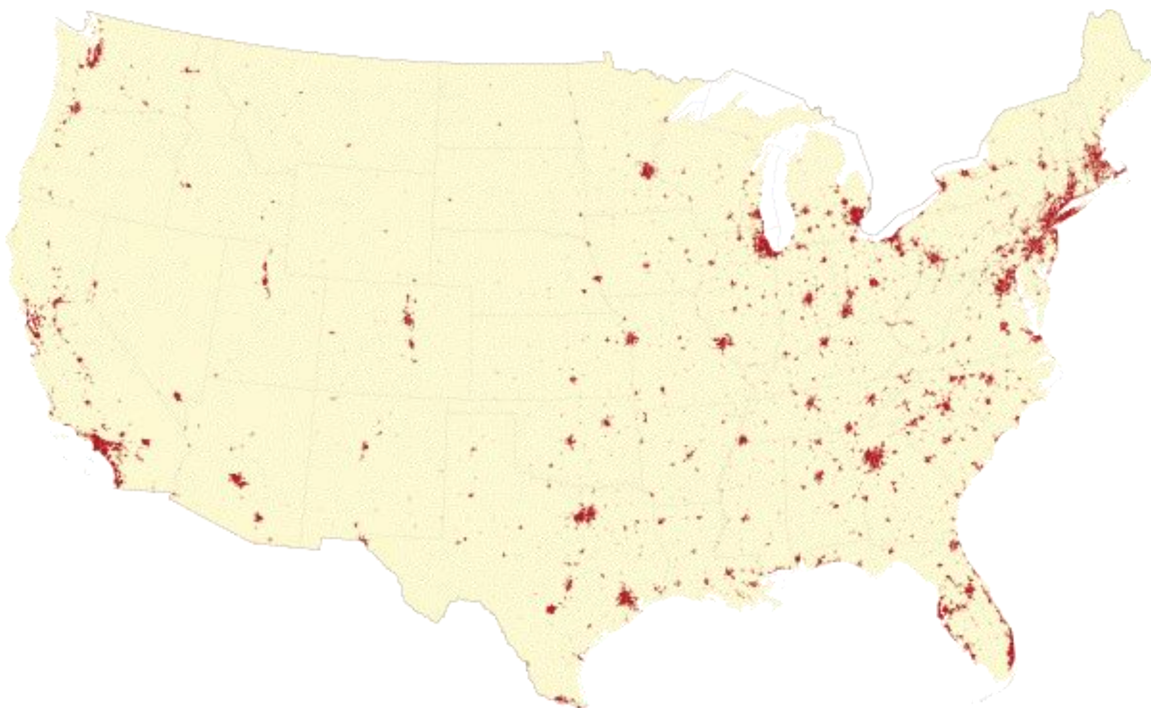


Figure 1. Urbanized areas in the United States. Source: https://en.wikipedia.org/wiki/United_States_urban_area#/media/File:USA-Urban-Areas.svg.

Table 1. Top 20 Urbanized Areas in US

Urban Code	Name	State	Population	Land Area (mi^2)	Population Density
63217	New York--Newark, NY--NJ--CT	NY	12,191,715	1563.15	7799.5
51445	Los Angeles--Long Beach--Anaheim, CA	CA	12,150,996	1736.02	6999.3
16264	Chicago, IL--IN	IL	8,018,716	2122.25	3778.4
63217	New York--Newark, NY--NJ--CT	NJ	6,159,466	1886.99	3264.2
56602	Miami, FL	FL	5,502,379	1238.61	4442.4
22042	Dallas--Fort Worth--Arlington, TX	TX	5,121,892	1779.13	2878.9
40429	Houston, TX	TX	4,944,332	1660.02	2978.5
3817	Atlanta, GA	GA	4,515,419	2645.35	1706.9
9271	Boston, MA--NH--RI	MA	4,087,709	1750.57	2335.1
69076	Philadelphia, PA--NJ--DE--MD	PA	3,760,387	1245.92	3018.2
23824	Detroit, MI	MI	3,734,090	1337.16	2792.5
69184	Phoenix--Mesa, AZ	AZ	3,629,114	1146.57	3165.2
78904	San Francisco--Oakland, CA	CA	3,281,212	523.62	6266.4
80389	Seattle, WA	WA	3,059,393	1010.31	3028.2
78661	San Diego, CA	CA	2,956,746	732.41	4037
57628	Minneapolis--St. Paul, MN--WI	MN	2,650,614	1021.31	2595.3
86599	Tampa--St. Petersburg, FL	FL	2,441,770	956.99	2551.5
23527	Denver--Aurora, CO	CO	2,374,203	667.95	3554.4
92242	Washington, DC--VA--MD	VA	2,235,884	696.16	3211.7
4843	Baltimore, MD	MD	2,203,663	717.04	3073.3

The term of "statistically valid" means that the information generated from any underlying data used in the estimation should be representative of the entire population with an 85% confidence interval. The term of "practical" means that the method is not relying on a new survey activity, doesn't cost more than $250,000 to implement the methods for all urbanized areas and states on an annual basis, and can be completed within 6 months after the end of year. Here, bus is defined as Class 4 vehicles in FHWA's 13 Vehicle Category Classification. According to FHWA's 13 Vehicle Category Classification, trucks are defined as Class 5 through Class 13 vehicles, but this project specifically considers Class 6-13 (as requested by the TOPR, see Figure 2) vehicles when estimating average truck occupancy. For bus occupancy rates, factors will cover both the public and private charters, transit, school, tourism and long-distance service buses.

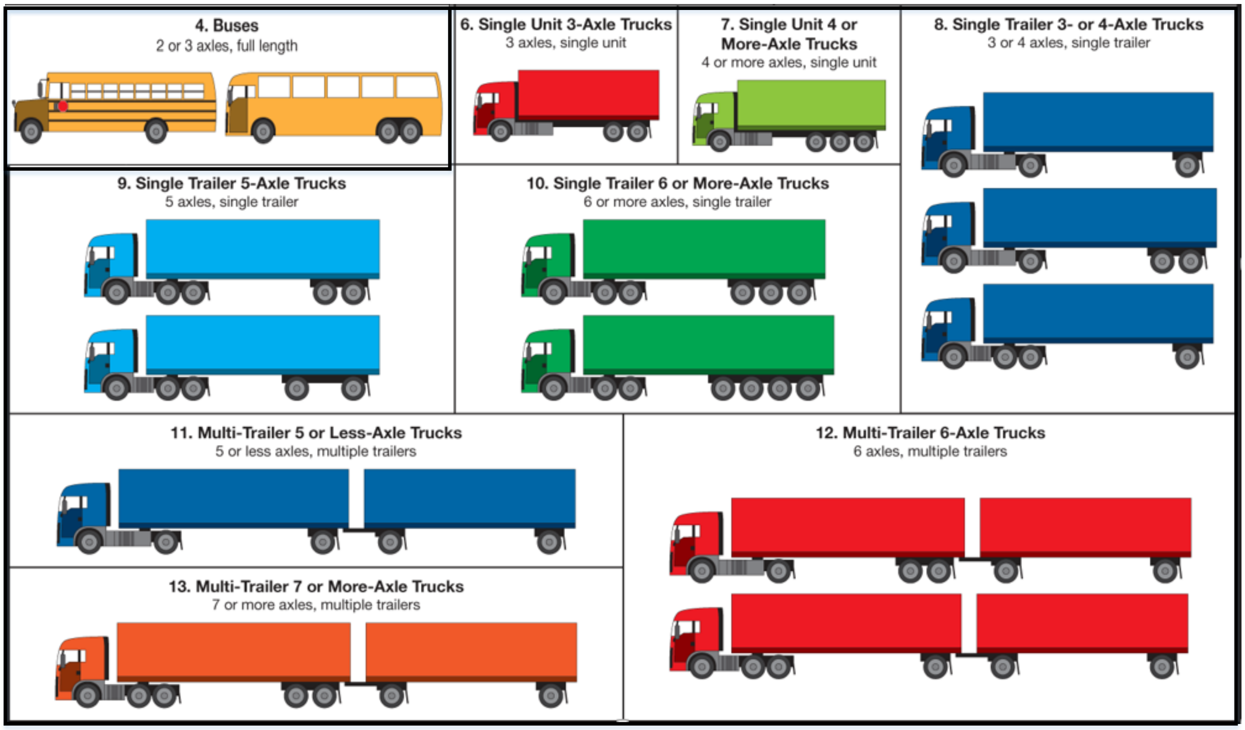


Figure 2. Definition of bus and truck based on FHWA vehicle classification. Source: https://www.agroclasi.com/freight-class-chart-pdf/using-truck-fleet-data-in-combination-with-other-sources-for-fhwa_classification_chart_/.

Methodology

Developing Bus Occupancy Factors

Methodology Framework

Generally, buses defined as Class 4 vehicles in FHWA's 13 Vehicle Category Classification can be subdivided into three categories: (1) transit bus (metro bus); (2) school bus; and (3) motorcoach. Total average bus occupancy can be estimated by aggregating the average vehicle occupancies (AVO) for the above three subgroups as shown below:

$$AVO_{Bus} = \frac{AVO_{Transit} \times VMT_{Transit} + AVO_{School} \times VMT_{School} + AVO_{Motorcoach} \times VMT_{Motorcoach}}{VMT_{Transit} + VMT_{School} + VMT_{Motorcoach}}$$

where AVO =Average Vehicle Occupancy; *VMT*=Annual Vehicle Miles Traveled. It is necessary to develop the bus occupancy factors based on the above three subgroups because their AVOs differ significantly. Our methodology estimates the AVOs for transit bus, school bus, and motorcoach independently based on multi-source datasets from state and urbanized area levels, and then aggregates them based on their proportion of total bus VMT. The VMT for each bus category can be calculated based on their average VMT (national level) and the vehicle count data from the Polk dataset which contains detailed vehicle registration information (Polk City Directory, 2018) by using the following equations:

$$VMT_{Transit} = Average\ VMT_{Transit} \times Vehicle\ Count_{Transit}$$
$$VMT_{School} = Average\ VMT_{School} \times Vehicle\ Count_{School}$$
$$VMT_{Motorcoach} = Average\ VMT_{Motorcoach} \times Vehicle\ Count_{Motorcoach}$$

where $Average\ VMT_{Transit} = 34{,}053$ miles per vehicle (U.S. Department of Energy, 2015); $Average\ VMT_{School} = 12{,}000$ miles per vehicle (American School Bus Council, 2015); $Average\ VMT_{Motorcoach} = 38{,}385$ miles per vehicle (American Bus Association, 2017). The state-level bus count by type is shown in Figure 3.

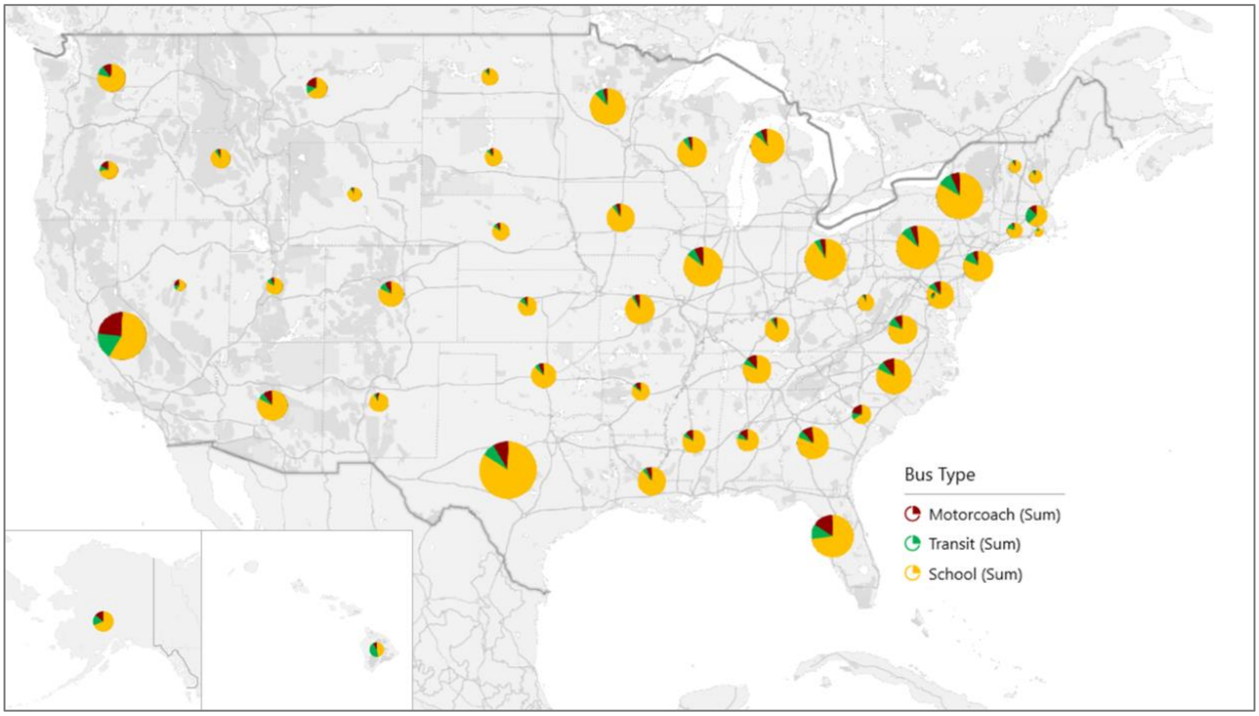


Figure 3. State level bus count by type.

Figure 4 illustrates the general framework of our methodology for developing bus occupancy factors. The details about how to estimate the AVOs for transit bus, school bus, and motorcoach will be explained in the following sections.

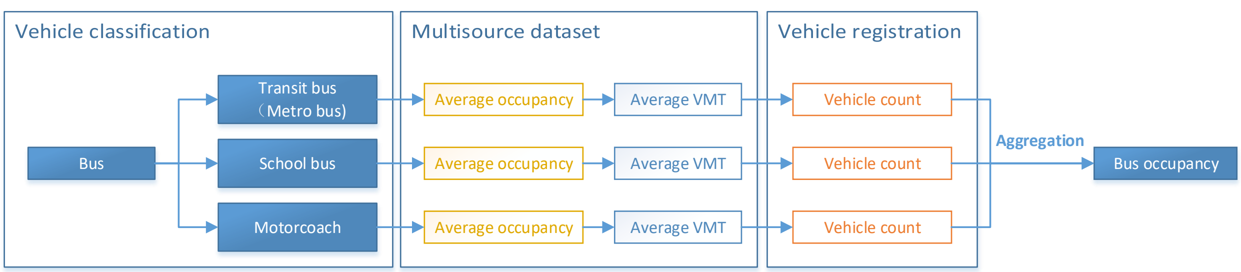


Figure 4. General framework for developing bus occupancy factors.

Methodology: Transit Bus

Data Sources

The primary dataset used for transit bus occupancy calculation is the Federal Transit Administration (FTA) National Transit Database (NTD). The most recent dataset is for the year 2017. All public bus companies that receive Federal funding are required to annually report operational and financial data to the FTA, including transit modes operated, number of vehicles in operation, service hours, etc. Passenger and vehicle miles traveled, the two variables used in occupancy calculation, are also included in the NTD.

Transit agencies are classified into three types of reporters, "Full Reporter", "Reduced Reporter", and "Rural Reporter." Only data from "Full Reporters" has been certified as to accuracy by each agency's CEO and subjected to audit according to the FHWA requirement (FHWA, 2017). After filtering out transit modes that are not considered in this project (e.g., rail and ferry transit), the final dataset includes five transit modes: Commuter Bus (CB), Demand Responsive (DR), Motor Bus (MB), Rapid Bus (Bus Rapid Transit) (RB), and Trolley Bus (TB). For these five modes, a total of 1,051 bus transit agencies were labeled as "Full Reporters" as of 2016. Table 2 presents the reporting rate for transit agencies of different modes. In general, NTD data shows a very high reporting rate (i.e., around 99% across all transit modes) and it is not necessary to impute missing data.

Table 2. Reporting Rate for Transit Agencies of Different Modes

Transit Mode	# of PMT/VMT Reports	Total Count	Report Rate
Commuter Bus (CB)	101	102	99.0%
Demand Responsive (Paratransit) (DR)	454	458	99.1%
Motor Bus (MB)	469	475	98.7%
Rapid Bus (Bus Rapid Transit) (RB)	11	11	100.0%
Trolley Bus (TB)	5	5	100.0%
Total	**1040**	**1051**	**99.0%**

Method for Estimating Occupancy Factors

State level

Two important data items to be used in occupancy calculation are passenger miles (PMT) and vehicle revenue miles (VMT). The average occupancy of transit bus can be expressed as

$$AVO_{transit} = average\_ridership + driver = \frac{\sum_i PMT_i}{\sum_i VMT_i} + 1$$

where $\sum_i PMT_i$ and $\sum_i VMT_i$ are total PMT and VMT from all transit agencies in the analysis area. Figure 5 shows the average transit occupancy by state. Average VMT for transit buses is an important variable to aggregate occupancy information among different bus types. Figure 6 also shows the average VMT by states based on 2016 NTD data. In general, transit occupancy is higher on the east and west coasts but average VMT is higher for the central region. All transit agencies in Wyoming are labelled as "Reduced Reporter" or "Rural Reporter" thus no PMT and VMT information is reported.

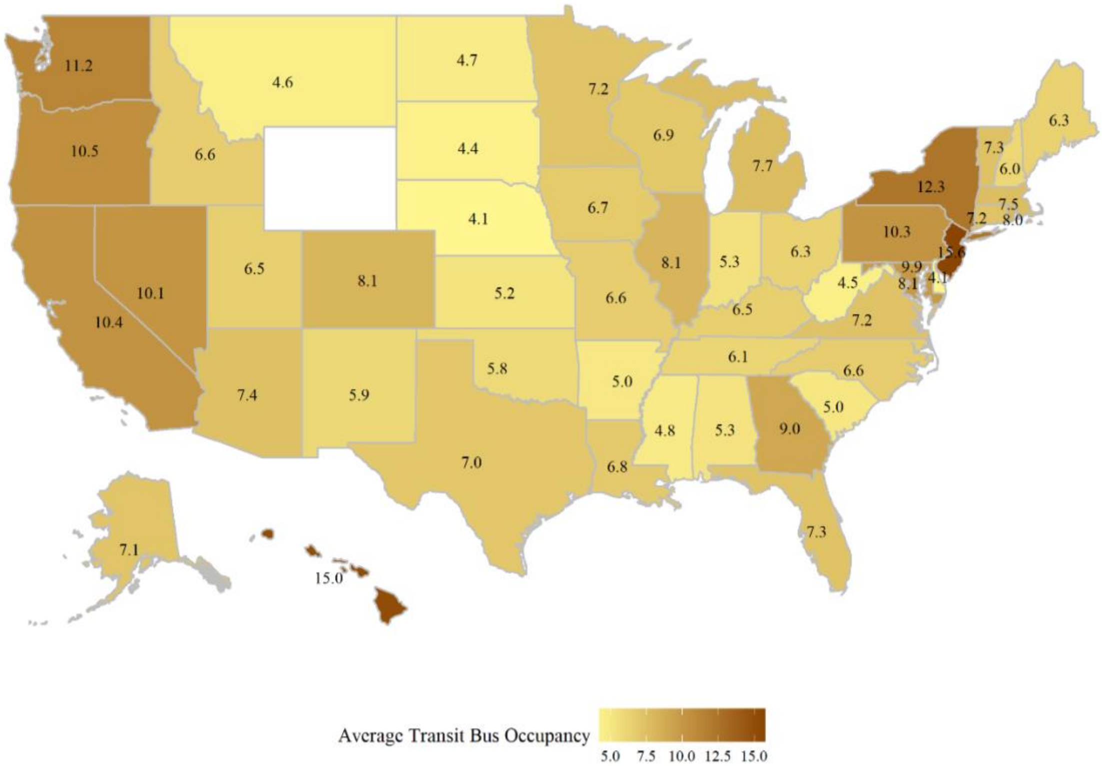


Figure 5. Average transit bus occupancy by state without Wyoming.

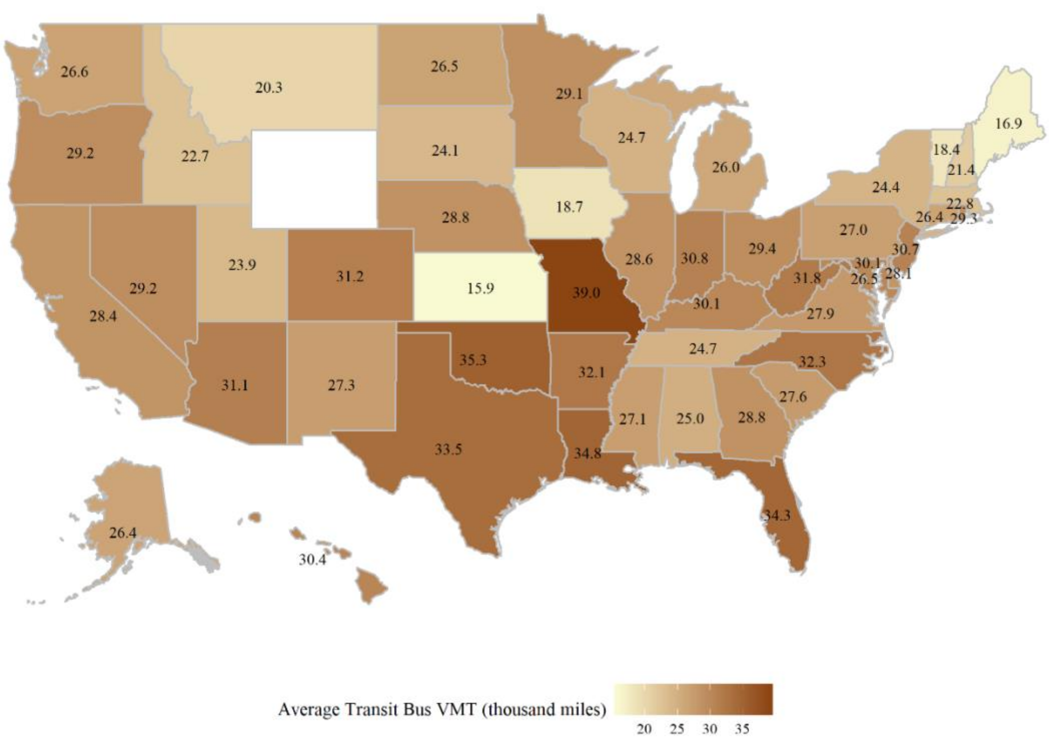


Figure 6. Average transit bus VMT by state without Wyoming.

A multiple linear regression model is developed to estimate the transit occupancy in Wyoming. Previous study has shown that transit occupancy is closely related with the local population and economics (Mittal et al., 2017). Thus, local GDP and population density data are used as two predictors in the regression model. Population density data by state and urbanized area have been collected from U.S. Census Bureau (U.S. Census Bureau, 2018). Annual GDP information by state and metropolitan area can be downloaded from the U.S. Bureau of Economic Analysis (BEA) (BEA, 2018). Note that BEA also provides GPS break down by different industries, and in the regression model development we tested both the total GDP and GDP in transit and ground passenger transportation.

To increase the sample size and obtain a more consistent estimate for model parameters, a total of five years (i.e., 2012-2016) of data were used to fit the regression model. Figure 7 (a-c) show the scatterplots of state average transit occupancy against all industry GDP, transit GDP, and population density, respectively. Smooth trend curves (orange curves) and local variations (grey shadow) are also displayed to represent general relationships between variables. According to the data, there is a positive relationship between transit occupancy and population density. But for GDP data, the relationship is more complicated, although the general trend is increasing. It is important to note that a linear regression model is not suitable to capture the curvilinear relationship between variables. Thus, more data pre-processing work is required before regression modeling. In addition, Hawaii transit agencies (points in red ovals) have significantly higher occupancy than other states and are removed from the final dataset, as our goal is to estimate transit occupancy only in Wyoming.

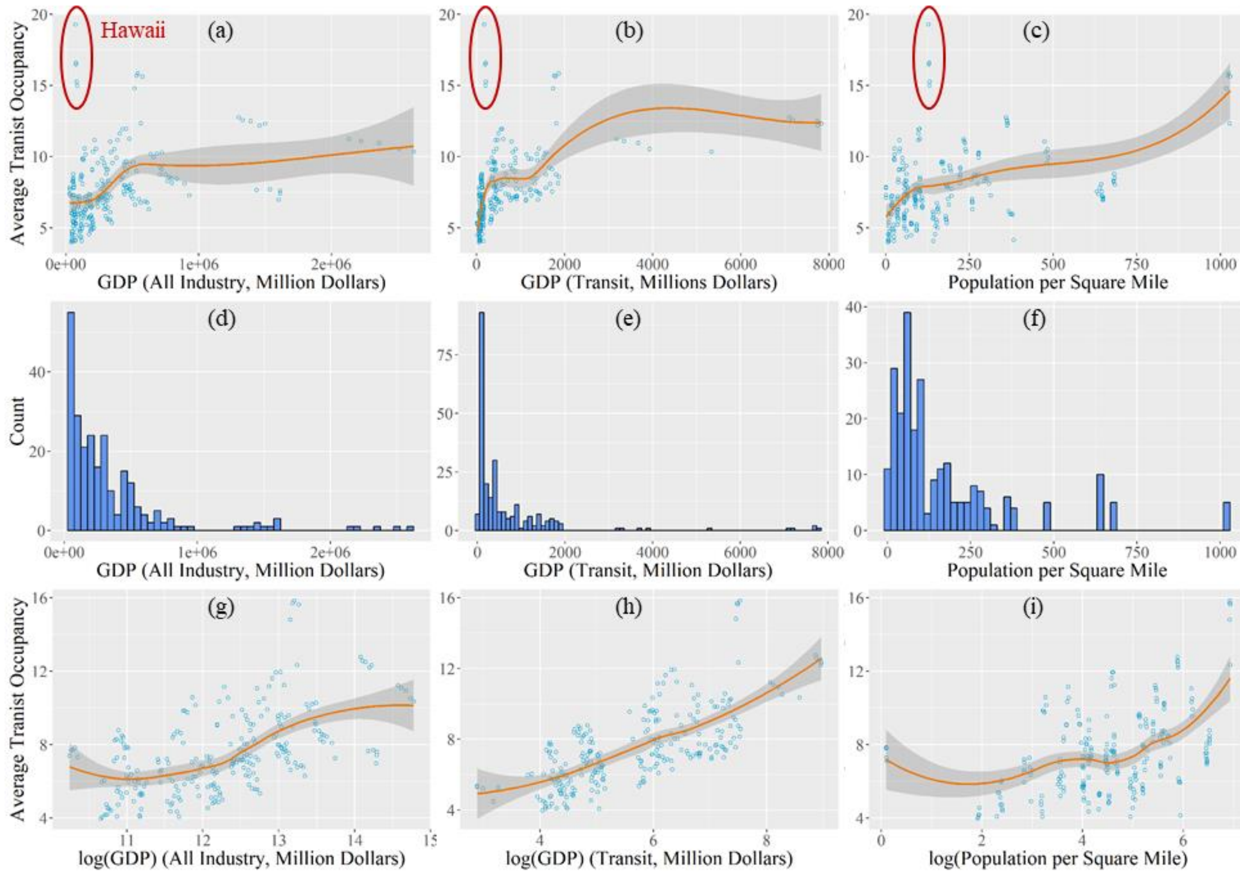


Figure 7. Explanatory analysis for regression modeling.

Figure 7 (d-f) show the distribution of candidate predictors (i.e., all industry GDP, transit GDP, population density). All candidate predictors have right-skewed distributions, indicating that logarithmic transformation may be needed to normalize the data. Figure 7 (g-i) show the scatterplots of average transit occupancy with log-transformed candidate predictors. The trend curves for all industry GDP and transit GDP become more linear after log-transformation, while the trend curve for population density is not significantly improved in terms of linearity. In this report, we use log to denote the natural logarithmic transformation.

A total of five regression models were trained using different variable settings. Table 3 presents the regression results for all five models. Model 1 takes all candidate predictors into regression, and the result shows that all industry GDP is not significant with transit GDP already in the model. After removing all industry GDP (Model 2), transit GDP becomes more significant as indicated by the higher t-value. The overall model fitting is almost the same (i.e., R^2 values are very close). As mentioned in the explanatory analysis, Model 3 tested regression results with log-transformed predictors. According to the smaller residual standard error (σ) and higher R^2, models with log-transformed predictors performed better than non-transformed data. Note that log(gdp_all) shows a negative impact on transit occupancy, while in the scatterplot the trend should be positive (as shown in Figure 7 (g)). This suggests that all industry GDP is highly correlated with Transit GDP and should be removed to avoid multicollinearity. Models 4 and 5 tested the performance of including transit GDP and population density with different data transformations. According to the results, Model 5 outperforms Model 4 in terms of the higher R^2, lower residual standard error (σ), as well as more significant coefficient estimates.

Table 3. Regression Results for Different Model Settings

Model 1: $occupancy \sim gdp\_all + gdp\_transit + pop\_density$				
Variable	Estimate	Std. Error	t-value	p-value
(Intercept)	6.5090	0.1998	32.574	$< 2 \times 10^{-16}$
gdp_all	2.64×10^{-7}	4.85×10^{-7}	0.544	0.5870
gdp_transit	7.21×10^{-4}	1.77×10^{-4}	4.064	6.48×10^{-5}
pop_density	3.55×10^{-3}	7.04×10^{-4}	5.045	8.80×10^{-7}
	$\sigma = 2.140$	$DF = 246$	$F = 34.55$	$R^2 = 0.2964$
Model 2: $occupancy \sim gdp\_transit + pop\_density$				
Variable	Estimate	Std. Error	t-value	p-value
(Intercept)	6.5538	0.1815	36.112	$< 2 \times 10^{-16}$
gdp_transit	7.92×10^{-4}	1.20×10^{-4}	6.612	2.33×10^{-10}
pop_density	3.54×10^{-3}	7.02×10^{-4}	5.037	9.13×10^{-7}
	$\sigma = 2.137$	$DF = 247$	$F = 51.82$	$R^2 = 0.2956$
Model 3: $occupancy \sim log(gdp\_all) + log(gdp\_transit) + log(pop\_density)$				
Variable	Estimate	Std. Error	t-value	p-value
(Intercept)	10.5275	2.1346	4.932	1.50×10^{-6}
log(gdp_all)	-1.1982	0.2494	-4.803	2.71×10^{-6}
log(gdp_transit)	1.8317	0.1936	9.459	$< 2 \times 10^{-16}$
log(pop_density)	0.3222	0.1161	2.776	5.92×10^{-3}
	$\sigma = 1.953$	$DF = 246$	$F = 57.97$	$R^2 = 0.4070$
Model 4: $occupancy \sim log(gdp\_transit) + log(pop\_density)$				
Variable	Estimate	Std. Error	t-value	p-value
(Intercept)	0.6759	0.6175	1.095	0.2748
log(gdp_transit)	1.0828	0.1199	9.033	$< 2 \times 10^{-16}$
log(pop_density)	0.1967	0.1180	1.667	0.0969
	$\sigma = 2.038$	$DF = 247$	$F = 69.23$	$R^2 = 0.3540$
Model 5: $occupancy \sim log(gdp\_transit) + pop\_density$				
Variable	Estimate	Std. Error	t-value	p-value
(Intercept)	1.5122	0.6073	2.490	0.01343
log(gdp_transit)	1.0227	0.1126	9.081	$< 2 \times 10^{-16}$
pop_density	2.26×10^{-3}	6.96×10^{-4}	3.241	0.00136
	$\sigma = 2.008$	$DF = 247$	$F = 75.19$	$R^2 = 0.3784$

The final model used to estimate the state-level transit occupancy is expressed as

$$AVO_{transit}(state) = 1.5122 + 1.0227 \times \log GDP_{transit}(state) + 2.26 \times pop\_density(state)$$

where $GDP_{transit}$ is the GDP for Transit and Ground Transportation Industry (\$ 1×10^6) and $pop\_density$ is the population density of the state (1,000 per mi^2). The estimated prediction error is 2. As of 2016, the transit GDP for Wyoming is \$ 33×10^6 and the population density is 5.980 people per mi^2. This gives a prediction of state average transit occupancy of 3.08, which is the lowest among all states and slightly smaller than the neighboring Montana and South Dakota.

Above illustrates the general procedure for estimate state-level transit bus occupancy when the data is missing. However, given that there is no urbanized area in Wyoming, it's might be more appropriate to fit the regression model only using nearby states that are more similar to Wyoming in terms of transit GDP and population density. Thus, for estimating Wyoming transit bus occupancy, we just focused on the nearby seven states (i.e., Idaho, Montana, North Dakota, South Dakota, Nebraska, Colorado, and Utah) that are relatively less-populated. Although Colorado, and Utah have some large urbanized areas, these two states are included to ensure sufficient variations in model input. The final model used to specifically estimate the transit bus occupancy in Wyoming is expressed as

$$
\begin{aligned}
&AVO_{transit}(state) \\
&\quad = 0.3353 + 0.9294 \times \log GDP_{transit}(state) + 55.24 \times pop\_density(state)
\end{aligned}
$$

Plug in the 2016 transit GDP and population density in Wyoming, the estimated Wyoming average transit bus occupancy is 3.92 (as shown in Figure 8), which is slightly higher than the regression estimate using all states as model input.

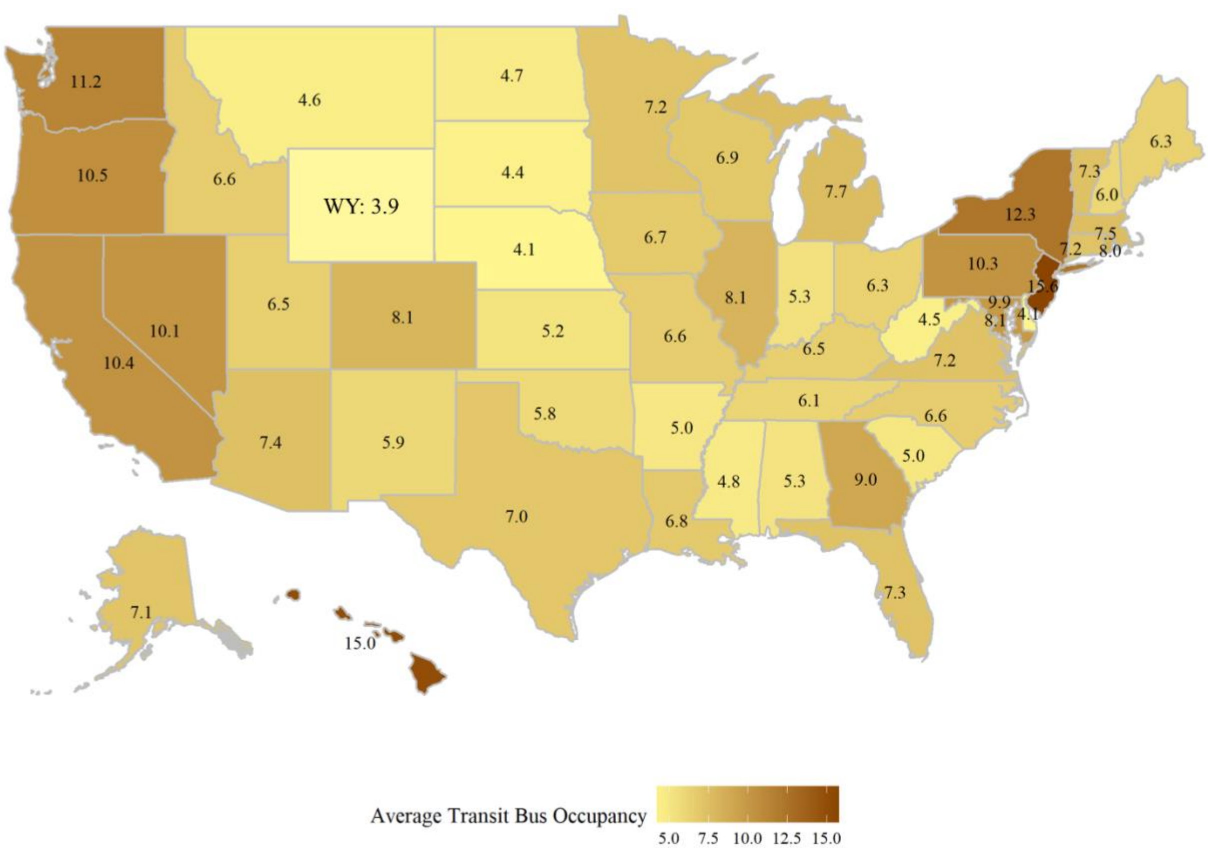


Figure 8. Average transit bus occupancy by state with Wyoming.

Urbanized area level

For data at the urbanized area level, transit agencies can be mapped into the corresponding urbanized area based on the zip code information. The NTD transit agencies have covered 161 of the total 183 urbanized areas considered in this project. For urbanized areas not covered by NTD data, a linear regression model was developed to estimate the average transit bus occupancy. Although U.S. BEA also has GDP summarized at the metropolitan statistical area (MSA) level, the data cannot be further broken down to the urbanized area level. Additionally, the MSA-level transit GDP data are missing in some areas, especially in small MSAs where the NTD information is also missing. Thus, we used the population density as the only predictor in the regression model to estimate the urban area level transit bus occupancy. Using calculated average transit bus occupancy for urbanized areas with NTD agencies, the fitted regression model is expressed as below

$$AVO_{transit}(urban\_area) = -19.2956 + 3.3793 \times \log pop\_density(urban\_area)$$

For the 22 urbanized areas where NTD information is missing, the average transit bus occupancy was estimated using the above equation. The average transit bus annual mileage was assumed to be the same as that in the corresponding state.

Table **4** summarizes the average transit occupancy results for top 20 urbanized areas (in terms of population).

Table 4. Transit Occupancy Results for Top 20 Urbanized Areas

Area Name	State	Average Occupancy	Average VMT (mi)
New York--Newark, NY--NJ--CT	New York	12.99	24109
Los Angeles--Long Beach--Anaheim, CA	California	15.81	29005
Chicago, IL--IN	Illinois	8.64	28313
New York--Newark, NY--NJ--CT	New Jersey	15.61	31311
Miami, FL	Florida	8.62	35389
Dallas--Fort Worth--Arlington, TX	Texas	5.57	36521
Houston, TX	Texas	4.84	16412
Atlanta, GA	Georgia	9.65	30390
Boston, MA--NH--RI	Massachusetts	8.29	23315
Philadelphia, PA--NJ--DE--MD	Pennsylvania	12.74	27210
Detroit, MI	Michigan	10.17	33035
Phoenix--Mesa, AZ	Arizona	7.02	32654
San Francisco--Oakland, CA	California	11.74	24422
Seattle, WA	Washington	14.27	26910
San Diego, CA	California	8.82	30955
Minneapolis--St. Paul, MN--WI	Minnesota	7.29	29334
Tampa--St. Petersburg, FL	Florida	7.43	33762
Denver--Aurora, CO	Colorado	8.31	32630
Washington, DC--VA--MD	Virginia	8.98	26418
Baltimore, MD	Maryland	11.01	29012

Methodology: School Bus

Data Sources

The U.S. State by State Transportation Statistics 2015-16 reported by SchoolBusFleet.com (Data Source: http://files.schoolbusfleet.com/stats/SBFFB18StateByState.pdf) is employed to calculate the school bus occupancy for state level. The report provides a breakdown of information for each of the 50 states, including the number of K-12 public and private school students transported daily, the number of school buses in each state and the total state aid paid for pupil transportation. The data is updated annually, so it is straight forward to use the new data with our developed methodology. Figure 9 shows an example of the data table in the report. In our method, the public K-12 students transported daily and the total annual route mileage are employed as the input data. Based on the data reported from American School Bus Council (ASBC) (Data Source: http://www.americanschoolbuscouncil.org/issues/environmental-benefits), we can know the following two important information:

(1) Average distance from home to school for bus riders (ASBC estimate, miles) = 5 miles
(2) Length of average school year (days) = 180 days

SCHOOL TRANSPORTATION: 2015-16 SCHOOL YEAR

State	Public K-12 students transported daily	Total K-12 public students enrolled	Percent of total public students transported	Private K-12 students transported daily	Total yellow school buses	District-owned yellow buses	Contractor-owned yellow buses	State-owned yellow buses	Total annual route mileage	Total state aid paid for pupil transportation
Alabama	362,567	734,119	49%	0	7,795	7,473	322	0	86,653,080	$339,228,938
Alaska	29,775	129,588	23%	n/a	1,072	228	844	0	7,702,265	$78,611,743
Arizona	301,135	1,082,643	28%	n/a	7,166	n/a	n/a	n/a	80,638,240	n/a
Arkansas	350,373	477,268	73%	n/a	4,532	n/a	n/a	n/a	537,988	$198,217,127
California	666,314*	6,226,737	11%	500,543	24,201	15,914	8,287	12	254,325,996	$491,112,000
Colorado	376,195	899,112	42%	n/a	3,982*	n/a	n/a	0	291,444	$56,438,573
Connecticut*	467,000**	548,181	85%	n/a	7,795	479	7,316	0	n/a	n/a
Delaware	117,000	135,000	87%	0	1,650	0	1,050	600	19,000,000	$92,000,000

Figure 9. Sample data of the U.S. State by State Transportation Statistics 2015-16. Source: http://files.schoolbusfleet.com/stats/SBFFB18StateByState.pdf.

Method for Estimating Occupancy Factors

State level

As a result, the average school bus occupancy for each state can be estimated based on the following equation:

$$AVO_{school} = \frac{\sum_i PMT_i}{\sum_i VMT_i} + 1 = \frac{Number\ of\ Student\ Transported\ Daily \times 180 \times (5 \times 2)}{Total\ Annual\ Route\ Mileage} + 1$$

where (5×2) is the average round trip distance from home to school. The estimated average school bus occupancy for the states are summarized in Figure 10. The total annual route mileage data are missing for 14 states, and these states require additional model to estimate the average school bus occupancy.

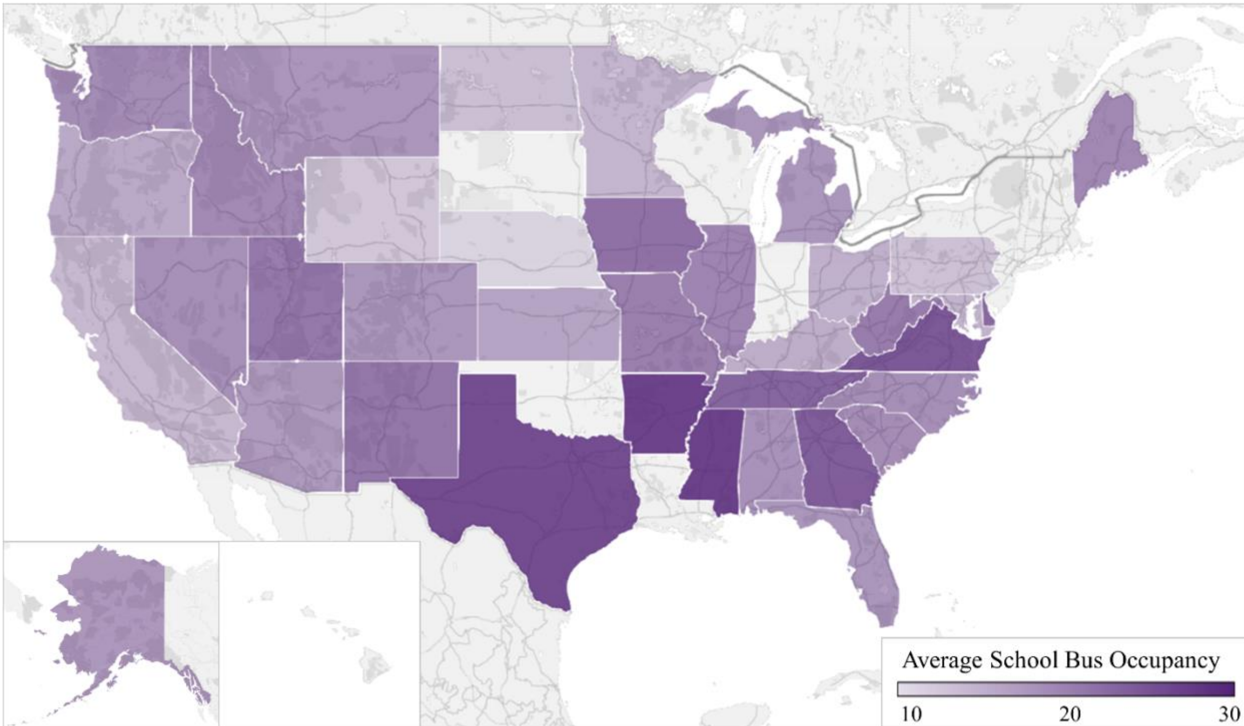


Figure 10. Average school bus occupancy by state (14 states missing).

To address the missing data issue, a local factors-based weighted model is developed by incorporating local factors such as total school enrollment, average district enrollment, total districts, total schools, total students transported daily, total yellow school buses as below

$$AVO_{school}(State\ i) = \sum_{j=1}^{N} w(i,j) \times AVO_{school}(State\ j)$$

where the weight $w(i,j)$ is defined as an index to describe the similarity between state *i* and state *j*. If the local factors of state *i* is close to those of state *j*, the similarity between them is high which implies a high value of weight $w(i,j)$. Let $F_l(\mathrm{i})$ be a local factor of state *i*, then the weight $w(i,j)$ can be defined as

$$w(i,j) = \frac{\sum_{l=1}^{L}\left(1 - \frac{|F_l(\mathrm{i}) - F_l(\mathrm{j})|}{max\{F_l(\mathrm{i}), F_l(\mathrm{j})\}}\right)}{\sum_{j=1}^{N}\sum_{l=1}^{L}\left(1 - \frac{|F_l(\mathrm{i}) - F_l(\mathrm{j})|}{max\{F_l(\mathrm{i}), F_l(\mathrm{j})\}}\right)}$$

where the design of the item $\frac{|F_l(\mathrm{i}) - F_l(\mathrm{j})|}{max\{F_l(\mathrm{i}), F_l(\mathrm{j})\}}$ can guarantee that the value ranges between 0 and 1. The data for these local factors can be found from SchoolBusFleet.com (Data Source: http://files.schoolbusfleet.com/stats/SBFFB18StateByState.pdf) and Governing.com (Data Source: http://www.governing.com/gov-data/education-data/school-district-totals-average-enrollment-statistics-for-states-metro-areas.html). By using weight $w(i,j)$, the state has similar local factors will have more impacts on the estimation of the average school bus occupancy for the targeted state. For example, our results indicate that North Dakota shows higher similarity ($w(i,j) = 0.495$) with South Dakota compared to any other state. Based on the developed local factors-based weighted model, the average school bus occupancies for all states are estimated and presented in Table 5 and Figure 11.

Table 5. Estimated Average School Bus Occupancy by State

State	Occupancy	State	Occupancy	State	Occupancy	State	Occupancy
Alabama	16.06	Illinois	18.21	Montana	15.42	South Carolina	17.01
Alaska	14.92	Indiana	12.52	Nebraska	7.09	South Dakota	12.09
Arizona	14.44	Iowa	21.83	Nevada	16.28	Tennessee	23.77
Arkansas	29.84	Kansas	12.98	New Hampshire	11.58	Texas	28.20
California	9.26	Kentucky	11.29	New Jersey	12.27	Utah	20.55
Colorado	15.26	Louisiana	13.29	New Mexico	20.75	Vermont	11.07
Connecticut	12.52	Maine	17.61	New York	12.26	Virginia	26.19
Delaware	23.17	Maryland	10.13	North Carolina	16.47	Washington	16.87
Distric of Columbia	10.59	Massachusetts	12.45	North Dakota	8.43	West Virginia	19.67
Florida	15.22	Michigan	15.17	Ohio	10.79	Wisconsin	12.29
Georgia	25.21	Minnesota	9.78	Oklahoma	12.13	Wyoming	7.23
Hawaii	9.67	Mississippi	30.07	Oregon	11.85		
Idaho	17.50	Missouri	19.33	Pennsylvania	7.95		

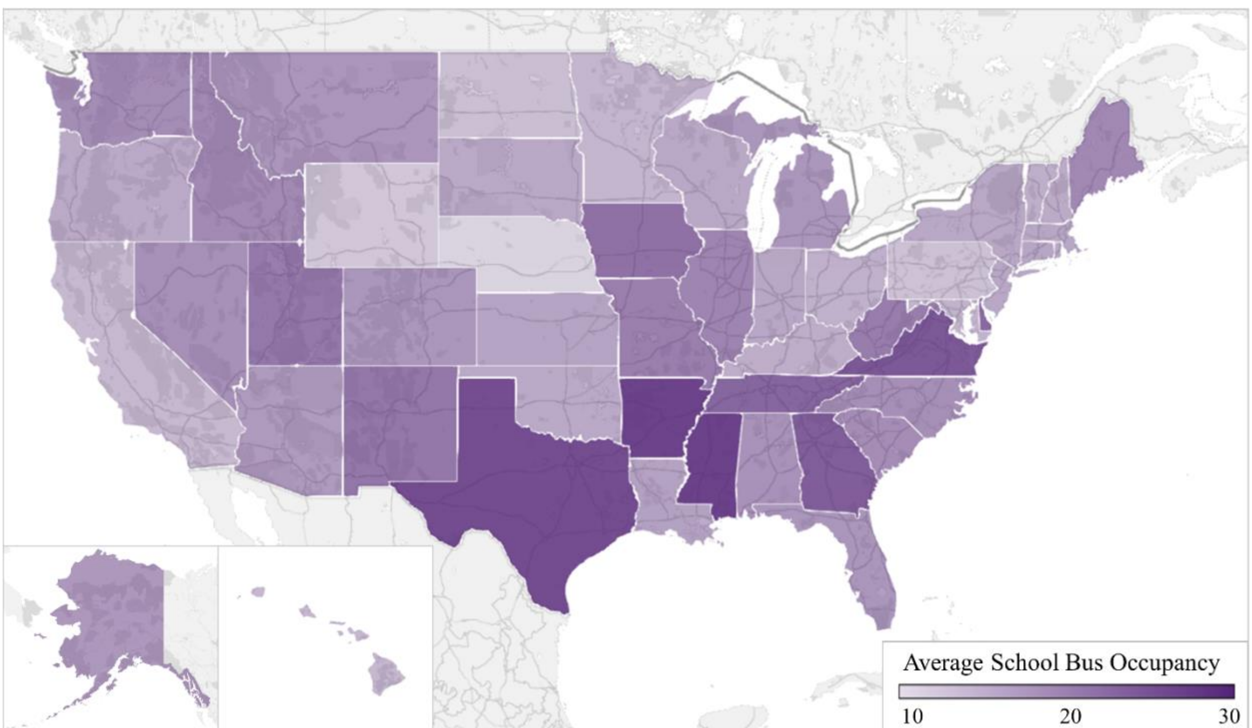


Figure 11. Average school bus occupancy by state (all states).

Urbanized area level

The Governing.com (Data Source: http://www.governing.com/gov-data/education-data/school-district-totals-average-enrollment-statistics-for-states-metro-areas.html) also provides metro area school district data includes total districts, total schools, total public school enrollment, and average district enrollment for an urbanized area as shown in Figure 12. The dataset covers over 490 metro areas which include all the urbanized area with population over 200,000.

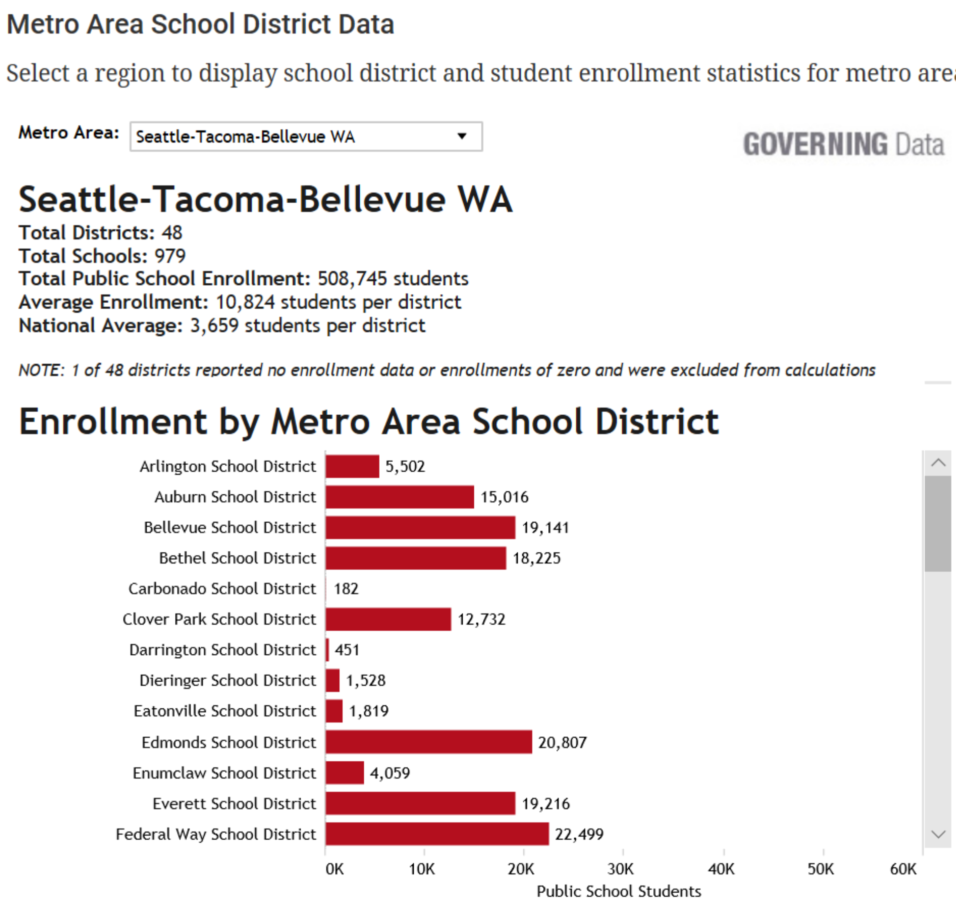


Figure 12. Example of the metro area school district data. Source: https://www.governing.com/gov-data/education-data/school-district-totals-average-enrollment-statistics-for-states-metro-areas.html.

To estimate the average school bus occupancy for the urbanized areas, the Empirical Bayes idea is employed to combine the state level estimation with local level factors. For an urbanized area, its state level school bus occupancy is used as a benchmark value with a weight defined based on the local level factors. Since the total districts, total schools, and total public school enrollment of an urbanized area are significantly less than those at the state level, the local average district enrollment (ADE) is selected to develop the weight. If the local ADE is close to the state level ADE, the weight for the benchmark value (state level school bus occupancy) will be high. The definition of the weight is expressed as below

$$w = 1 - \frac{|ADE_u - ADE_s|}{max\{ADE_u, ADE_s\}}$$

where ADE_u is the average district enrollment for an urbanized area, ADE_s is the average district enrollment for the corresponding state. Therefore, the empirical Bayes model for estimating the urbanized area average school bus occupancy is developed as below

$$AVO_{school}(urban\_area) = w \times AVO_{school}(state) + (1 - w) \times EAVO_{school}(urban\_area)$$

where $EAVO_{School}(urban\_area)$ is the expected average school bus occupancy for the urbanized area. In order to estimate $EAVO_{School}(urban\_area)$, the factors such as total districts, total schools, total public school enrollment, and average district enrollment are explored to identify their relationship with the average school bus occupancy as shown in Figure 13. The state level data including total districts, total schools, total public school enrollment, and average district enrollment are used to establish the regression models to estimate the average school bus occupancy. The outliers such as California, Texas, Nevada, Florida, Maryland (points in red ovals) that have significant higher values than other states are removed from the final datasets. Five different regression models including linear regression, log regression exponential regression, polynomial regression, and power regression are tested based on the final datasets for different factors. The models with best performance are selected and shown in Figure 13.

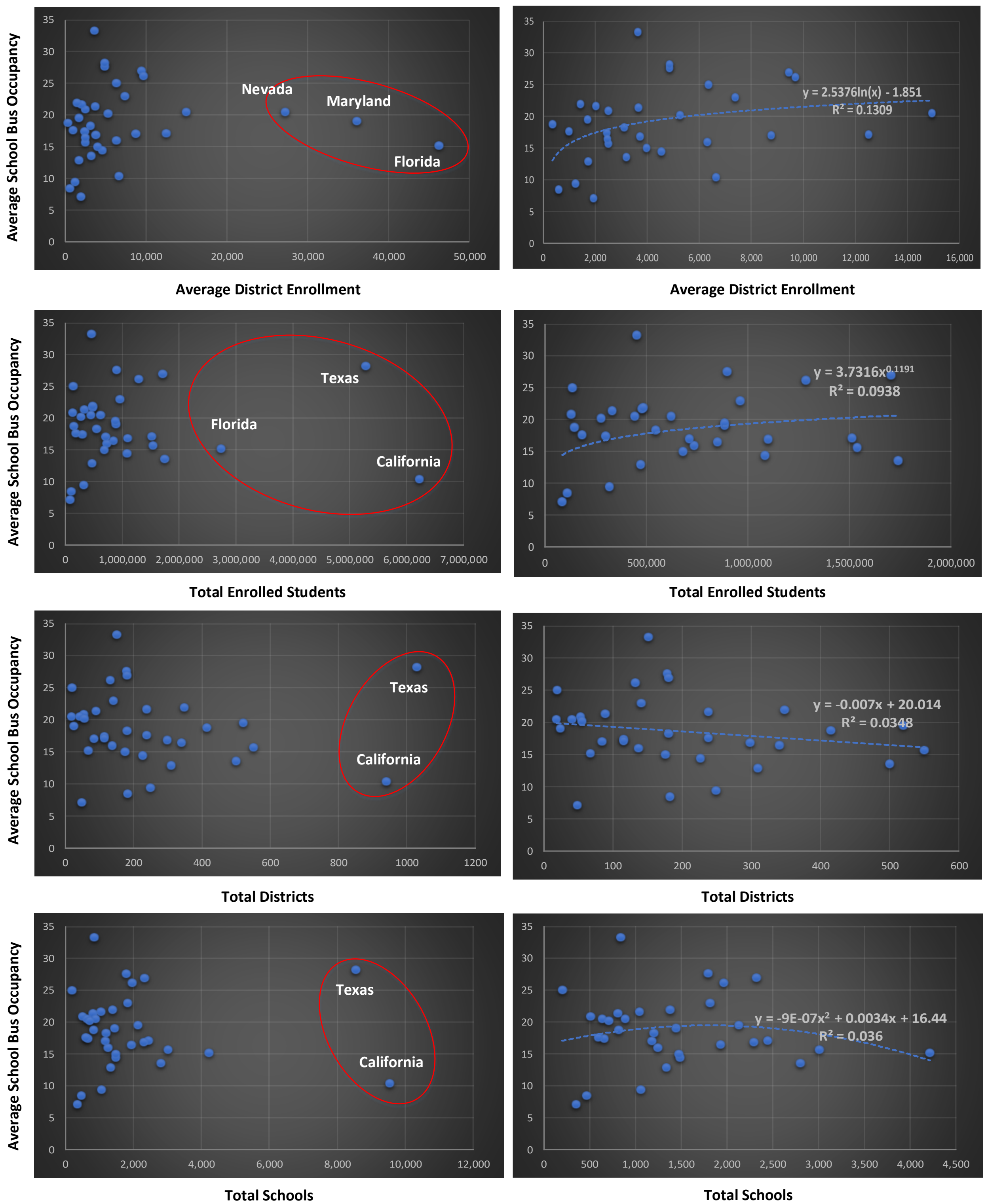


Figure 13. Regression analysis for urbanized area level school bus occupancy estimation.

The results show that the log regression model based on the final dataset of average district enrollment performances best as compared to the other models ($R^2 = 0.1309$). As a result, the final model used to estimate the expected average school bus occupancy for the urbanized areas is expressed as

$$EAVO_{school}(urban\_area) = 2.5376 \times \log ADE_u - 1.851$$

Based on the above method, the average school bus occupancy for all the urbanized areas required in the project can be estimated. The average school bus occupancy rates for top 20 urbanized areas are presented in Table 6.

Table 6. School Bus Occupancy Results for Top 20 Urbanized Areas

Area Name	State	Average Occupancy	Average VMT (mi)
New York--Newark, NY--NJ--CT	New York	13.82	12000
Los Angeles--Long Beach--Anaheim, CA	California	17.32	10509
Chicago, IL--IN	Illinois	18.78	7553
New York--Newark, NY--NJ--CT	New Jersey	13.78	12000
Miami, FL	Florida	22.26	17219
Dallas--Fort Worth--Arlington, TX	Texas	24.57	2477
Houston, TX	Texas	24.45	2477
Atlanta, GA	Georgia	24.38	9642
Boston, MA--NH--RI	Massachusetts	13.01	12000
Philadelphia, PA--NJ--DE--MD	Pennsylvania	7.99	18253
Detroit, MI	Michigan	17.78	10212
Phoenix--Mesa, AZ	Arizona	15.33	11253
San Francisco--Oakland, CA	California	10.10	10509
Seattle, WA	Washington	19.94	12529
San Diego, CA	California	14.94	10509
Minneapolis--St. Paul, MN--WI	Minnesota	15.94	13919
Tampa--St. Petersburg, FL	Florida	21.68	17219
Denver--Aurora, CO	Colorado	19.92	12356
Washington, DC--VA--MD	Virginia	25.42	7680
Baltimore, MD	Maryland	12.44	17262

As an alternative method to estimate the school bus occupancy, we also conducted surveys to get local data for school bus occupancy related information. Such information includes the minimum busing distance, total travel distance, and school bus loading factor. Survey results were collected from two urbanized areas, Milwaukee and Madison in Wisconsin, and summarized in Table 7. The distribution of school bus capacity is mined from Polk data and based on the vehicle model and manufacturer website (as shown in Figure 14). The average school bus capacity for Milwaukee and Madison are 72.29 and 76.82, respectively.

Table 7. School Bus Occupancy Survey Results from Milwaukee and Madison

Variable	Item	Milwaukee	Madison
d_{min}	Minimum busing distance	0.5 mile	1 mile
d_{total}	Total travel distance	12 mile	15 mile
L	School bus loading factor	85 %	80 %
C	Average school bus capacity	72.29	76.82

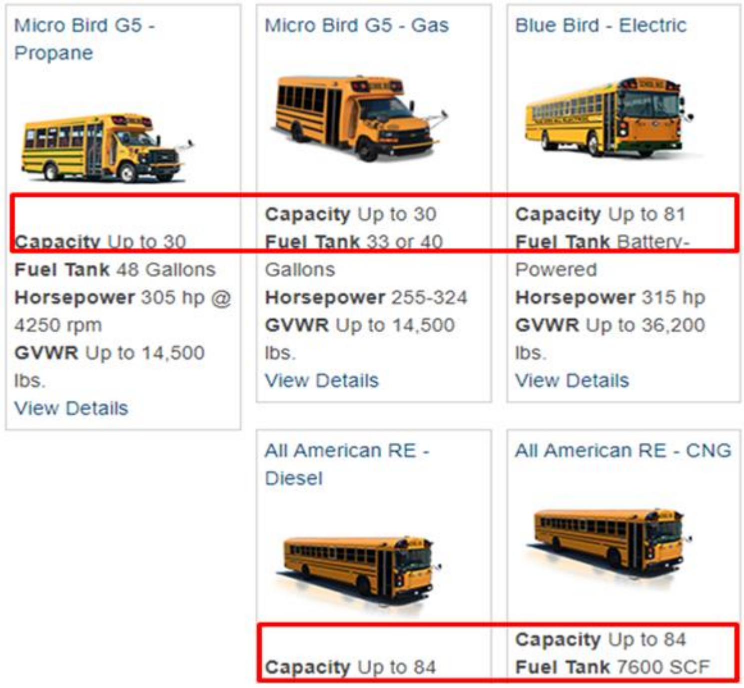


Figure 14. Example of school bus capacity information from the website. Source: https://www.blue-bird.com/buses.

To calculate the average school bus occupancy, Figure 15 shows the change of school bus loading rate during a typical route. During the morning peak trip, the school bus is assumed to leave the base station and go to pick up students one by one. The loading ratio will gradually increase until arrives the peak level (usually around 75%-95%). After the school bus picked up the last student, it will travel another minimum bussing distance and eventually let all the student get off at the school. Then it will go back to the base station with empty load. Therefore, the average loading factor during the route should be

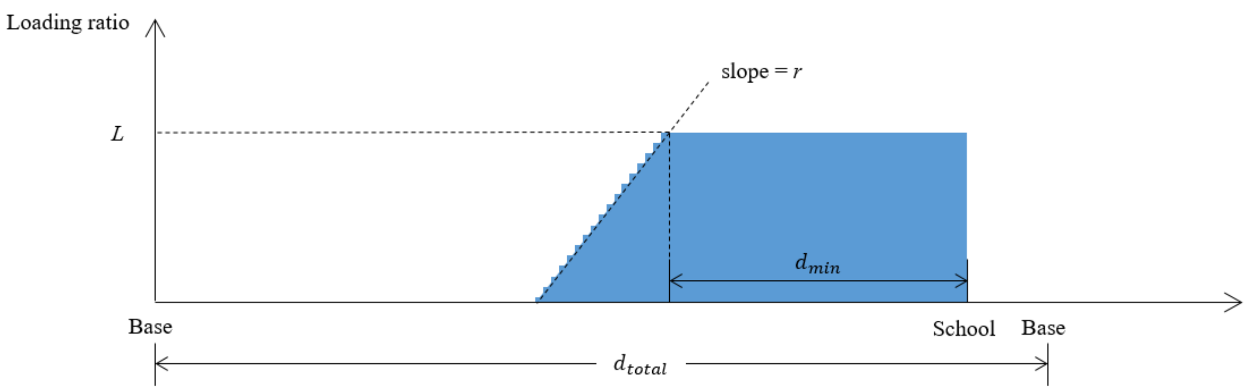


Figure 15. Changes of school bus loading ratio during a typical route (morning peak).

$$\bar{L} = \frac{\frac{L^2}{2r} + L \times d_{min}}{d_{total}}$$

Further assume that the school bus base is located or very close to the school served, then the length of the outbound trip with only the driver would be approximately equal to the length of the trip back to school with students. This is expressed as

$$\frac{L}{r} + d_{min} = \frac{d_{total}}{2}$$

This gives the average loading factor as

$$\bar{L} = \left(\frac{1}{4} + \frac{d_{min}}{2d_{total}}\right) L$$

So the school bus occupancy can be calculated as

$$AVO_{School} = 1 + C \times \bar{L}$$

Based on the above model, the estimated average school bus occupancy for Milwaukee and Madison are 17.65 and 18.39, respectively.

Methodology: Motorcoach (Private Bus)

Data Sources

The Port Authority of New York and New Jersey (PANYNJ) provided motorcoach and passenger hourly arrivals and departures data at the Port Authority Bus Terminal (PABT) for 2015. The PABT data were collected by surveying bus carriers who have direct service to PANYNJ, and the annual survey results can be requested periodically. This dataset covers 24 states and 35 urbanized areas. The PABT is the main gateway for interstate buses into Manhattan in New York City. The PABT is located in Midtown at 625 Eighth Avenue between 40th Street and 42nd Street, one block east of the Lincoln Tunnel and one block west of Times Square. It is one of three bus terminals operated by the PANYNJ, the others being the George Washington Bridge Bus Station in Upper Manhattan and the Journal Square Transportation Center in Jersey City. The PABT serves as a terminus and departure point for commuter routes as well as for long-distance intercity routes and is a major transit hub.

The Motorcoach Census Report 2015 developed by American Bus Association Foundation and John Dunham & Associates are also used as a data source to obtain the national level motorcoach occupancy information (American Bus Association. 2017). Additionally, some local reports such as Motor Coach Tourism in Savannah produced by the Armstrong Atlantic State University for the City of Savannah are also referenced as alternative methods to estimate the urbanized area level motorcoach occupancy (Armstrong Atlantic State University. 2013).

Method for Estimating Occupancy Factors

State level

The Port Authority Bus Terminal data included detailed total bus and passenger hourly arrivals and departures for 256 routes identified by origin and destination. The motorcoach occupancy for a route can be estimated by using the following equation

$$AVO_{motorcoach}(route) = \frac{Daily\ Passenger\ Departures + Daily\ Passenger\ Arrivals}{Daily\ Bus\ Departures + Daily\ Bus\ Arrivals} + 1$$

Here both the arrivals and departures data are used to estimate the average motorcoach occupancy. Since the interstate bus usually goes across several states, the average motorcoach occupancy for a state can be estimated by using the following equation

$$AVO_{motorcoach}(state) = \frac{\sum_{route \ni state} AVO_{motorcoach}(route) \times bus\_count(route)}{\sum_{route \ni state} bus\_count(route)}$$

where $route \ni state$ represents aggregating across all routes that pass the state. Based on the above model, the average motorcoach occupancies for 25 states are estimated as shown in Table 8 and Figure 16.

Table 8. Estimated Average Motorcoach Occupancy by State

State	Occupancy	State	Occupancy	State	Occupancy	State	Occupancy
Alabama	47.48	Illinois	47.13	Montana	NA	Rhode Island	44.03
Alaska	NA	Indiana	NA	Nebraska	NA	South Carolina	45.23
Arizona	NA	Iowa	NA	Nevada	NA	South Dakota	NA
Arkansas	NA	Kansas	NA	New Hampshire	41.09	Tennessee	47.48
California	33.40	Kentucky	45.81	New Jersey	29.47	Texas	NA
Colorado	NA	Louisiana	NA	New Mexico	NA	Utah	NA
Connecticut	38.94	Maine	38.00	New York	31.86	Vermont	NA
Delaware	39.28	Maryland	48.19	North Carolina	45.03	Virginia	42.71
District of Columbia	48.32	Massachusetts	44.19	North Dakota	NA	Washington	NA
Florida	40.31	Michigan	40.69	Ohio	43.42	West Virginia	NA
Georgia	41.53	Minnesota	NA	Oklahoma	NA	Wisconsin	NA
Hawaii	NA	Mississippi	NA	Oregon	NA	Wyoming	NA
Idaho	NA	Missouri	33.40	Pennsylvania	38.19		

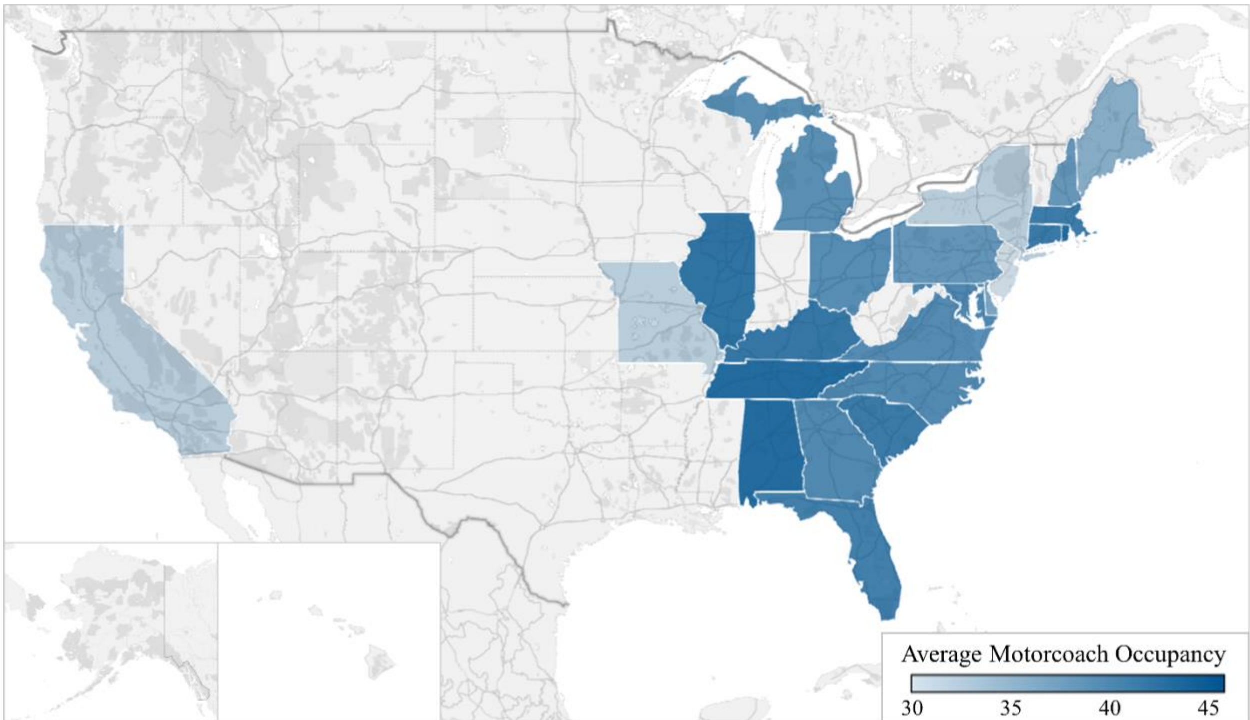


Figure 16. Average motorcoach occupancy by state (20 states).

In order to estimate the average motorcoach occupancy for remaining states, a geographical distance based weighted linear regression model is developed. Similar to the regression model for estimating state level average transit bus occupancy, population density and GDP in transit and ground passenger transportation were used as two regression predictors. The general regression equation is expressed as

$$AVO_{motorcoach}(state) = \beta_0 + \beta_1 \times \log GDP_{transit}(state) + \beta_2 \times pop\_density(state)$$

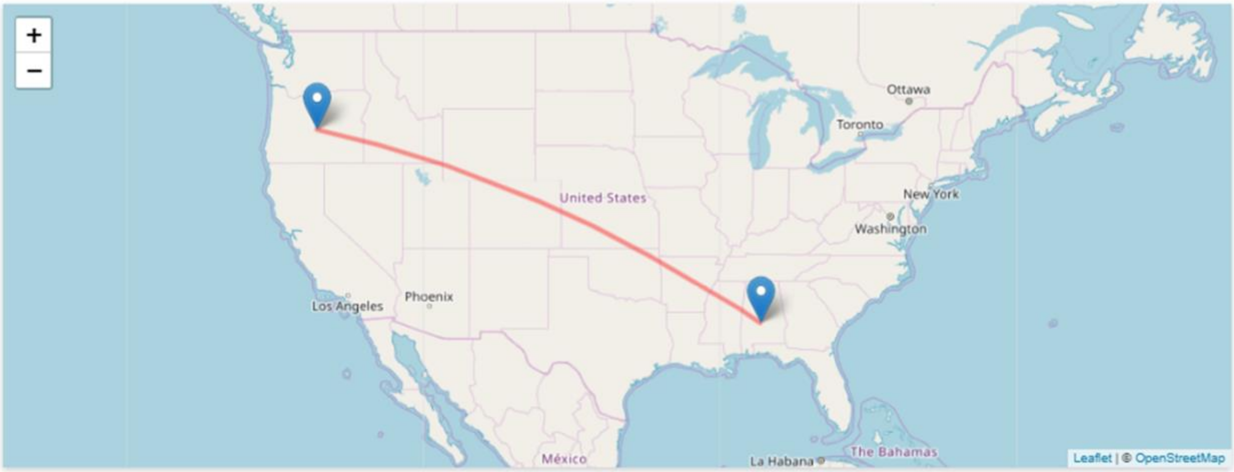
Since the motorcoach operation is spatially correlated, nearby states tend to have similar average motorcoach occupancies. Thus, the geographical distance between states were used as regression weights. The primary difference between a weighted linear regression and a simple linear regression is that, instead of minimizing the sum of squared residuals (SSR), a weighted linear model estimates the regression parameters by minimizing the weighted sum of squared residuals (WSSR), which is

$$WSSR_i = \sum_j w(i,j) \times \left(y_j - \hat{y}_j\right)^2$$

The regression weight $w(i,j) = 1/dist(i,j)$ is defined as the inversed distance between two states, i and j. The closer two states are, the higher regression weight $w(i,j)$ will reflect a strong correlation between the two states. Note that this will result in a unique linear regression model for each state where we need to estimate the average motorcoach occupancy. The center location for each state as well as distances between states can be obtained from the website DistanceFromTo (https://www.distancefromto.net/) as shown in Figure 17.

Distance from Alabama to Oregon

Distance from Alabama to Oregon is 3,189 kilometers. This air travel distance is equal to 1,982 miles.



Alabama

Alabama is located in United States.

GPS Coordinates (DMS)	32° 19´ 5.6280" N 86° 54´ 8.2800" W
Latitude	32.31823
Longitude	-86.90230
Altitude	65 m
Country	United States

Oregon

Oregon is located in United States.

GPS Coordinates	43° 48´ 14.8680" N 120° 33´ 15.1200" W
Latitude	43.80413
Longitude	-120.55420
Altitude	1415 m
Country	United States

Figure 17. Example of calculating distance between two states using DistanceFromTo. Source: https://www.distancefromto.net/.

The complete state level average motorcoach occupancy is presented in Figure 18. In general, the average motorcoach occupancy is higher in less populated areas and lower in more populated areas. According to the 2015 Motorcoach Census Report, the national average motorcoach occupancy is 36.4, which generally agrees with the results estimated using PABT data.

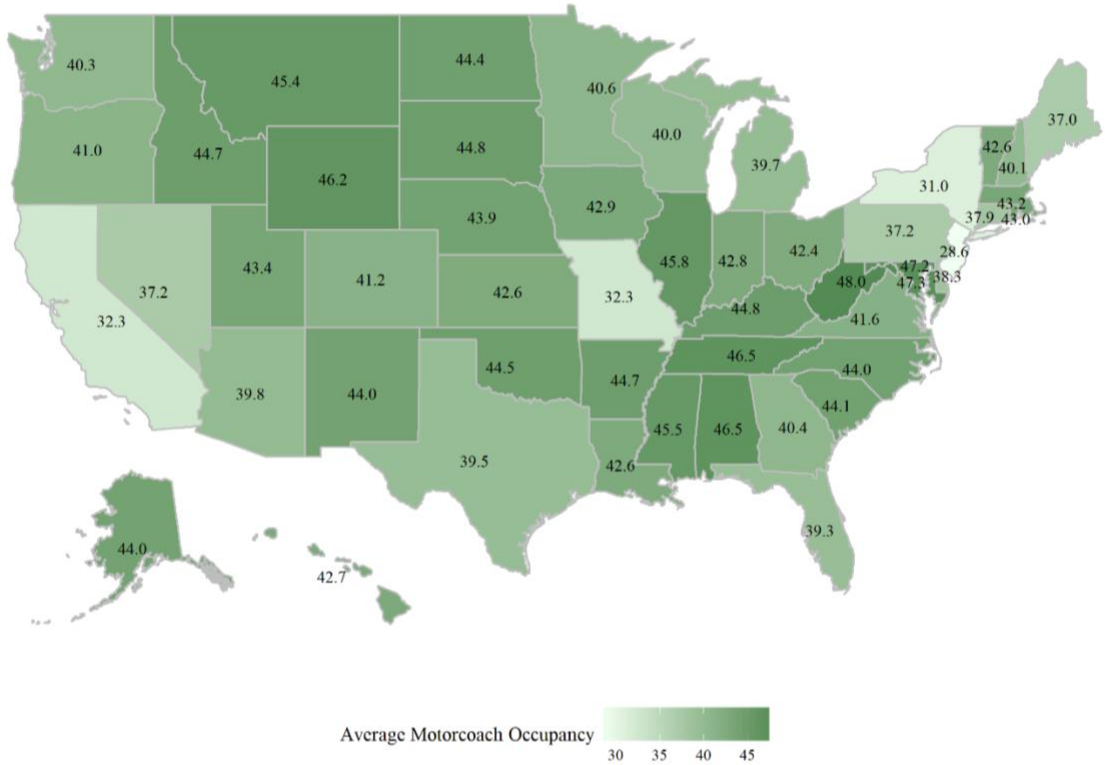


Figure 18. Average motorcoach occupancy by state (all states).

Urbanized area level

Similar to the state level motor coach occupancy calculation, the equation to estimate the average motorcoach accuracy at the urbanized area level is

$$AVO_{motorcoach}(urban\_area) = \frac{\sum_{route \ni urban\_area} AVO_{motorcoach}(route) \times bus\_count(route)}{\sum_{route \ni urban\_area} bus\_count(route)}$$

where $route \ni state$ represents aggregating across all routes that pass the urbanized area. The 2015 PABT data covered 35 urbanized areas. For urbanized areas where PABT data are missing, we employed a similar Empirical Bayesian method as that used to estimate urbanized area level school bus occupancy. The empirical weight to adjust between the state level and the urbanized area level motorcoach occupancy is defined using the population density, which can be written as

$$w = 1 - \frac{|pop\_density_u - pop\_density_s|}{max\{pop\_density_u, pop\_density_s\}}$$

The Empirical Bayesian equation is expressed as

$$AVO_{motorcoach}(urban\_area) = w \times AVO_{motorcoach}(state) + (1 - w) \times EAVO_{motorcoach}(urban\_area)$$

where $EAVO_{motorcoach}(urban\_area)$ is the expected average motorcoach occupancy for the urbanized area, and is estimated by a linear regression model fitted by calculated motorcoach occupancy data in the 35 urbanized areas covered by the 2015 PABT data. The regression equation is expressed as

$$EAVO_{motorcoach}(urban\_area) = 45.705 - 0.761 \times \log pop\_density(urban\_area)$$

Following the Empirical Bayesian equation, the estimated average motorcoach occupancy rates for top 20 urbanized areas are presented in Table 9.

Table 9. Motorcoach Occupancy Results for Top 20 Urbanized Areas

Area Name	State	Average Occupancy
New York--Newark, NY--NJ--CT	New York	31.86
Los Angeles--Long Beach--Anaheim, CA	California	33.40
Chicago, IL--IN	Illinois	47.13
New York--Newark, NY--NJ--CT	New Jersey	29.37
Miami, FL	Florida	36.14
Dallas--Fort Worth--Arlington, TX	Texas	39.68
Houston, TX	Texas	39.65
Atlanta, GA	Georgia	41.35
Boston, MA--NH--RI	Massachusetts	44.82
Philadelphia, PA--NJ--DE--MD	Pennsylvania	45.81
Detroit, MI	Michigan	40.69
Phoenix--Mesa, AZ	Arizona	39.59
San Francisco--Oakland, CA	California	38.84
Seattle, WA	Washington	39.66
San Diego, CA	California	39.03
Minneapolis--St. Paul, MN--WI	Minnesota	39.77
Tampa--St. Petersburg, FL	Florida	46.73
Denver--Aurora, CO	Colorado	39.52
Washington, DC--VA--MD	Virginia	39.75
Baltimore, MD	Maryland	48.35

Some local reports such as Motor Coach Tourism in Savannah can also be used as supplementary data sources. The report from the City of Savannah summarized motorcoach occupancy and related information such as passengers per coach and bus type market share for different bus type in 2013 (see Figure 19). The average motorcoach occupancy in Savannah can be directly calculated as

$$AVO_{motorcoach}(Savannah) = \sum_{t=1}^{T} Passengers\ per\ Coach\ (t) \times Bus\ Type\ Market\ Share\ (t) + 1 = 41.72$$

The estimated average motorcoach occupancy for Savannah in 2013 is 41.72 while the result based on the 2015 PABT data is 46.12. The estimation difference between two methods is around 10%.

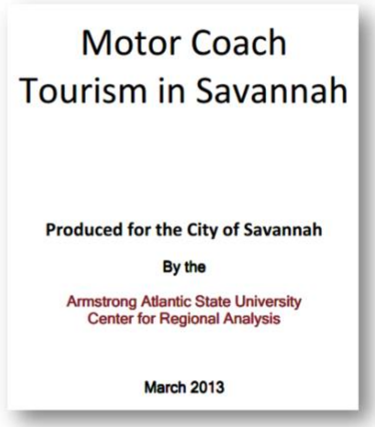


Table 1
Estimated Number of MC-Based Tourists

Bus Type	Number of Seats	Bus Occupancy	Passengers per Coach	Bus Type Market Share	Permits by Type	Estimated Passengers by Type
45 feet	59	71%	41.89	80%	1,578	66,119
40 feet	51	95%	48.45	10%	197	9,559
33 feet	29.5	80%	23.60	10%	197	4,656
				Total Passengers		**80,335**

Figure 19. Occupancy related information in Motor Coach Tourism in Savannah. Source: http://www.savannahga.gov/DocumentCenter/View/4364/FINAL-CoachStudy_AASU_031213?bidId=.

Developing Truck Occupancy Factors

Methodology Framework

The estimation of average truck occupancy relies on accident reports. As the truck accident dataset is usually aggregated (e.g., crashes that involve different types of truck are all included in the same data), it's not necessarily to calculate the average truck occupancy by each truck class. An overall average truck occupancy number can be calculated for all truck types. According to the project scope, pickup trucks (i.e., FHWA class 3) and 2-axle single unit trucks (FHWA class 5) are not considered in this project. Those trucks are filtered out from the crash data before estimating the average truck occupancy. However, the methodology being introduced below is generally applicable to all truck types, and it is straightforward to include class 3 and 5 trucks into calculation if there is a future need.

Methodology: Truck

Data Sources

The NHTSA's Trucks in Fatal Accidents (TIFA) data were used as the primary dataset for truck occupancy estimation. The TIFA data were built based on cases that involved medium and heavy trucks in Fatality Analysis Reporting System (FARS). Additional information was also provided beyond FARS such as more accurate vehicle classification and truck details (e.g., fuel type, weight type) processed from VIN numbers (Jarossi et al., 2012). To obtain a sufficient sample size and improve our estimation accuracy, 5 years (i.e., 2006-2010) of TIFA data were collected to estimate truck occupancy.

Table 10 summarized the sample size as well as the average occupancy and standard error calculated for each year. Note that there is a general decreasing trend of truck crashes, indicating the necessity of using data from earlier years to get enough samples. According to the table, the average truck occupancy varies between 1.15 and 1.20 during the 5 years, and there is no obvious change over time.

Table 10. Summary Statistics of TIFA Data from 2006 to 2010

Year	Count	Average Occupancy	Standard Error
2006	5250	1.209	0.573
2007	5049	1.162	0.460
2008	4352	1.179	0.514
2009	3450	1.193	0.573
2010	3699	1.174	0.508

Method for Estimating Occupancy Factors

State level

Figure 20 shows the estimated average truck occupancy by state after aggregating the 5 years of TIFA data. In general, average truck occupancy is higher in the Rocky Mountain region and lower in the Eastern US.

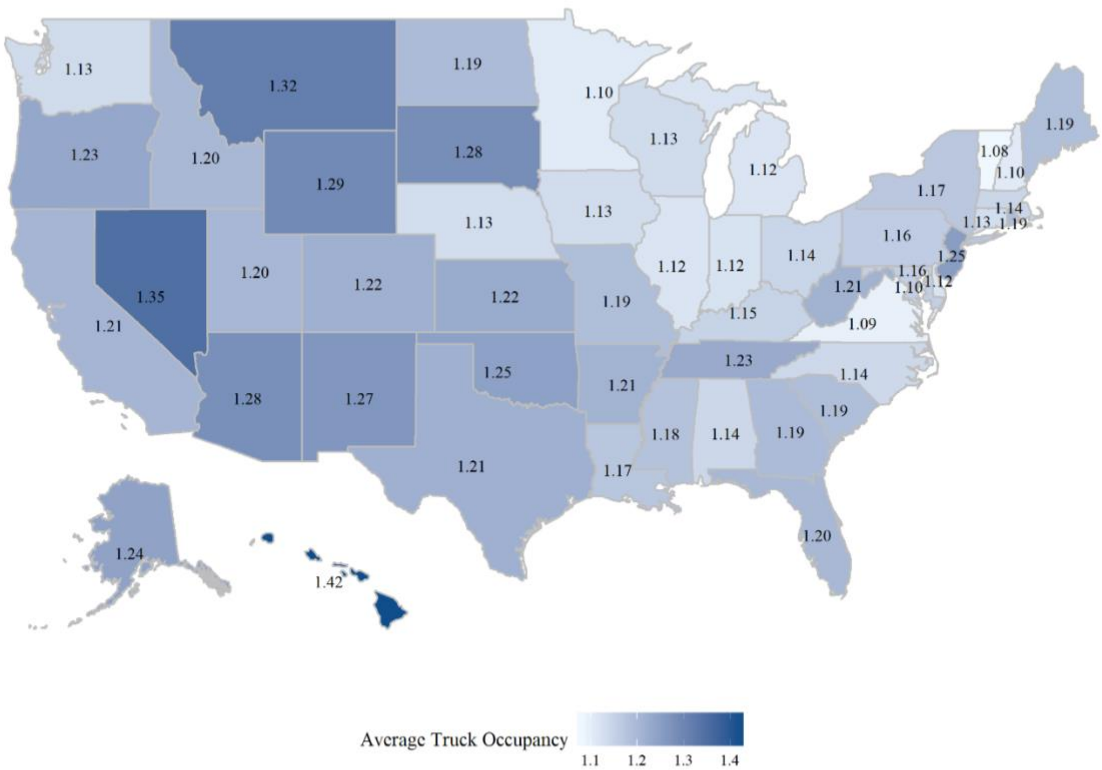


Figure 20. Average truck occupancy by state.

Urbanized area level

One major concern of using TIFA data is the limited sample size. Although combining 5 years of data provides sufficient samples (e.g., hundreds of crashes) for estimating state-level truck occupancy, the sample size might not be sufficient when looking into each urbanized area. The limited number of carashes in each urbanized area may result in greater variance and thus less confidence in the estimated average occupancy.

To overcome the data limitation issue, a Bayesian method is developed to estimate the truck occupancy specifically for urbanized areas. The Bayesian theorem applies a rational estimate procedure that updates a prior belief with new information. In the truck occupancy estimation task, we can regard the state-level truck occupancy as our "prior" belief for urbanized areas within the state. Then truck crashes actually happening in each urbanized area can be considered as the "new information" to generate more accurate localized estimates. This method is based on the assumption that trucks observed in each urbanized area most likely also have travelled to other areas in the same state. Additionally, local truck policies and regulations that can possibly influence regional truck occupancy are more consistent within each state. Thus, the state-level truck occupancy can serve as our prior belief before looking at truck crashes in each specific urbanized area.

The equations for the Bayesian method depend on the specific distribution of the data. The overall distribution of truck occupancy data is shown in Figure 21. Based on the distribution shape and the discrete nature of occupancy data, Poisson distribution seems to be a good candidate to model the truck occupancy. Note that the minimum value for truck occupancy is 1 (as we only want to consider trucks in operation), but the minimum possible value for Poisson distribution is 0. Thus we assume the truck occupancy follows

$$O_{truck} - 1 \sim \text{Poisson}(\lambda)$$

where $\lambda = \bar{O}_{truck} - 1$

The dashed trend line in Figure 21 shows the theoretical probability mass function (pmf) calculated from the corresponding Poisson distribution ($\lambda = 0.184$). The theoretical pmf matched pretty well with the actual distribution of truck count, indicating that truck occupancy is approximately Poisson distributed.

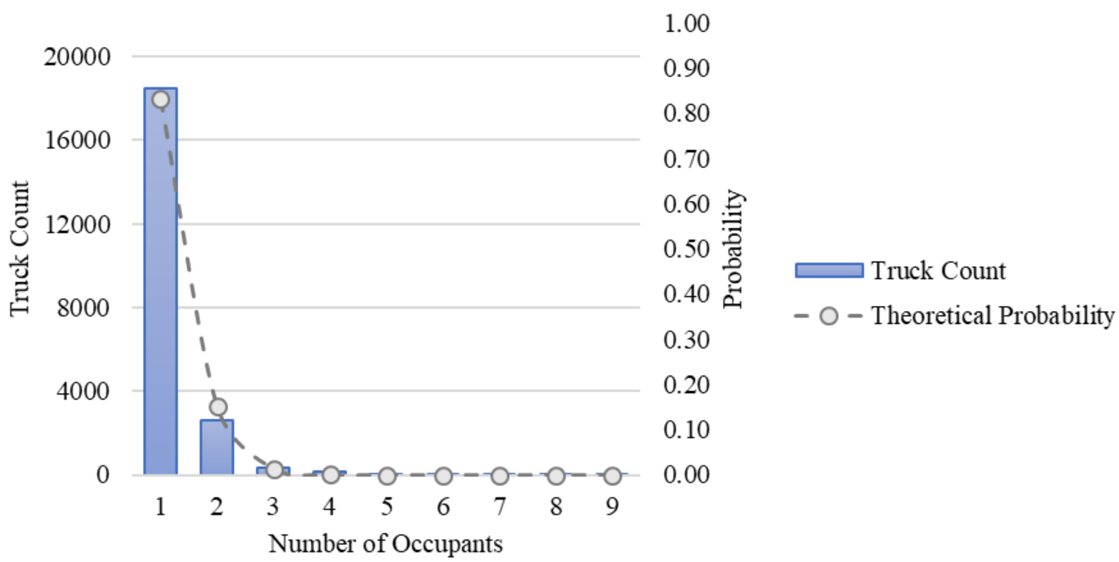


Figure 21. Distribution of truck occupancy and theoretical probability.

The Bayesian equation can thus be derived based on Poisson distributed truck occupancy data. Given $O_{truck} - 1 \sim \text{Poisson}(\lambda)$, the joint probability of observing $O_{t1}, O_{t1}, \dots O_{tn}$ is

$$p(O_{t1} = o_{t1}, O_{t2} = o_{t2}, \dots, O_{tn} = o_{tn} | \lambda) = \prod_{i=1}^{n} e^{-\lambda} \frac{\lambda^{o_{ti}-1}}{o_{ti} - 1!} \propto \lambda^{\Sigma o_{ti} - n} e^{-n\lambda}$$

Based on Bayesian theorem

$$p(\lambda | o_{t1}, \dots, o_{tn}) = \frac{p(o_{t1}, \dots, o_{tn} | \lambda) \times p(\lambda)}{p(o_{t1}, \dots, o_{tn})} \propto p(\lambda) \times \lambda^{\Sigma o_{ti} - n} e^{-n\lambda}$$

Thus, the density of our parameter (λ) estimate include terms like $\lambda^{c_1} e^{-c_2 \lambda}$. The simplest probability distribution that includes such terms is the family of Gamma distributions, and the corresponding probability distribution function is

$$p(\lambda) = \frac{b^a}{\Gamma(a)} \lambda^{a-1} e^{-b\lambda}$$

where a, b are distribution parameters and $\Gamma()$ is the Gamma function. The mean and variance of Gamma distribution is

$$E(\lambda) = \frac{a}{b}$$
$$Var(\lambda) = \frac{a}{b^2}$$

For a particular state s_i, if we have observed n_s truck crashes with occupancy $o_{s_1}, o_{s_2}, \dots, o_{s_{ns}}$, our estimated average occupancy is $\Sigma o_{si} / n_s$, which corresponds to a parameter estimate of

$$\lambda_s = \frac{\Sigma o_{si}}{n_s} - 1 = \frac{\Sigma o_{si} - n_s}{n_s}$$

Thus, the state-level parameter λ_s follows a Gamma distribution with $a_s = \Sigma o_{si} - n_s$ and $b_s = n_s$. Use this as our prior belief of λ. For an urbanized area within this state, if we have n_u truck crashes with occupancy $o_{u_1}, o_{u_2}, \dots, o_{u_{nu}}$, then the posterior distribution of λ is

$$p(\lambda | o_{u_1}, \dots, o_{u_{nu}}) \propto p(\lambda) \times \lambda^{\Sigma o_{uj} - n_u} e^{-n_u \lambda} \propto \lambda^{a_s - 1} e^{-b_s \lambda} \times \lambda^{\Sigma o_{uj} - n_u} e^{-n_u \lambda}$$
$$\propto \lambda^{(a_s + \Sigma o_{uj} - n_u) - 1} e^{-(b_s + n_u)\lambda}$$

This follows a Gamma$(a_s + \Sigma o_{uj} - n_u, b_s + n_u)$ distribution and the posterior parameter estimate for the urbanized area is

$$E(\lambda_u) = \frac{a_s + \Sigma o_{uj} - n_u}{b_s + n_u} = \frac{\Sigma o_{si} + \Sigma o_{uj} - n_s - n_u}{n_s + n_u}$$

And the corresponding estimation of urbanized average truck occupancy is

$$O_u = E(\lambda_u) + 1 = \frac{\Sigma o_{si} + \Sigma o_{uj}}{n_s + n_u}$$

Note that the final equation for estimating average truck occupancy takes the similar form of a weighted average computation, indicating that our confidence in prior belief and new information is proportional to the number of truck crashes observed in the state and urbanized area, respectively. The major benefit of using a Bayesian method to estimate the urbanized average truck occupancy is the significant decrease in estimation error. If we denote $p = n_u/n_s$ which is the proportion of truck crashes occurred in the urbanized area compared to the state, one can simply derive that comparing to only using crash data from the urbanized area, using the proposed Bayesian method achieve a variance reduction rate of around $p/(1+p)$. The Bayesian method significantly increase the estimation accuracy, especially for urbanized areas with very few truck crashes.

To obtain the average occupancy at the urbanized area level, the TIFA data have been mapped into the corresponding urbanized areas based on the state and county codes.

Table 11 presents the average truck occupancy results for top 20 urbanized areas.

Table 11. Average Truck Occupancy Results for Top 20 Urbanized Areas

Urbanized Area Name	State	Crash Count	Average Occupancy
Atlanta, GA	Georgia	327	1.26
Baltimore, MD	Maryland	158	1.18
Boston, MA--NH--RI	Massachusetts	92	1.13
Chicago, IL--IN	Illinois	286	1.10
Dallas--Fort Worth--Arlington, TX	Texas	330	1.19
Denver--Aurora, CO	Colorado	110	1.18
Detroit, MI	Michigan	169	1.11
Houston, TX	Texas	281	1.23
Los Angeles--Long Beach--Anaheim, CA	California	584	1.24
Miami, FL	Florida	284	1.23
Minneapolis--St. Paul, MN--WI	Minnesota	86	1.08
New York--Newark, NY--NJ--CT	New Jersey	244	1.28
New York--Newark, NY--NJ--CT	New York	269	1.25
Philadelphia, PA--NJ--DE--MD	Pennsylvania	147	1.14
Phoenix--Mesa, AZ	Arizona	231	1.27
San Diego, CA	California	73	1.18
San Francisco--Oakland, CA	California	122	1.17
Seattle, WA	Washington	104	1.19
Tampa--St. Petersburg, FL	Florida	223	1.17
Washington, DC--VA--MD	Virginia	69	1.09

Testing Result

The following tables present the method testing result for five states and two urbanized areas. The selected states include California, Florida, Maryland, Pennsylvania, and Tennessee. The selected urbanized areas include Miami, FL and the Philadelphia urbanized area which includes portions of PA, NJ, DE, and MD.

Table 12. Methodology Testing Results for Five Selected States

State	California	Florida	Maryland	Pennsylvania	Tennessee
Transit Bus Occupancy	10.35	7.27	9.91	10.27	6.09
Transit Bus Average VMT	28431	34336	30083	26991	24711
Transit Bus Count	2862	1379	403	1059	407
School Bus Occupancy	9.26	15.22	10.13	7.95	23.77
School Bus Average VMT	10509	17219	17214	18253	16177
School Bus Count	9257	8841	4378	11368	4683
Private Bus Occupancy	32.33	43.51	42.30	40.21	46.48
Private Bus Average VMT	38385	38385	38385	38385	38385
Private Bus Count	3748	1922	413	762	678
Average Bus Occupancy	**19.83**	**21.48**	**15.04**	**11.75**	**27.47**
Average Truck Occupancy	**1.21**	**1.20**	**1.16**	**1.16**	**1.23**

Table 13. Methodology Testing Results for Two Selected Urbanized Areas

Urbanized Area Name	Miami, FL	Philadelphia, PA--NJ--DE--MD
State	Florida	Pennsylvania
Transit Bus Occupancy	8.62	12.74
Transit Bus Average VMT	35389	27210
Transit Bus Count	364	204
School Bus Occupancy	10.22	23.65
School Bus Average VMT	17219.03	18253.18
School Bus Count	1919	1819
Private Bus Occupancy	43.51	40.21
Private Bus Average VMT	38385	38385
Private Bus Count	375	171
Average Bus Occupancy	**17.82**	**24.72**
Area Truck Occupancy	1.23	1.14
Area Crash Count	284	147
State Truck Occupancy	1.20	1.16
State Crash Count	1360	923
Average Truck Occupancy	**1.20**	**1.16**

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