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Exploring Non-Traditional Methods of Obtaining Vehicle Volumes

by

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13. Abstract
Big data analytics is being used to generate traffic data that may be used by an agency to supplement its routine data collection. StreetLight InSight ® and Streetlytics, produced by StreetLight Data and Bentley Systems respectively, are two such tools that promise to provide traffic volumes, including AADTs, for every roadway in the US. This study collected ground truth data from continuous counters from 14 permanent stations (AADT), full- month traffic volumes from 30 locations, and 24-hour daily volumes from 60 locations and compared against corresponding data from StreetLight and Streetlytics. The five measures used are accuracy, completeness, timeliness, validity, and accessibility of the estimating data from the two tools. While the assessments done for timeliness and accessibility were for information purposes, scores were generated for accuracy, completeness, and validity. The primary accuracy metric used was mean absolute percentage error (MAPE) but secondary metrics, comprising percent root mean square error (%RMSE) and median/maximum absolute percentage error were also generated to provide more insights on the validation effort. MAPE results for the permanent stations showed StreetLight outperforming Streetlytics. However, MAPE results for both the full-month and 24-hour locations showed Streetlytics outperforming StreetLight. Furthermore, when considering only low-volume roadways of less than 500 vpd, Streetlytics outperformed StreetLight for locations with volumes under 300 vpd while StreetLight generally outperformed Streetlytics for locations with volumes over 300 vpd. However, data from both tools were determined to be valid for use for traffic assessments. Due to the favorable results obtained for both tools, a hands-on demonstration of each tool has been recommended to allow potential users to evaluate the user-friendliness of the individual interfaces as well as the ease of use of the various tools on each platform.

Project Review Committee

Each research project will have an advisory committee appointed by the LTRC Director. The Project Review Committee is responsible for assisting the LTRC Administrator or Manager in the development of acceptable research problem statements, requests for proposals, review of research proposals, oversight of approved research projects, and implementation of findings.

LTRC appreciates the dedication of the following Project Review Committee Members in guiding this research study to fruition.

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This study collected ground truth data from continuous counters from 14 permanent stations (AADT), full-month traffic volumes from 30 locations, and 24-hour daily volumes from 60 locations and compared against corresponding data from StreetLight and Streetlytics. The five measures used are accuracy, completeness, timeliness, validity, and accessibility of the estimating data from the two tools. While the assessments done for timeliness and accessibility were for information purposes, scores were generated for accuracy, completeness, and validity. The primary accuracy metric used was mean absolute percentage error (MAPE) but secondary metrics, comprising percent root mean square error (%RMSE) and median/maximum absolute percentage error, were also generated to provide more insights on the validation effort.

MAPE results for the permanent stations showed StreetLight outperforming Streetlytics. However, MAPE results for both the full-month and 24-hour locations showed Streetlytics outperforming StreetLight. Furthermore, when considering only low-volume roadways of less than 500 vpd, Streetlytics outperformed StreetLight for locations with volumes under 300 vpd while StreetLight generally outperformed Streetlytics for locations with volumes over 300 vpd. However, data from both tools were determined to be valid for use for traffic assessments.

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Acknowledgments

This project was completed with the support of the Louisiana Department of Transportation and Development (DOTD) and the Louisiana Transportation Research Center (LTRC). The research team also gratefully acknowledges the assistance received from StreetLight Data and Bentley Systems for providing not only the data to be validated but also availing resources above and beyond that needed for the project. Lastly, the research team acknowledges the Project Review Committee (PRC) members for their valuable feedback and all other DOTD personnel involved during the course of this project.

Implementation Statement

The results obtained from this study is intended to provide DOTD an objective evaluation of the suitability of StreetLight or Streetlytics in providing annual average daily traffic (AADT) for all roadways in the state of Louisiana. Findings from the study can aid in the development of documents to serve as justification for a sole-source vendor that will lead to the adoption of Streetlytics or StreetLight by DOTD. A statewide subscription license will enable all state and local agencies instant access to the following data for every roadway within the state: traffic volumes or counts, primary direction of flow, traffic congestion patterns, demographics of drivers, daily trip purpose, and origin and destination patterns. This information will be critical in roadway planning, roadway safety assessments, and roadway maintenance.

DOTD has an in-house data collection team that undertake systemic traffic data collection for the state. The adoption of StreetLight or Streetlytics will be supplementary to this in-house effort and is not meant to replace it. Rather, it will provide useful data for sections that are not included in the systemic data collection program.

Furthermore, all the permanent (continuous) counters should be routinely maintained to ensure they collect traffic volumes all year round.

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Introduction

Annual average daily traffic (AADT) [1] is a fundamental traffic element that represents the average traffic volume each day at a particular roadway segment over an entire year. Federal, state, metropolitan planning organizations (MPOs), cities, and local agencies rely on AADT especially for roadway planning, pavement maintenance, roadway design, traffic operations, air quality assessments, revenue planning from roadway user fees, and roadway safety assessments. AADT is also required to calibrate and validate travel demand models, estimate state-wide vehicle miles traveled in compliance with the 1990 Clean Air Act Amendment, and be reported annually by a state's Department of Transportation (DOT) to the Federal Highway Administration (FHWA) as part of the traffic monitoring program.

DOTD presently collects traffic counts on approximately 16,000 miles of state roadways on a three-year cycle at about 4,800 locations, and on over 44,000 miles of non-state roadways on a 10-year cycle but at very limited locations. Traffic counting on non-state roadways is the responsibility of local governments. Major cities, such as New Orleans, Baton Rouge, Lafayette, Lake Charles, etc., have their counts collected or estimated by their respective MPOs. However, other non-state roadways in rural and small urban areas do not have systemic traffic counts or estimation programs.

Due to the issues highlighted above, there is a lack of timely traffic volumes across the state, especially on local roads, hindering roadway safety assessments and development of cost-effective safety improvement projects. A potential alternative for having systemic AADTs on all state and non-state roadways within Louisiana has been made available by Streetlytics [2] and StreetLight Data [3]. Both products promise to provide, for every roadway, traffic volumes as AADT (for morning and evening peaks, off peak, and daily); predominant direction of traffic flow (morning and evening); congestion patterns (for morning and evening peaks, off peak, and daily); driver demographics (age, income, household size, and gender); trip purpose (work, home, or other); travel patterns (origin and destination nodes); and many more. Later sections of this report highlight some of the functionalities of Streetlytics and StreetLight.

LTRC Project 16-3SA "Evaluating Cell Phone Data for AADT Estimation" [4] evaluated the accuracy of Streetlytics' volume counts when compared to traditional DOTD counts. Results showed that, while there were differences, the greatest disparities were observed for locations with traditional AADTs under 300 vpd (vehicles per day). This was because the Streetlytics volume counts had been capped at 300 vpd. Furthermore, because the Streetlytics volume counts were single AADT values for 2015, the traditional counts had to be AADTs for 2015 and the traditional data obtained could not be verified. Streetlytics has since undergone major upgrades and is now able to produce lower average daily traffic (ADT) as well as produce calibrated volumes for specific months of the year that takes into account seasonal variations. StreetLight was not included in the earlier evaluation.

This study therefore seeks to undertake a similar analysis, but also includes StreetLight in addition to Streetlytics. In addition to analyzing AADTs, the study expands the validation study by also analyzing monthly and daily traffic volumes and using more credible traditional counts for the validation effort. Furthermore, low-volume roadways with AADTs under 500 vpd were selected for the monthly and daily analysis. Results were further stratified to roadways with AADTs under 300 vpd to provide for the limitations of the previous study [4]. It is anticipated that the study findings will present a more accurate assessment of the capability of the Streetlytics and StreetLight tools to predict actual volumes observed on the roadways, especially at low-volume roadways across Louisiana.

Objectives

The primary objective of this project was to evaluate the accuracy of StreetLight and Streetlytics traffic volumes for rural roads with counts under 500 vpd and to make a recommendation as to whether the state of Louisiana can adopt any of these tools to provide accurate AADT for these areas. Specifically, the main tasks to fulfill the objectives were to:

- Conduct a review of all available big data AADT estimation tools, documenting their pros and cons as well as their differences and how each can serve Louisiana's needs better.
- Develop a list of rural roads with counts under 500 vpd to be used for the comparative study. This only applies to the monthly and daily traffic counts analysis.
- Obtain Streetlytics and StreetLight traffic volumes for the selected sample. Also, obtain corresponding traditional volume counts for the selected sample.
- Undertake comparative analysis to evaluate accuracy of Streetlytics and StreetLight traffic volumes, using the traditional counts as ground truth.
- Make a recommendation on whether each tool can provide acceptable volume counts for the state of Louisiana based on the results obtained.

Scope

The literature review on the two products, StreetLight and Streetlytics, was conducted based on information obtained from the respective vendors. The study area was a sample list of roadways throughout Louisiana and locations with anticipated traffic volumes of less than 500 vpd were purposely selected for the monthly and daily assessments. For the AADT assessments, locations were limited to sites of permanent (continuous) traffic counters.

There are variety of features that both StreetLight and Streetlytics provide, but the study focused only on their traffic volume feature. The research team partly relied on DOTD's MS2 platform [5] and partly collected on-site data collection to provide the traditional count data for all roadways included in the sample.

Literature Review

Research on AADT Estimation

According to Lowry and Dixon [6], there are three primary areas of research on AADT estimation: expanding short-duration counts to annual values [7], forecasting future-year counts from historical values [8], and spatially extrapolating counts from one location to another. As it will be too expensive to continuously collect traditional (manual) traffic volumes for a year at all desired AADT locations, short-term traffic volume counts are collected at such locations, usually 24 or 48 hours, and then converted to AADT using different expansion factors like seasonal, monthly, and daily factors. A report from Chowdhury et al. [9] reported that 38 of 39 agencies use expansion factors to estimate AADT from short-term traffic count stations.

Some studies have used different methodologies to forecast future AADT from short-duration traffic counts [10], [11], [12]. In addition, every state has their own traffic forecasting guidelines [13], [14] that help to determine appropriate expansion factors under various conditions to help them produce accurate AADT estimates.

Spatial extrapolation is no new research area and several notable studies [15], [16], [17], [18] have long been conducted in this area. All these studies used characteristics of specific roadways and surrounding areas to create spatially transferrable models that utilized multiple linear regression to estimate AADT. Recently there have been a number of studies [19], [20], [21], [6] on a branch of spatial extrapolation, called kriging, which refers to cases where AADT is estimated for "unobserved locations" or roadways for which no prior AADT observations have been recorded. These studies showed that the kriging technique could reduce average-absolute-error anywhere to between 16%-79% and was more accurate than the earlier research methods.

Other widely used AADT estimation methods are linear regression and machine learning techniques [17], [22]. A research by Khan et al. [23] used two machine learning techniques: Artificial Neural Network (ANN) and Support Vector Regression (SVR) to estimate AADT for different roadway functional classes. The study selected SVR as superior technique for the AADT estimation with a minimum root mean square error (RMSE) of 0.22 and a mean absolute percentage error (MAPE) of 11.3% for the interstate/expressway functional class. For regression models, Wu and Xu [24] compared the performance of multiple linear regression (MLR), random forest, and neural network models and finally recommended MLR for the AADT estimation. Also, another study by Shojaeshafiei et al. [25] compared daily traffic count technologies using two machine learning techniques (K* Classification and Random Forest) to the linear regression models in small- and medium-sized communities and found the linear regression model as the best for the specific community of the study. In an empirical study by Jiang et al., [8] the result showed an improvement in accuracy of AADT estimation by using existing imagery of highway segments, containing traffic information, with ground-based traffic data. Wang et al. [26] used a travel demand modeling method to estimate AADT of local roads in Broward County, Florida. The study found significantly lower mean absolute percentage errors from this method.

Doustmohammadi and Anderson [27] also focused on a Bayesian Regression Model to estimate average daily traffic volumes for low-volume roadways for 12 counties in Alabama. The study collected data on socio-economic and low-volume traffic counts. The model used variables like the number of households in the area, employment in the area, and population to job ratio access to major roads. There were 205 low-volume counts collected from several rural counties in Alabama along with some demographic variables near the count locations. The team developed a traditional linear regression model and a Bayesian regression model for the data set. 150 locations were used in developing the model and 55 for the validation. The study found the Bayesian regression model as slightly better than the linear regression model in predicting ADT for low-volume roads, with RMSEs of 31.09% and 32.81% respectively.

In estimating historical hourly traffic volumes via machine learning using vehicle probe data in Maryland [28], an ANN model was used in finding the relation between traffic volumes and a variety of influencing factors that will help generate volumes for unobserved areas. The results showed that volumes can be approximated with a MAPE of about 21% at sites where the average number of observed probes is between 30 and 47 vehicles/h.

Summarizing the various research on statistical and machine learning approach, Das et al. [29] did a study on interpretable machine learning approach to estimate AADT on low-volume roads in Vermont Counties. Data from U.S Census and the American Community Survey were used to develop the model. The results showed work area characteristic (WAC) and population density as the best predictor variables in estimating AADT. Moreover, the machine learning models yielded better estimates than statistical methods by improving the AADT accuracy from 45% to 77%.

Milligan et al. [30] modeled AADT prediction models using factors like duration of short-term counts, number of locations for short-term counts, use of weekday versus weekend counts, and distance from a count to its expansion control station. The results showed that by using a 48-hour volume count, instead of a 24-hour count, the error in the data decreased significantly.

In modeling the effects of AADT on predicting multiple-vehicle crashes at urban and suburban signalized intersections, Chen and Yie [31] wrote an article using Generalized Additive Models (GAMs) and Piecewise Linear Negative Binomial (PLNB) regression models. For the model evaluation and comparison, data collected randomly from a total of 48 three-approach signalized (3SG) intersections and 52 four-approach (4SG) intersections from signalized urban and non-urban intersections in Massachusetts were used. AADT was estimated based on short duration of Turning Movements Counts using hourly and seasonal expansion factors. None of the selected signalized intersections had permanent traffic counters to record AADT. The modeling results showed that the non-linear functional form was more suitable. Also, the study found that the ratio of minor- to major-approach AADT had a significant impact on intersection safety.

Other studies have looked at predicting AADT's using methods such as modified support vector regression technique with data-dependent analysis (SVR-DP), Geographically Weighted Regression (GWR) method, neural network method, and parcel-level travel demand modelling [32], [33], [34] and [35].

Table 1 provides a summary of the studies reviewed in this study and provides a description of the variable that was modeled (response variable), the independent variables that were used to predict the response variable (explanatory variable), the statistical or machine learning algorithm that was used to perform the modeling (estimation model), and the estimation model that resulted in the highest accuracy (preferred model) in cases where several estimation models were tested. It can be seen that a variety of models have been used and different preferred models emerged. No single model surpasses all other models in terms of accuracy, as a lot depends on the set of explanatory variables used. An agency can utilize any model of choice depending on availability of data for its explanatory variables, and the modeling skill of its personnel.

Table 1. Summary of literature

Study Reference	Response Variable	Explanatory Variable	Estimation Models	Preferred Model
[6]	AADT	Functional class of roads	Linear Regression	Linear Regression
[7]	AADT	Annual traffic census data	Time Series, Neural Network, Non-Parametric Regression, and Gaussian maximum likelihood (GML) methods	GML Method
[10]	AADT	Traffic data from count stations Demographics and economic data Roadway Functional class	Aggregate Model Disaggregate Model	Both models
[11]	AADT	Socioeconomic and Demographic variables, Functional class of roads Total miles of roads	Linear Regression Models Cross-tabulation models	—
[12]	AADT	Traffic volumes Economic and demographic factors	Linear Regression Model Multiple Regression Model Growth factor Idaho (USA) Method	Idaho (USA) Method
[19]	AADT	Roadway functional classification	Ordinary Regression Model Spatial Regression Model	Spatial Regression Model
[21]	AADT	Roadway Functional Classification	Artificial Neural Network (ANN) Support Vector Regression (SVR)	SVR
[22]	AADT	Functional class of roads Number of track lanes	Multiple Linear Regression (MLR) Random Forest Neural Network	MLR
[25]	AADT	—	K* Classification Random Forest Linear Regression Model	Linear Regression Model

Study Reference	Response Variable	Explanatory Variable	Estimation Models	Preferred Model
[27]	AADT	Socio-economic data	Linear Regression Model Bayesian Regression Model	Bayesian Regression Model
[29]	AADT	Data from American Community Survey U.S. Census Data	Statistical Methods Machine Learning Models	Machine Learning Models
[31]	AADT	Traffic data	Generalized Additive Models (GAMs) Piecewise Linear Negative Binomial (PLNB) regression	GAM (non-linear model)
[32]	AADT	Road functional class And Land use type	Holt exponential smoothing (Holt-ES) Ordinary Least Square regression (OLS-regression) SVR-DP	SVR-DP
[33]	AADT	Roadway characteristics data, Regional Accessibility data, and Demographics and socio-economic data	GWR Geographic Information Systems (GIS) Reduced Regression Models	GWR model
[34]	AADT	Number of Lanes, Function Classification, Accessibility to Regional Employment, and Direct Access	Parcel-Level Travel Demand Modeling Regression Models	Parcel-Travel Demand Modeling
[35]	AADT	Traffic volume data	Neural Network Method Regression Analysis	Neural Network

Review on StreetLight

StreetLight Data, a company founded in 2011, has emerged to be a big data source for transportation planning, engineering, and modeling. Their traffic volume estimation tool, StreetLight, provides data on AADT, Origin-Destination, Trip Purpose, Demographics, and Bicycle and Pedestrians. StreetLight Data published a white paper [36] on the methodology and validation behind their 2018 AADT V3 model within United States and Canada. The company used six unique data sources for the development of the algorithm: two of these are big data inputs, three are contextual inputs and one input is data from permanent counters. These are further described at later sections of this report. Figure 1 shows a map of states for which permanent counters were used for the training and testing, and Table 2 shows the number of permanent counters per state.

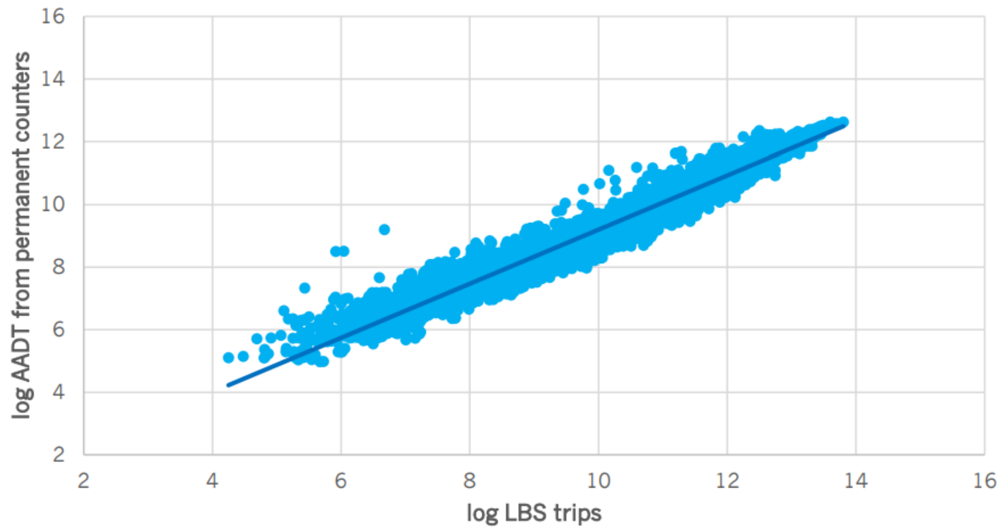
Figure 1. Map for all permanent counters used for training and testing the StreetLight AADT 2018 V3 metric [36]

According to the white paper, which was updated in August 2019, StreetLight Data's first attempt at cross-validating the models proved successful. The model was run numerous times during this process with different training and testing datasets from randomly selected zones. A comparison of normalized Location-Based Services (LBS) data was compared to AADT data from permanent count stations to check the correlation before selecting the best algorithm to use. As shown in Figure 2, the comparison revealed a strong positive correlation between the two datasets. Next, the algorithms considered for use were Ordinary Least Squares (OLS) and Random Forest. Though both models have their own pros and cons, ultimately, a 12-feature Random Forest model was built and selected because it performed better with the prediction of AADT for unusual roads. The output from the final model was also cross validated.

Table 2. States and no. of permanent counters used for training and testing the StreetLight 2018 AADT metric [36]

State/Province	# Permanent Counters	State/Province	# Permanent Counters	Country
AL	494	NH	163	U.S.
AZ	485	NY	484	U.S.
CA	769	OH	453	U.S.
CO	308	OK	56	U.S.
FL	631	PA	111	U.S.
GA	585	RI	339	U.S.
IL	269	TX	933	U.S.
IN	151	UT	109	U.S.
IA	129	VT	132	U.S.
MA	331	VA	941	U.S.
MI	227	WA	466	U.S.
MN	84	WV	151	U.S.
MT	263	WY	125	U.S.
AB	1014	ON	346	Canada
BC	164	PE	14	Canada
MB	204	SK	60	Canada

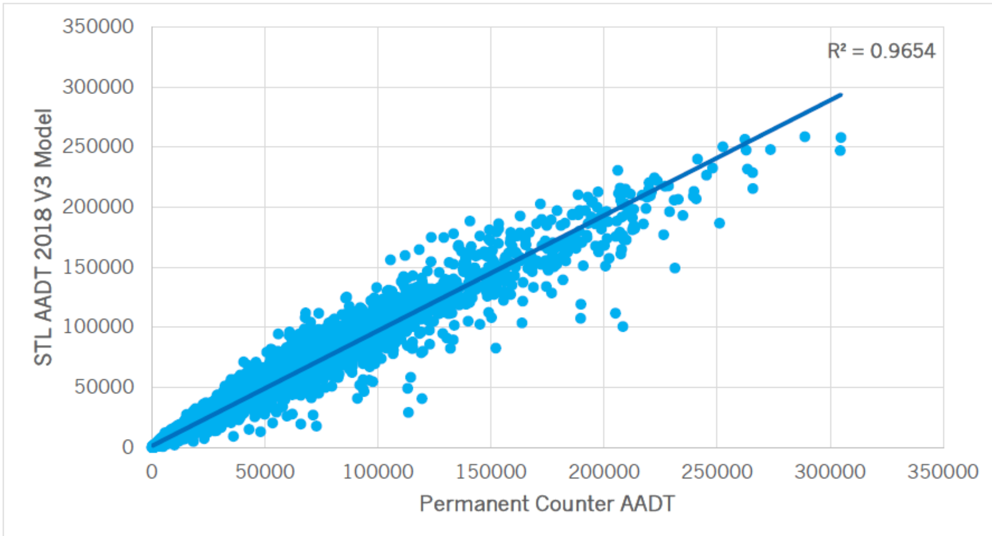
Figure 2. Correlation of normalized location-based services data to permanent loop counter data for StreetLight AADT 2018 V3 model [36]



A second method of cross-validating was employed by the researchers, this time pulling out each state as a test set to simulate the experience of clients in states whose data was not used in developing the model. This method also revealed a high accuracy since the output was very close to the permanent counts. The study also reported that state-specific models performed much better when their algorithms were tuned accordingly.

StreetLight Data released AADT 2018 V3 metrics (August 2019), which was an update of AADT 2018 V2 and AADT 2017 models. Major improvements like increment in the training size, training data from varieties of road features like unidirectional roads, including ramps and freeway-to-freeway connectors, and local/minor roads were incorporated in the model. The accuracy of AADT of the updated model is shown in Figure 3 with R square of 0.965.

Figure 3. StreetLight AADT 2018 V3 for test data compared to permanent counter AADT [36]



StreetLight Data updated its 2019 StreetLight AADT algorithm ("AADT 2019 V2") later in May 2020 by training data and using an updated AADT 2019 V2 model known as "hybrid model" approach. Training data increased from 29 states in the previous version to 48. Permanent counter locations nearly doubled with the training data from 6,000 in the prior model to 10,700. The "hybrid model" enhanced the performance on low- and high-volume roads. As reported by StreetLight Data, the overall accuracy of their AADT 2019 V2 model has increased with an R square of 0.978 as compared to 0.965 previously.

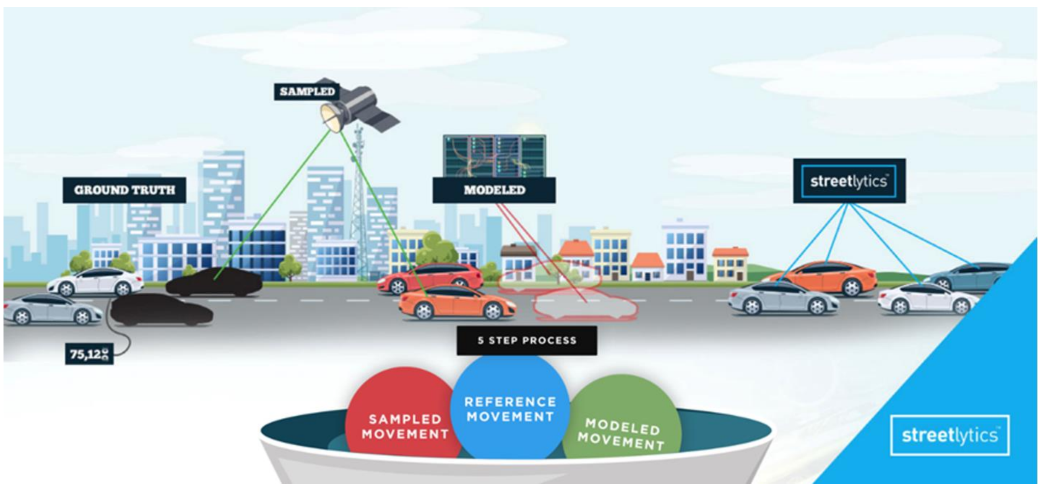
Review on Streetlytics

In 2016, Citilabs [37] and AirSage [38] announced a partnership by combining Citilab's transportation analytics and Airsage's location data from cellular and GPS devices and launched a product called Streetlytics. Bentley Systems [39] acquired Citilabs in October 2019, and owned Streetlytics in the process. Streetlytics sources its data from mobile phone locations, traffic counts, government surveys, and hourly speeds, points of interest, routable transportation systems, and demographic and business data.

For the past two decades, Bentley Systems [40] has provided travel demand modeling software that predicts how people move in a changing transportation system. Streetlytics combines Bentley's travel demand modeling understanding with multiple measurements of movement to understand total vehicular movement of every household in the U.S. The data supports core business activities undertaken in governments, insurance companies, mobility providers, and commercial real estate firms. The Bentley team supporting Streetlytics is comprised of a group of traffic engineers, data scientists, and mathematicians. The same group worked with the Louisiana Transportation Research Center (LTRC) research team on the LTRC 16-3SA study [4] since 2017.

As illustrated in Figure 4, the Streetlytics process combines Referenced, Sampled, and Modeled Movement data to provide monthly Optimized Total Movement data for the full population within the Continental United States, Hawaii, Puerto Rico, and throughout Canada.

Figure 4. Streetlytics proprietary data [40]

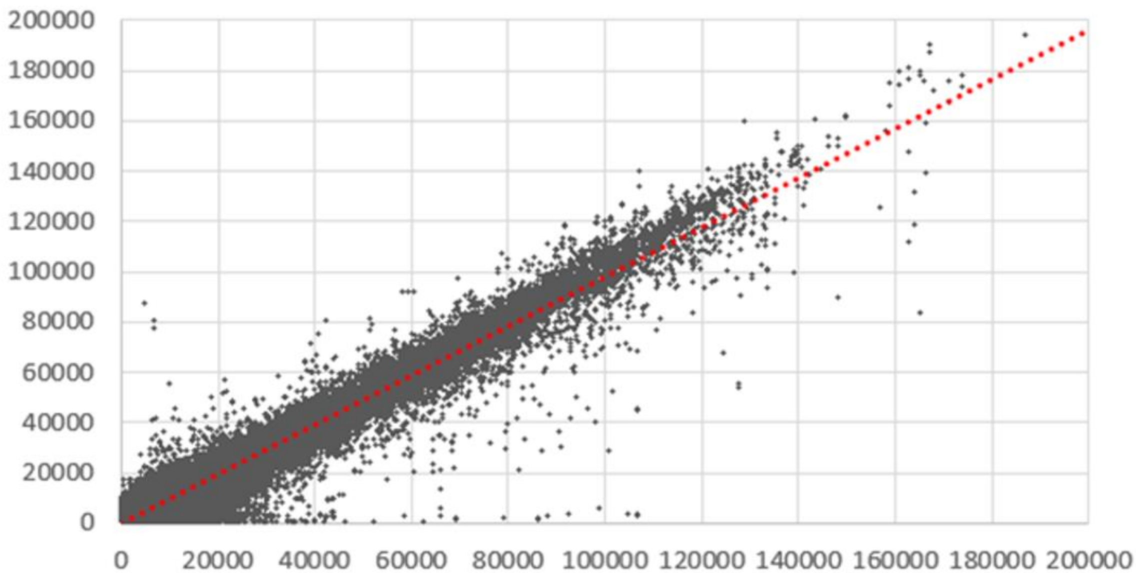


This process leverages a wide variety of complimentary source datasets. The primary independent datasets used in the Streetlytics process are:

- Sampled Movement data derived by AirSage and Safegraph from observed device-level Geospatial Positioning System (GPS) sources
- Referenced Movement data including observed traffic counts from published government sources and travel speeds from HERE
- Data underlying Modeled Movement estimates including demographic, employment, and point of interest data from ESRI and a routable transportation network built on the HERE network dataset

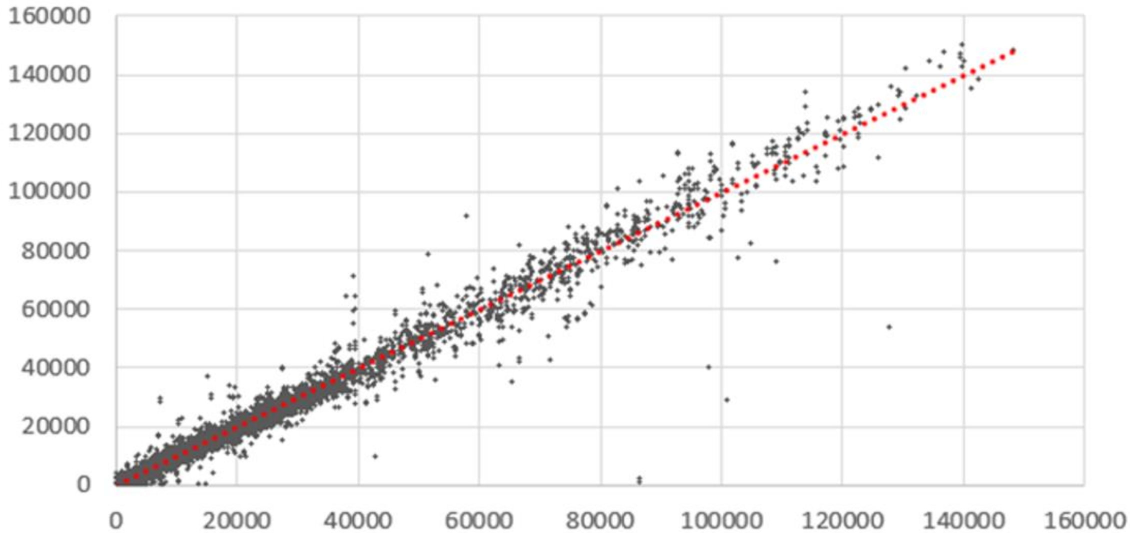
According to Bentley Systems, several in-house validation studies have been undertaken for Streetlytic's ability to estimate AADTs, daily vehicle volumes, and seasonal averages. Figure 5 illustrates the results of how well Streetlytics estimates compared to more than one million AADT source counts. The corresponding R squared and RMSE values for the Streetlytics daily vehicle volume validation were 0.96 and 38.3%, respectively. The relatively small set of outliers in the scatter plot were expected and were primarily attributed to error in the source count data collection method, rather than error in Streetlytics.

Figure 5. Streetlytics daily volumes vs. all source counts [40]



Alternatively, Figure 6 shows the results when Streetlytics daily vehicle volumes were validated against a smaller set of data from automatic traffic recorders (ATR). The corresponding R squared and RMSE values were 0.98 and 21.4%, respectively.

Figure 6. Streetlytics daily vehicle volume vs. ATR source counts [40]



Similarly, the daily volumes have been optimized to estimate volumes for weekdays, Fridays, Saturdays, and Sundays. Validation efforts produced a consistent R squared of 0.98 for all three types of volumes, and RMSE values ranging from 20.0% to 20.7% with an overall RMSE of 20.8%.

Lastly, Streetlytics volumes have been validated against season average volumes from ATRs and the validation statistics remain consistent across all four seasons. The R squared value obtained for each of the four seasons remained at a consistent 0.98 with an overall R squared also at 0.98. For the RMSE, an overall value of 20.8% was achieved with values of 20.8%, 20.9%, 20.4% and 21.0% reported for spring, summer, fall, and winter, respectively.

For each of the estimation process, Streetlytics takes the best of each data source, maintaining the important spatial and temporal patterns provided by its location data, and then applies behavioral models on current population and employment data, while constraining the calculated movements to the measured ground truth.

Independent Studies Validating StreetLight Data and Streetlytics

StreetLight Data

In 2017, a study conducted by Turner et al. [41] evaluated the accuracy of StreetLight 2017 AADT algorithm in estimating AADT volumes and average annual hourly volumes (AAHV) by comparing to traditional traffic volume counts from Minnesota Department of Transportation (MnDOT) traffic monitoring sites. The study used mean absolute percentage error, mean absolute difference, and mean signed difference as performance measures. AADT volumes were retrieved from 7,837 short-duration count sites that did not include sites with AADT of less than 300 vpd due to perceived low mobile device sample size and low confidence in the prediction accuracy from StreetLight Data for such low volumes. The study found higher MAPE of 68% at 5,090 MnDOT sites with traffic volumes of 300 to 5,000 AADT and the lowest MAPE of 29% at 346 sites with traffic volumes of 20,000 to 50,000 AADT. Therefore, the results showed better accuracy for higher traffic volumes than for lower traffic volumes. Overall, the study found MAPE of 61% from all the sites. The positive mean signed difference for all the volume categories showed that AADT estimates from StreetLight Data were consistently higher than MnDOT AADT. For the AAHV assessments, 69 permanent monitoring sites were used. The study found a correlation (R-square) of 90% for weekday hourly volumes and 95% for weekend hourly volumes. Traffic volumes of less than 1,000 vpd reported a higher MAPE of 49%, and volumes between 5,000 and 10,000 vpd reported the lowest MAPE of 16%. Therefore, this result also showed better accuracy for higher traffic volumes than for lower traffic volumes. Overall, the study found larger MAPE for AADT evaluation compared to AAHV evaluation.

More recently in 2019, another study [42] undertook a validation study of the StreetLight 2017 AADT Metric using data from 180 automatic traffic recorders in Oregon. The mean, median and maximum absolute percentage error and percentage error were used as the measures to define accuracy of the estimate. The study found mean and median absolute percentage errors of 26% and 18%, respectively. These measures decreased by an increase in AADT values for AADT of 75,000 vpd and above, ending with the lowest MAPE of 15% for AADT of 300 vpd or less. A similar analysis undertaken with short-term AADT estimates for 66 sites yielded a mean and median absolute percentage error of 59% and 32%, respectively.

Streetlytics

In 2018, Codjoe et al. [4] validated AADT estimates from Streetlytics by comparing Streetlytics data to traditional count data. The analysis was done at three different levels: all data, routine and permanent count data, and data from observed versus unobserved locations. Comparison of all types of data from traditional count data to the Streetlytics data produced a percentage difference of 44.5% with the former reporting higher values. Similarly, the routine and permanent counts from DOTD (when compared to the Streetlytics) produced percentage differences of 45.01% and 43.00% respectively. However, a high percentage difference of 110.38% was produced between the traditional count data and Streetlytics data for volumes of under 300 vpd. The data set used for the study showed 10% of the data under 300 vpd and 3% falling below 50 vpd. The research suggested that to supplement DOTD's Traffic Monitoring Unit performance, DOTD may use the on-street dataset of Streetlytics. It further suggested that Streetlytics change their lowest AADT threshold from 300 vpd to at least 50 vpd.

The research team could not find other independent validation papers for Streetlytics, and Bentley Systems were not aware of any such publications as well.

Methodology

The research team performed several tasks to achieve the study objectives. The data collection effort is presented along with a description of the three types of data for the study. The methods used for the analysis are also discussed.

Data Description

The three data types considered for the analysis were traditional count data, StreetLight volume data and Streetlytics volume data. Each data type was further grouped under three -selection criteria that is permanent data, full-month data, and 24-hour data. The following sub-sections provide further information on the description and collection criteria used.

Traditional Count Data

Traditional count data were collected through a combination of DOTD's MS2's Traffic Count Database System (TCDS) [5] and field data collections. These were the data that were considered as the ground-truth data, against which StreetLight and Streetlytics count data were validated. The data were grouped into three types: permanent traditional count data, full-month traditional count data, and 24-hour traditional count data. Each is further described below.

Permanent Traditional Count Data: MS2 TCDS platform [5] was used to query the location of "Permanent or continuous counters." The query resulted in a total of 65 permanent or continuous counters, out of which only 25 counters were found to have volume data for some days in 2018. These were further checked for the quality of the recorded data in terms of the number of days in 2018 that it collected volumes and illustrated in Figure 7. As it shows, only 14 counters recorded a count coverage of more than 50% (i.e., counted more than 182 days in a year). Ideally, counters with 100% count coverage should be used to represent accurate AADT estimation, as those would have provided a complete ground truth data for comparisons. However, the research team had to work with the limitation of using 50% count coverage or more to retain a sizeable sample to use for the study.

Figure 7. Distribution of counters based on the coverage

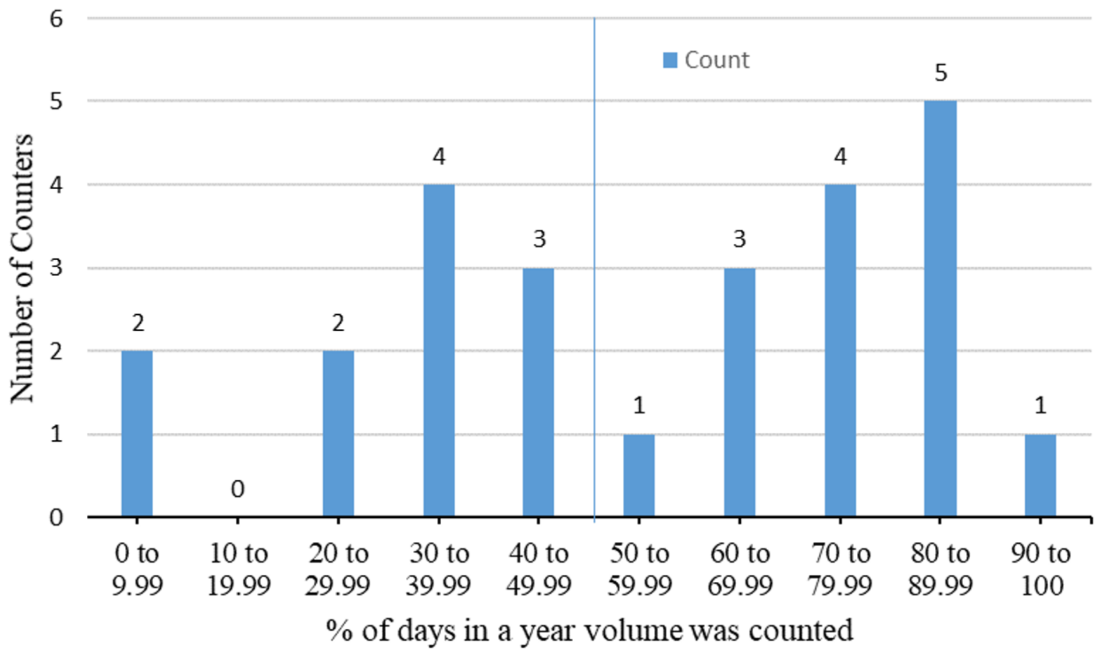


Figure 8 shows the locations of the selected 14 permanent counters that provided 2018 AADT values for the study. Six locations had AADT of less than 10,000 vpd (vehicle per day), three locations had AADT between 10,001 and 20,000 vpd, and the remaining five locations had AADT ranging from 30,000 to 97000 vpd. The size of the dot in the Figure 8 is an indication of the AADT value at the site. Coordinates and volume count at each location has been provided Appendix A.

Full-Month Traditional Count Data: Data for the full-month traditional counts were obtained through field data collection. There were 30 locations of low-volume roadways (< 500 vpd) initially selected using the MS2 TCDS platform. To increase the randomness and the geographic representativeness of the locations, the research team ensured that the selected locations were farther away from the 14 permanent traditional count locations. Because of the low-volume criteria (< 500 vpd), all 30 locations ended up being in two-way roadways in rural areas of Louisiana. Data was collected by Quality Counts Limited Liability Company (LLC) [43] for the full-month of November 2019, using pneumatic tubes, in accordance with the *DOTD Traffic Monitoring Manual* [44].

Figure 8. Location of the 14 permanent counters with their 2018 AADT counts

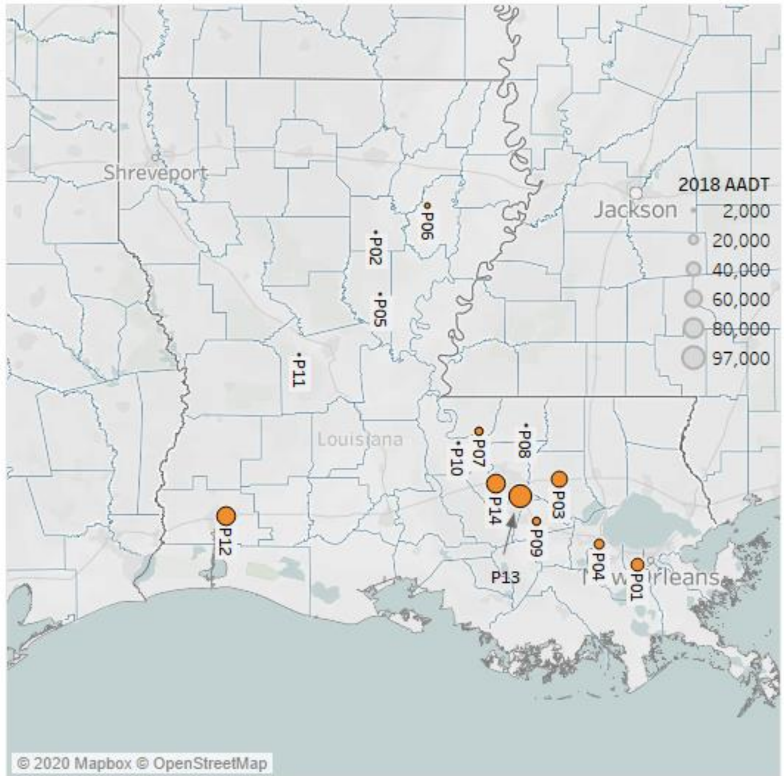


Figure 9 shows the location of selected sites for pneumatic road tube installation across the state. Except at location M30 where the volume was exceptionally large compared to other locations (1-month traffic count of 167,084 vehicles), volumes for the remaining 29 locations ranged from 3,186 to 15,448 vehicles per month (vpm) or 106 to 515 vpd. The validation was done for the 29 locations. Seven locations recorded volumes less than 5,000 vpm; 13 locations had volumes ranging from 5,001 to 10,000 vpm; and the remaining nine locations had volumes greater than 10,000 vpm but less than 15,449 vpm. Coordinates of all 30 site locations and volumes collected at each site have been included in Appendix B.

24-Hour Traditional Count Data: MS2 TCDS platform [5] was used to query the location of "short counters" to obtain locations of counters with 24-hour volumes for 2018 and 2019. The query initially resulted in a total of 3,700 locations, so the following criteria were set to reduce the sample size to the 60 locations required for this study:

- Balanced number of sites in each of the two years, i.e., 2018 and 2019

- Counters from both urban and rural areas: A variable in the available dataset already defined the counter to be in either urban or rural area
- Counters from both low-volume (≤ 500 vpd) and high-volume (> 500 vpd) locations
- Different ranges of low and high volumes
- Different roadway types
- Counters geographically spread across the state, if possible
- Counters away from the sites of the permanent traditional counters and full-month traditional counters

Figure 9. Pneumatic road tube locations with their full-month count data

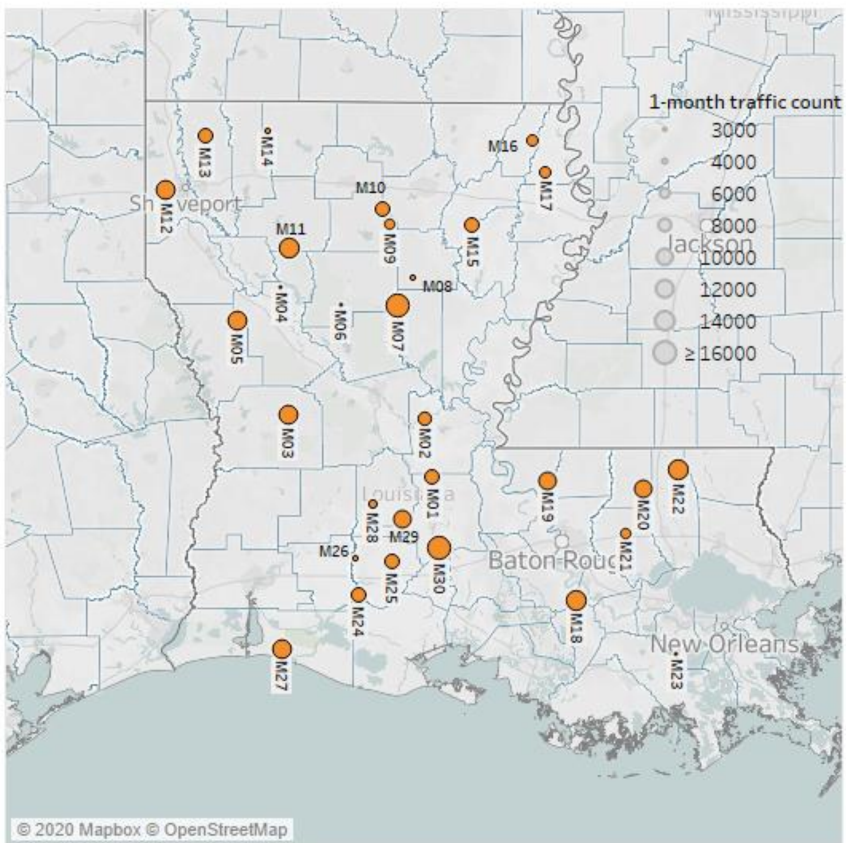


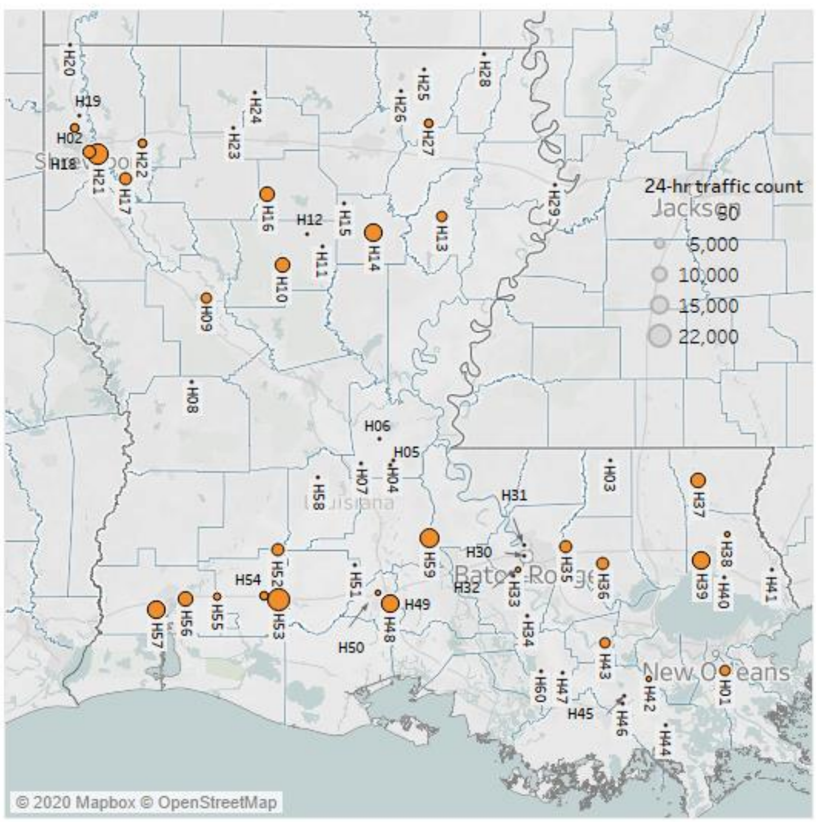
Table 3 shows the distribution of number of locations with high-volume and low-volume roadways in 2018 and 2019 and for rural and urban areas. A total of 31 counters were selected from rural locations and 29 counters for urban locations.

Table 3. Distribution of 60 sites across rural and urban areas with different volumes

Year	2018	2019
Rural	21	10
Low-Volume	11	5
High-Volume	10	5
Urban	21	8
Low-Volume	9	3
High-Volume	12	5

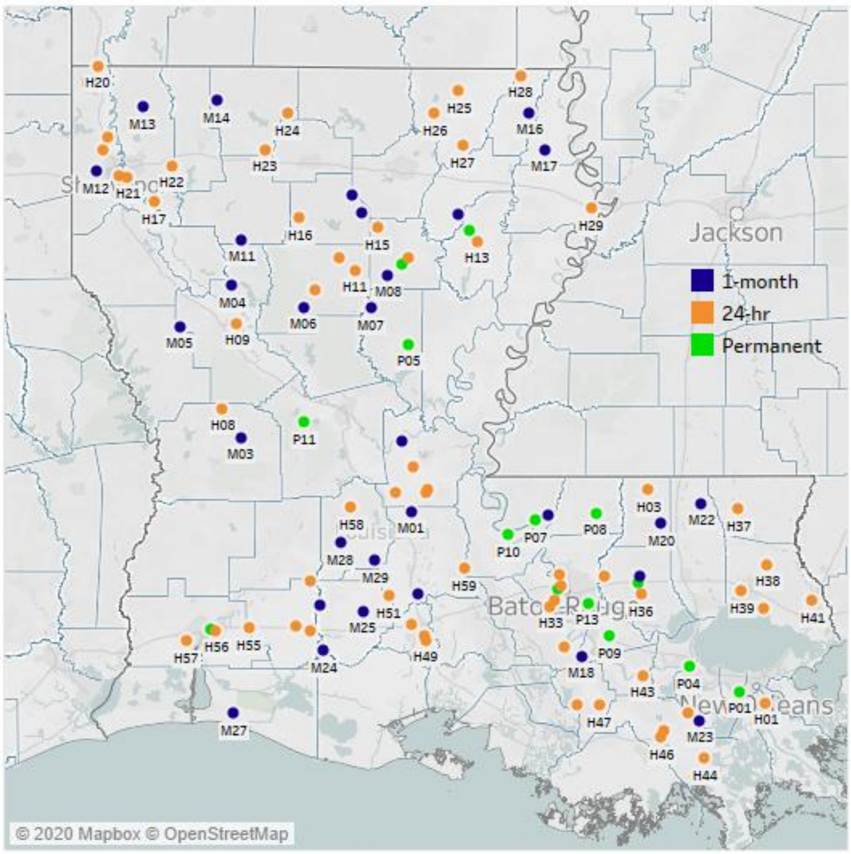
Figure 10 shows the location of all 60 sites, for which 24-hour traffic volumes were available. 28 locations were low-volume roadways with volume ranging from 60 to 480 vpd, and 32 locations had high volumes ranging from 825 to 21,420 vpd. Coordinates of the site locations and volumes collected at each site have been included in Appendices C and D.

Figure 10. 60 locations with their 24-hour count volume



In summary, Figure 11 shows all locations for which data were collected under this study: 14 locations for permanent counters, 30 locations for full-month counts, and 60 locations for 24-hour counts.

Figure 11. Selected locations for evaluation



StreetLight Volume Data

Three data types corresponding to the three traditional data counts were provided from the StreetLight InSight ® platform [36].

StreetLight AADT 2018 V3: This is 2018 AADT generated for all the 14 locations where 2018 AADT values were required for the validation. The data was generated by using a machine learning algorithm trained with real world data, Navigation-GPS and LBS Data to estimate the AADT for 2018. Six locations had AADT of less than 10,000 vpd, three locations had AADT between 10,001 and 25,000 vpd, and the remaining five locations had AADT ranging from 30,000 to 97000 vpd. The estimated 2018 AADT values for each of the 14 locations have been included in Appendix A.

Full-Month StreetLight Volumes: The StreetLight full-month volume is an average for all days in the November 2019 data period, multiplied by 30, and represents a blend of the StreetLight AADT with seasonal factors, which estimates trip counts to show variations in monthly, seasonal, and annual trends. Except at locations M18 and M30 where the volumes were exceptionally large compared to other locations (1-month traffic count of 151,500 for M18 and 154,890 for M30), volumes for the remaining 28 locations ranged from 9,240 to 20,730 vpm. Five locations had volumes ranging from 9,240 to 10,000 vpm, and the remaining 23 locations had volumes greater than 10,000 vpm but less than 20,731 vpm. The estimated full-month StreetLight volumes for each of the 30 locations have been included in Appendix B.

24-Hour StreetLight Volumes: Similar to full-month StreetLight volumes, the 24-hour StreetLight volume is a blend of the StreetLight AADT with seasonal factors that estimates trip counts to show variations in monthly, seasonal, and annual trends. There are two volume estimates for each station: (1) an estimate of average daily weekday traffic on a typical day, and (2) an estimate of average daily traffic for the specific day of the week corresponding to the date 24-hour traditional count data was collected. Five locations (H12, H25, H34, H47, and H49) were recorded as outliers for specific day, while three locations (H25, H47, and H49) were recorded as outliers for typical day. Eleven locations were low-volume roadways with volumes less than 500 vpd, and 44 locations had higher volumes than 500 vpd for specific day. Likewise, 15 locations were low-volume roadways with volumes less than 500 vpd, and 42 locations had higher volumes than 500 vpd for typical day. Details of the estimated 24-hour volume is attached in Appendices C and D.

Streetlytics Volume Data

The Streetlytics optimization applies varying weights to the millions of referenced, sampled, and modeled movements (described earlier in the report) based on their characteristics and quality of the underlying data to combine the independent views into an optimized understanding of total population movement nationwide. This process produces a robust and accurate understanding of the entire moving population—where people are coming from and going to, what they pass by, when they travel, where they live and work, and what modes they are likely using. Streetlytics is currently available as a monthly dataset with coverage spanning February 2018 through November 2019.

Monthly data is aggregated to seasonal and annual datasets. The process is robust and customizable such that additional datasets could be produced to cover customer defined time periods and geographic extents. The traffic volumes corresponding to the three traditional data counts—2018 AADT, full-month counts, and 24-hour counts–were developed using this Streetlytics process. The data generated for each is described below:

Streetlytics 2018 AADT: Five locations had AADT of less than 10,000 vpd (vehicles per day) three locations had AADT between 10,001 and 20,000 vpd and the remaining six locations had AADT ranging from 21,000 to 108,000 vpd. The estimated 2018 AADT values for each of the 14 locations have been included in Appendix A.

Full-Month Streetlytics Volume: Location M30 was seen as an outlier and excluded from the analysis (1-month traffic count of 107,100 for M30)). Volumes for the remaining 29 locations ranged from 1,500 to 29,940 vpm. Eleven locations recorded volumes less than 5,000 vpm, six locations had volumes ranging from 5,001 to 10,000 vpm, and the remaining twelve locations had volumes greater than 10,000 vpm but less than 30,000 vpm. The estimated full-month Streetlytics volumes for each of the 30 locations have been included in Appendix B.

24-Hour Streetlytics Volume: Two locations (H47, H49) were recorded as outliers for both typical and specific day volume count. There were 23 low-volume roadways with volume less than 500 vpd, and 35 locations had high volumes with hourly traffic of more than 500 vpd for typical day volume count. Likewise, 21 locations were low-volume roadways with volumes less than 500 vpd and the remaining 37 locations had high volumes of more than 500 vpd for specific day volume count**.** Details of the estimated 24-hour volume is attached in Appendices C and D.

Data Analysis

This section gives a description of the five measures of effectiveness that were used to assess the quality of data. These measures of effectiveness are accuracy, completeness, timeliness, validity, and accessibility. Each is fully described below.

Accuracy of Data

The Federal Highway Administration (FHWA) defines accuracy [45] as a "measure of degree of agreement between a data value or set of values and a source assumed to be correct. It can also be defined as a qualitative assessment of freedom from error, with a high assessment corresponding to a small error." For this study, the source assumed to be correct was the traditional count data. The data values evaluated are the corresponding StreetLight and Streetlytics volume data. The primary performance metric used to evaluate accuracy is the mean absolute percentage error (MAPE). However, other metrics are provided as secondary information, and each is further described below.

Mean Absolute Percentage Error (MAPE): Absolute percentage error (APE) was determined for each observed data point, first, between the traditional count data and StreetLight volume data, and secondly, between the traditional count data and Streetlytics volume data. In this sense, for each comparison, 14 APE values were obtained for the Permanent data, 30 APE values for the full-month data and 60 APE values for the 24-hour data. APE measures how precise the estimated volumes from StreetLight and Streetlytics are when compared to the traditional counts. APE is determined using equation [1]. The mean of all the APEs are then determined from equation [2] to represent the MAPE. Smaller values of MAPE implies the estimated volumes are more precise and hence the estimating tool is good.

$$APE_i(\%) = \left|\frac{Volume_{traditional} - Volume_{estimated}}{Volume_{traditional}}\right| \text{ x } 100 \qquad [1]$$

$$MAPE\ (\%) = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{Volume_{traditional} - Volume_{estimated}}{Volume_{traditional}}\right| \text{ x } 100 \qquad [2]$$

where,

APE_i = APE calculated for a given location

$Volume_{traditional}$ = traditional count data

$Volume_{estimated}$ = StreetLight or Streetlytics volume data

n = number of locations, i.e.,14 for permanent data, 30 for full-month data, and 60 for 24-hour data

Secondary Performance Metrics: Even though MAPE is the parameter of interest (because condensing a set of errors into a single value removes a lot of information about the distribution of the errors) the median and maximum APEs are provided in addition to give a more complete picture of the precision of the estimated volumes. However, these are provided for information and not used for the comparative assessments between the two estimating tools.

The APE is determined as previously in equation [1]. Following, the median APE (MdAPE) and maximum APE (MaxAPE) are computed using equations [3] and [4], respectively.

$$MdAPE\ (\%) = median\ (APE_1, APE_2, \ldots, APE_n) \quad [3]$$

$$MaxAPE\ (\%) = maximum\ (APE_1, APE_2, \ldots, APE_n) \quad [4]$$

where,

APE_i = APE calculated for a given i location

n = number of locations, i.e., 14 for permanent data, 30 for full-month data, and 60 for 24-hour data

Another secondary metric used is the percent root mean square error (%RMSE). Again, this is provided to give more information on the data disparity but is not used as a primary metric for the comparative assessments of the two estimating tools. To determine %RMSE, first the root mean square error (RMSE) is determined, and then the %RMSE is calculated. RMSE, also known as root mean squared deviation, is a measure of how well the model performed (the error rate of a model) [46]. RMSE is the standard deviation of the residuals (prediction errors). Residuals are a measure of how far from the regression line data points are so basically; RMSE becomes a measure of how spread out these residuals are. In other words, it gives an idea of the closeness of the estimated data (StreetLight/Streetlytics Volume Data) to the observed/ground truth data (Traditional Count Data). %RMSE is commonly used in climatology, forecasting, and regression analysis to verify experimental results. Equation [5] shows the formula used to calculate RMSE and variables are as defined in equation [2].

$$RMSE = \sqrt{\frac{\sum_1^n (Volume_{estimated} - Volume_{traditional})^2}{n}} \quad [5]$$

Percent root mean square error (%RMSE) is further estimated by dividing the RMSE by the average value of the observed traffic count (traditional volume count). The %RMSE penalizes variance as it gives errors with larger absolute values more weight than errors with smaller absolute values. It is therefore useful in exposing large errors, and in this case, large disparities between the traditional counts and the estimated volumes from StreetLight or Streetlytics. Smaller values of %RMSE indicates the estimated volumes are closer to the traditional volumes, and hence depicts more accuracy.

Equation [6] shows the formula used to calculate %RMSE and the variables are as defined in equation [2].

$$\%RMSE = \frac{RMSE}{Average\ of\ Traditional\ Count} = \frac{RMSE}{\frac{1}{n}\sum_{i=1}^{n} volume_{traditional}} \qquad [6]$$

Together, both %RMSE and APE give a more complete picture of the accuracy of the estimating tools. In literature, there is no consensus on which metric is superior. Some agencies prefer to use MAPE, while others prefer to use %RMSE. However, for this study, MAPE was the preferred metric to be used. Nevertheless, results based on %RMSE are presented for each comparative assessment.

Completeness of Data

This measure of effectiveness is also known as availability of data. FHWA [45] defines this metric as the “degree to which data values are present in the attributes (e.g., volume and speed are attributes of traffic) that require them.” Completeness is typically described in terms of percentages or number of data values and can refer to both the temporal and spatial aspect of data quality in the sense that it measures how much data is available compared to how much data should be available. Turner, 2004 [47] also defined completeness as “the degree to which values are present in the attributes that require them.” Equation [7] shows the formula used in calculating completeness of data.

$$\text{Percentage Complete (\%)} = \frac{n_{available\ values}}{n_{total\ expected}} * 100 \qquad [7]$$

where,

$n_{\text{available values}} =$ the number of available values present for each analysis type (permanent, full-month, or 24-hour data) as supplied by either StreetLight Data or Bentley Systems (Streetlytics)

$n_{\text{total expected}} =$ the total number of expected values as provided by DOTD (traditional count data) for each analysis type (permanent, full-month, or 24-hour data).

Timeliness of Data

Also referred to as currency, Turner, 2004 [47], described timeliness as the "degree to which data values are up to date." FHWA [45] defines timeliness as the "degree to which data values or a set of values are provided at the time required or specified." Timeliness can be expressed in absolute or relative terms**.** For this study, timeliness will be defined as the date ranges for which data is available for StreetLight and Streetlytics volume data for each of the three data types used for the analysis—permanent data (AADT), full-month data, and 24-hour data.

Validity

FHWA [45] defines validity as "the degree to which data values satisfy acceptance requirements of the validation criteria or fall within the respective domain of acceptable values." In this study, a threshold will be defined to show the percentage of data values that either pass or fail the validity checks. The checks will be based on mean absolute percentage error.

Accessibility

This is not a mathematical measure. It shows how data is accessible from both qualitative and quantitative terms. For instance, how accounts can be created on the webpage, user-friendliness of interface, options of online queries, ability to download data, and average time required for the data retrieval and manipulation. It also includes all other applications, other than traffic volumes, that the tool can produce. For this study, accessibility will include a summary of what other users are using the estimating tools for.

Discussion of Results

Comparative analyses for the three different data sets were undertaken to validate the data provided by StreetLight Data and Streetlytics against the traditional count data in terms of accuracy, completeness, timeliness, validity, and accessibility. The following sub-sections provide the results for each analysis.

Accuracy of Data

Permanent Data

Data was evaluated for 14 locations where permanent data were collected to calculate 2018 AADT volumes. Estimated volumes refer to either the StreetLight AADT 2018 V3 or Streetlytics 2018 AADT data. Traditional volumes refer to the permanent traditional count data.

The difference between estimated volumes and traditional volumes has been illustrated in Figure 12 for both StreetLight and Streetlytics. Darker red colors indicate lower estimated volumes, while darker green colors show higher estimated volumes than traditional volumes. The size of the circle also gives an indication of the magnitude of the difference: the smaller the size, the closer the estimated volume is to the traditional data; and the bigger the size, the bigger the difference between the estimated and traditional volumes. The figure shows that StreetLight had mixed results, with some locations reporting underestimated and others overestimated volumes as well as quite big differences in either direction. On the other hand, Streetlytics mainly reported overestimated volumes with few sizeable differences.

While Figure 12 provides a visual presentation of the data, the metric used to quantify the accuracy of data is MAPE. Figure 13 is a box plot that shows the distribution of the APEs across the 14 permanent count locations. It shows that the StreetLight data points were less variable than the Streetlytics data points and also illustrates the slightly better performance by how relatively closer the StreetLight data points are to the reference zero line than the Streetlytics data points. Furthermore, no obvious outliers were detected so all 14 data points were used for further evaluation.

Figure 12. Difference in estimated volumes and traditional volumes at permanent count stations

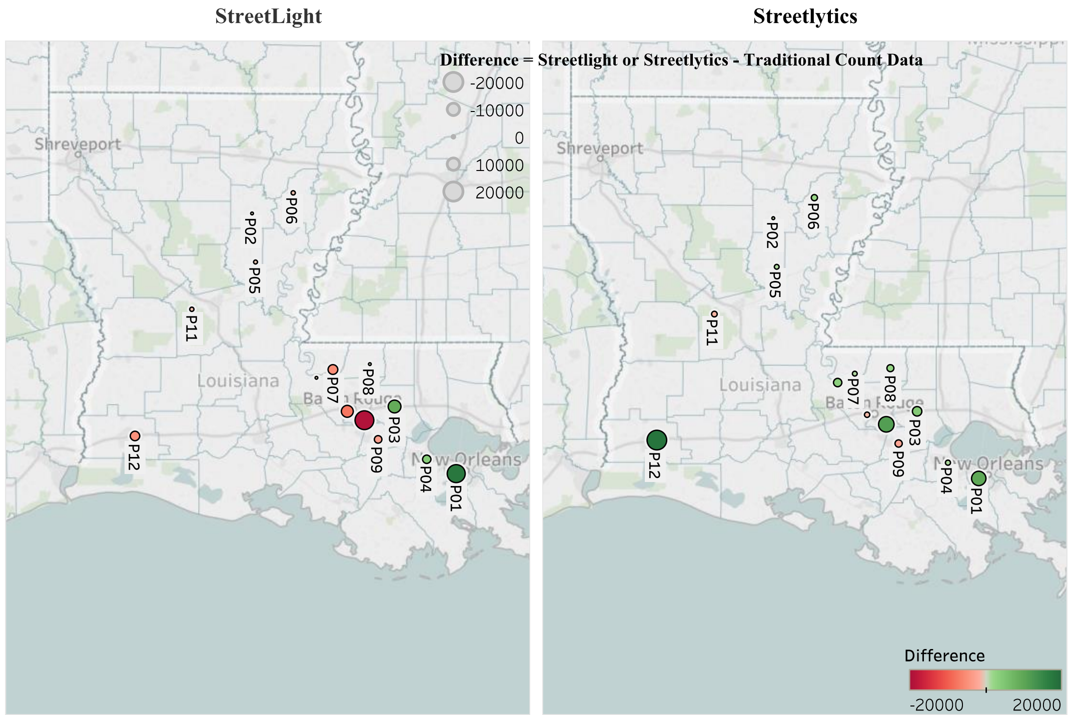


Figure 13. Box plot of absolute percentage error for 14 permanent count stations

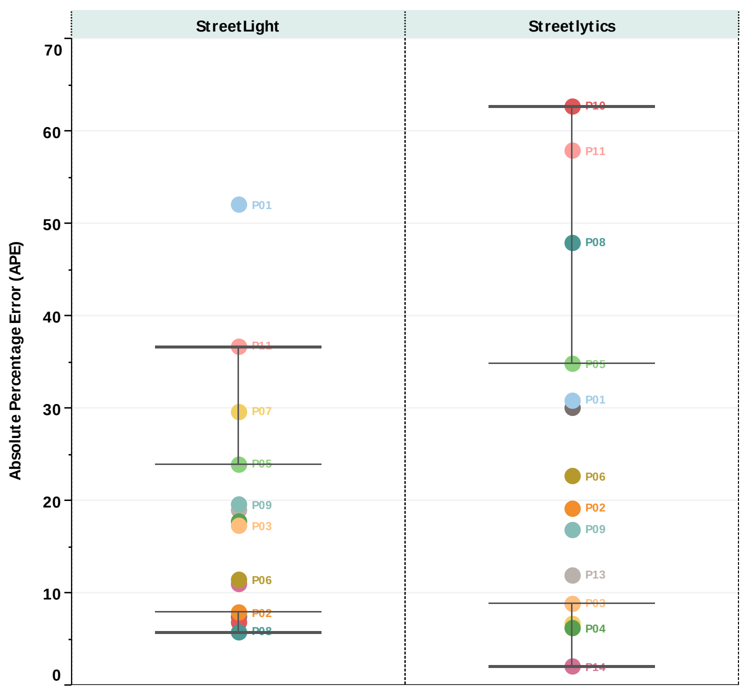


Table 4 shows the MAPE, along with MdAPE, MaxAPE, and %RMSE for the 14 permanent count locations for both StreetLight and Streetlytics. Using MAPE as the primary metric, the results show that StreetLight AADT 2018 V3 performed better than Streetlytics 2018 AADT. On the other hand, if %RMSE was the primary metric, Streetlytics would have performed slightly better than StreetLight.

Table 4. Summary of accuracy metrics for permanent count data validation at 14 locations

	StreetLight	**Streetlytics**
Mean APE (MAPE) %	18.93	25.55
Median APE (MdAPE) %	17.40	20.83
Maximum APE (MaxAPE) %	51.94	62.69
Percent Root Mean Square Error (%RMSE)	27.61	24.23
Number of locations	14	14

Full-Month Data

Data was evaluated for 30 locations where full-month data were collected for November 2019 data validation. Estimated volumes refer to either full-month StreetLight volume or full-month Streetlytics volume data. Traditional volumes refer to full-month traditional count data.

As in Figure 12, the difference between estimated volumes and traditional volumes has been illustrated in Figure 14 for both StreetLight and Streetlytics at all 30 locations. While very few data points stand out, there are a couple of noticeable overestimated data points and a bigger underestimated data point for Streetlytics.

Figure 15 is a box plot that shows the distribution of the APEs across the locations where full-month data were estimated. It shows that the Streetlytics data points were less variable than the StreetLight data points, and it also illustrates the slightly better performance by how relatively closer the Streetlytics data points are to the reference zero line than the StreetLight data points. As can be seen from the box plot, location M18 was considered an outlier for StreetLight. M30 was removed from the analysis due to the exceptionally large counts. All other 29 locations met this requirement.

Figure 14. Difference between StreetLight/Streetlytics and traditional full-month counts

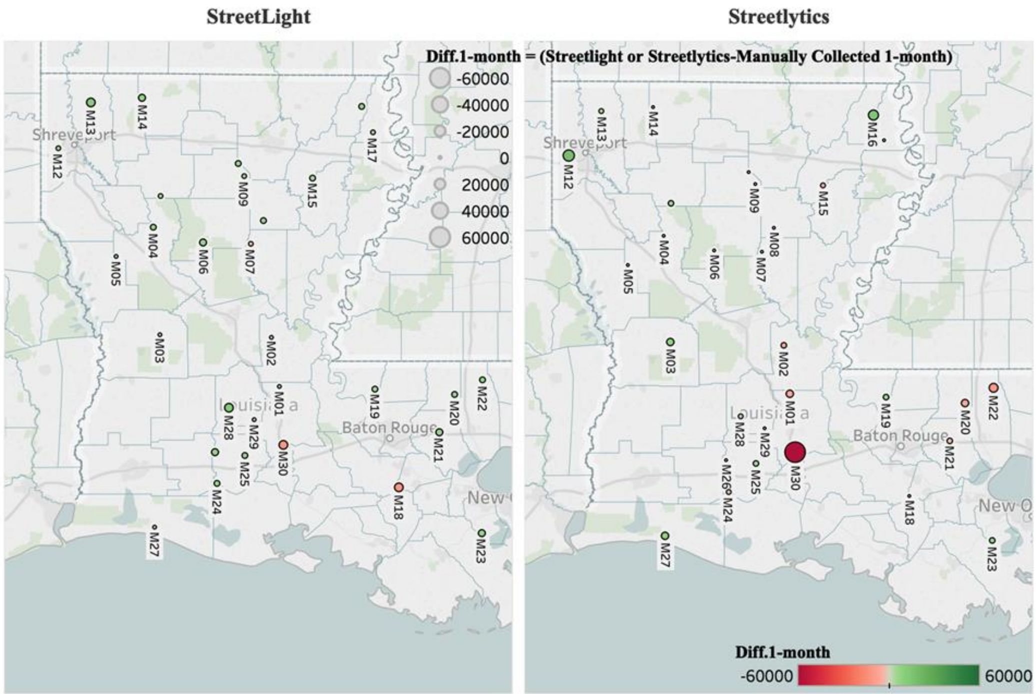


Figure 15. Box plot of absolute percentage error for full-month data

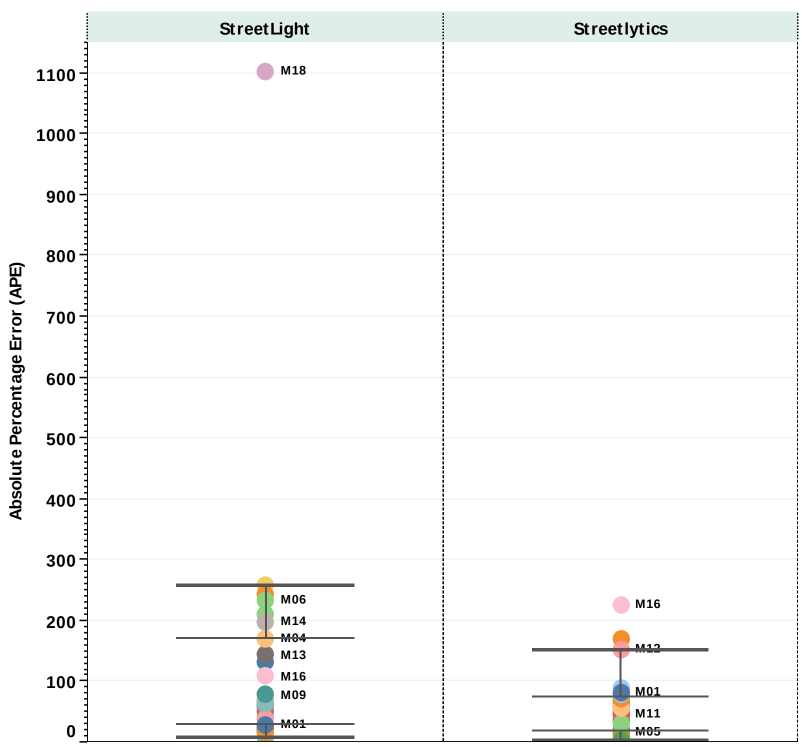


Table 5 shows the MAPE, along with MdAPE, MaxAPE, and %RMSE for the 28 full-month count locations for StreetLight and 29 full-month count locations for Streetlytics. As discussed earlier, M18 and M30 were removed from StreetLight and M30 from Streetlytics. Using MAPE as the primary metric, the results show that for the full-month validation effort, the full-month Streetlytics volume performed much better than the full-month StreetLight volume. On the other hand, if %RMSE was used as the primary metric, both tools would have performed similarly.

Table 5. Summary of accuracy metrics for full-month data validation

	StreetLight	Streetlytics
Mean APE (MAPE) %	93.82	57.17
Median APE (MdAPE) %	62.78	47.01
Maximum APE (MaxAPE) %	258.68	226.11
Percent Root Mean Square Error (%RMSE)	75.22	75.59
Number of locations	28	29

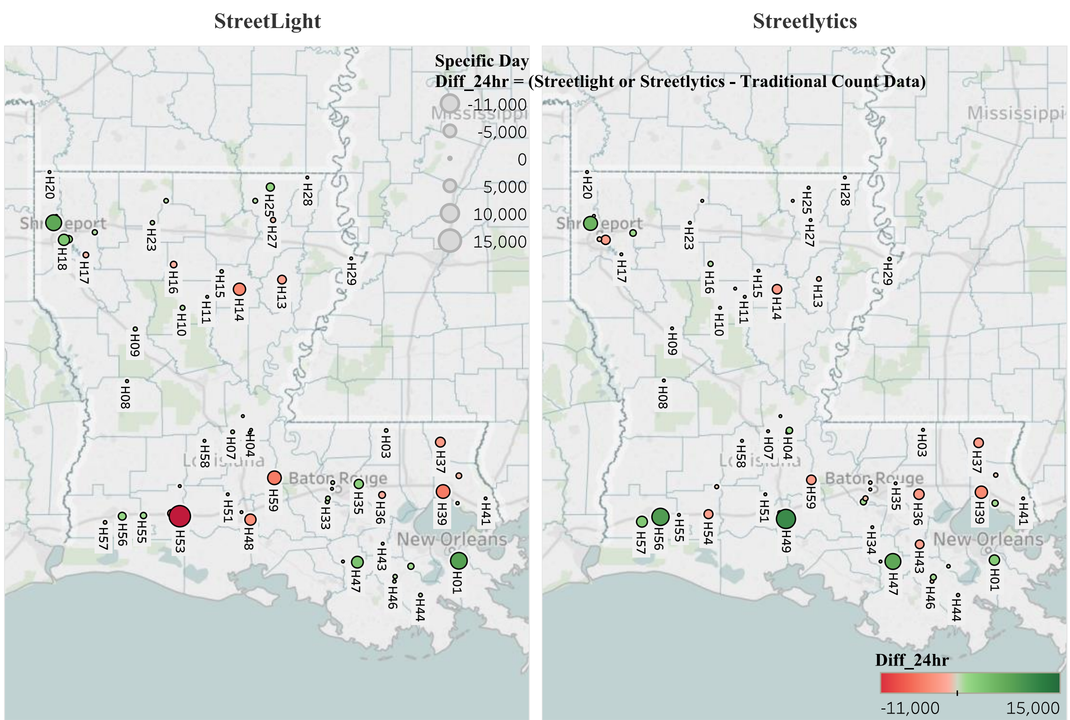
24-Hour Data

Data was evaluated for 60 locations where 24-hour data were collected for specific days throughout 2018 and 2019. Traditional volumes refer to 24-hour traditional count data. After the data collection was complete, it was found that one location, H49, had extremely high value because it collected data for a main road, rather than the service road being used. This station was considered as an outlier and removed from further evaluation. Therefore, 59 locations were finally evaluated.

For the estimated volumes, both StreetLight and Streetlytics provided two different data types: specific day volumes and typical day volumes. Specific day estimates refer to volumes that were generated for the specific day of the week for which the 24-hour traditional count data was provided for. For instance, if the 24-hour traditional count data was on a Tuesday in March 2018, then the specific day estimate would be generated for a typical Tuesday for March 2018. On the other hand, typical day estimates refer to volumes generated for either a typical weekday or weekend for which the 24-hour traditional count data was collected for. In the example that was just provided, a typical day estimate would be for a typical weekday in March 2018. All data collected from Mondays to Thursdays fall under a weekday, while data collected from Fridays to Sundays fall under weekends. Two types of validation were therefore performed for the 24-hour data and results are presented as below.

Specific Day Validation: As in Figures 12 and 14, the difference between 24-hour specific day estimated volumes and traditional volumes has been illustrated in Figure 16 for both StreetLight and Streetlytics.

Figure 16. Difference between StreetLight/Streetlytics and traditional specific day counts



While it is generally difficult to tell any obvious visual differences, it can be observed that StreetLight has more and larger underestimated data points (bigger red color) and Streetlytics has more and larger overestimated data points (bigger green color). Again, MAPE was used as the primary metric to quantify the differences.

Figure 17 is a box plot that shows the distribution of the APEs across the 24-hour data locations. It shows that StreetLight data points for H25 and H47, and Streetlytics data point for H47 are to be considered as outliers, and hence were removed from the accuracy evaluation. In addition, H12 and H34 were excluded from StreetLight volume data due to unavailable estimates.

Altogether, five locations from StreetLight (H12, H25, H34, H47 and H49) and two locations from Streetlytics (H47 and H49) were removed as outliers. With the outliers removed, the figure shows that while StreetLight and Streetlytics data points behave very much alike in terms of spread and how close they are to the reference zero line, H23 still demonstrated a high deviation. H23 was however not considered an outlier since it did not exhibit enough variation to be considered as such. Inadvertently, it contributes to the overall data accuracy and must therefore be included in the evaluation.

Figure 17. Absolute percentage error for 24-hour (specific day) volume count

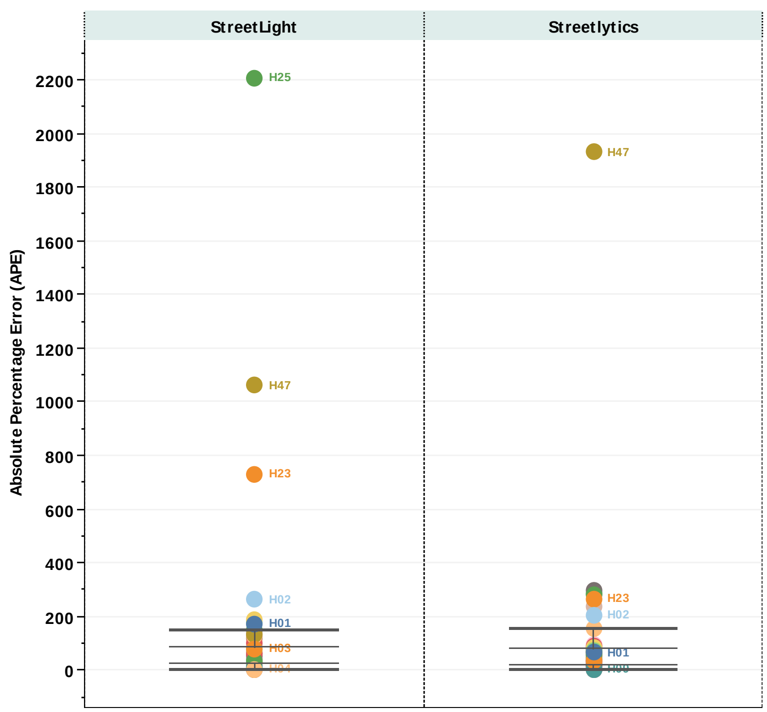


Table 6 shows the MAPE along with MdAPE, MaxAPE, and %RMSE for the 24-hour count locations for both StreetLight and Streetlytics, with the outliers removed. Using MAPE as the primary metric, the results show that for the specific day validation, the 24-hour Streetlytics (specific day) volume out-performed the 24-hour StreetLight (specific day) volume. However, if %RMSE had been the preferred metric, StreetLight would have performed better than Streetlytics.

Table 6. Summary of accuracy metrics for 24-hour specific day validation

	StreetLight	Streetlytics
Mean APE (MAPE) %	70.43	64.33
Median APE (MdAPE) %	42.77	40.10
Maximum APE (MaxAPE) %	729.73	297.88
Percent Root Mean Square Error (%RMSE)	68.70	74.79
Number of locations	55	58

Typical Day Validation: The difference between 24-hour typical day estimated volumes and traditional volumes has been illustrated in Figure 18 for both StreetLight and Streetlytics for the typical day validation. As in the specific day validation assessment, it can generally be observed that StreetLight has more and larger underestimated data points (bigger red color) and Streetlytics has more and larger overestimated data points (bigger green color). As before, MAPE was used as the primary metric to quantify the differences.

Figure 18. Difference between StreetLight/Streetlytics and traditional typical day count

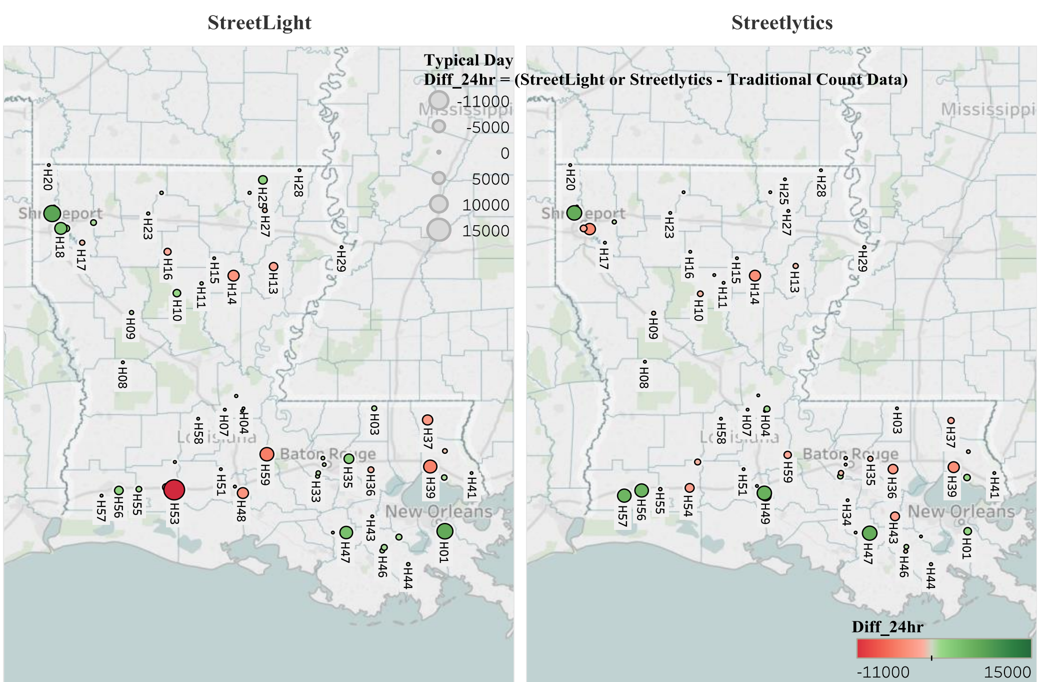


Figure 19 is a box plot that shows the distribution of the APEs across the 24-hour data locations for the typical day validation effort. Based on the plots, it was decided that StreetLight data points for H25 and H47, and Streetlytics data points for H47 be considered as outliers and removed from further evaluations. Similar to specific day counts, H49 was already moved because of the unexpectedly high traditional counts collected for the wrong roadway. Altogether, three locations from StreetLight (H25, H47, and H49) and two locations from Streetlytics (H47 and H49) were removed as outliers. With the outliers removed, the figure shows that the StreetLight data points performed quite similar as the Streetlytics data points, but the latter showed slightly less spread.

Figure 19. Absolute percentage error for 24-hour (typical day) volume count

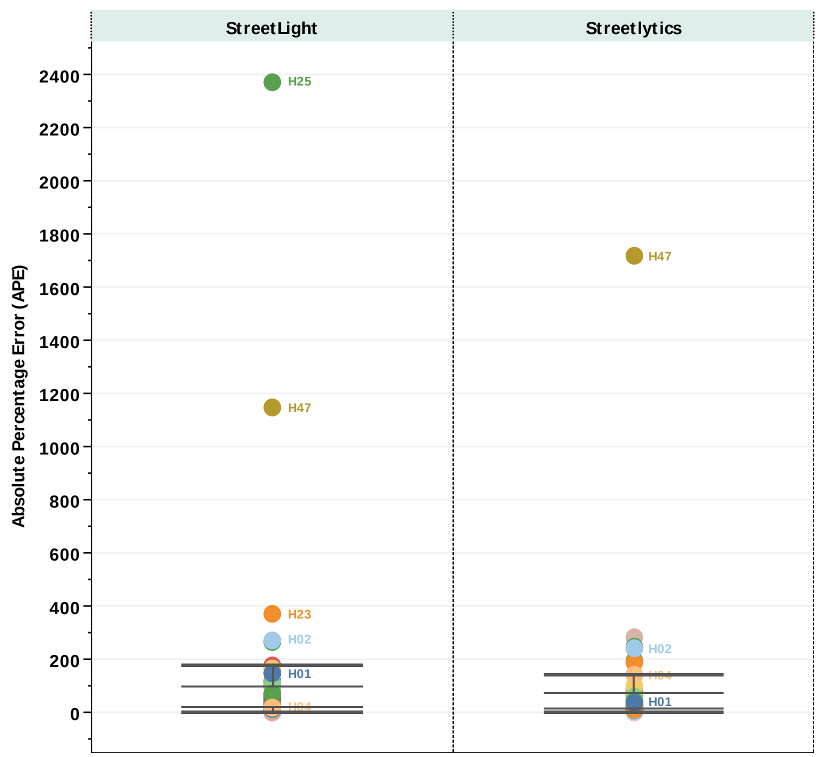


Table 7 shows the MAPE, MdAPE, MaxAPE, and %RMSE for the 24-hour count locations for both StreetLight and Streetlytics with the outliers removed. Using MAPE as the primary metric, the results show that for the typical day validation, the 24-hour Streetlytics (typical day) volume performed better than the 24-hour StreetLight (typical day) volume for all the APE metrics used. On the other hand, if %RMSE had been used as the primary metric, StreetLight would have performed better than Streetlytics.

Table 7. Summary of accuracy metrics for 24-hour typical day validation

	StreetLight	Streetlytics
Mean APE (MAPE) %	70.54	59.03
Median APE (MdAPE) %	41.11	38.67
Maximum APE (MaxAPE) %	370.27	285.21
Percent Root Mean Square Error (%RMSE)	64.00	69.56
Number of locations	57	58

Summary of Analysis on Accuracy

While a number of metrics were used to define accuracy, a summary is provided below using MAPE as the primary metric for the comparative assessment of the two estimating tools. Figure 20 illustrates all MAPEs computed for both estimating tools for:

1. Permanent Data
2. Full-Month Data
3. 24-Hour Specific Day Data
4. 24-Hour Typical Day Data

Figure 20 shows the summary of MAPE for all three count types at both StreetLight and Streetlytics. It shows that the StreetLight's estimated data was more accurate for one out of the four data types listed above, i.e. permanent data (AADT). On the other hand, Streetlytics estimated data was more accurate for the remaining three data types out of the four: full-month data, 24-hour specific day data, and 24-hour typical day data. To be able to effectively compare which of the two estimating tools had an overall better MAPE, a weighted MAPE value was computed using equation [8].

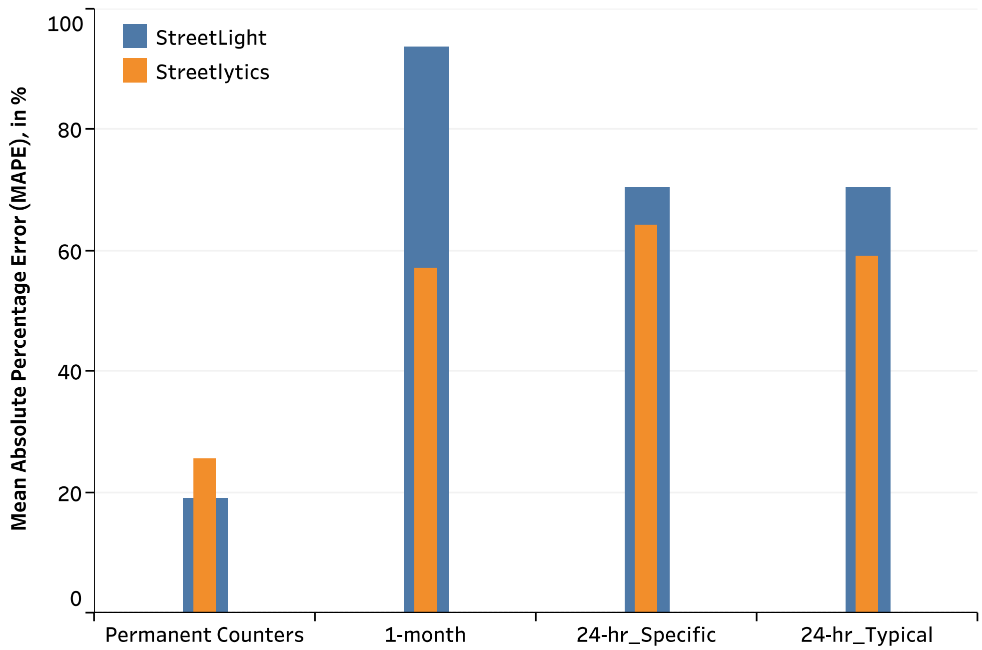
$$Weighted\ MAPE(\%) = \frac{(MAPE)*(n_{available})}{\sum n_{available}} \qquad [8]$$

where,

$MAPE =$ MAPE as previously calculated for each data type

$n_{\text{available values}} =$ the number of StreetLight or Streetlytics data points used in estimating the MAPE (refers to "Number of locations" in Tables 4, 5, 6, and 7)

Figure 20. Summary of mean absolute percentage error (MAPE)



The $n_{\text{available values}}$ together with the corresponding MAPEs computed for each of the data types, along with the weighted MAPEs for StreetLight and Streetlytics are presented in Table 8 below. For example using equation [8], weighted MAPE for StreetLight can be estimated as $\frac{18.93*14+93.82*28+70.43*55+70.54*57}{14+28+55+57} = \frac{10786.41}{154} = 70.04$.

Table 8. Illustration of weighted MAPE

	Mean Absolute Percentage Error (MAPE) %	
	StreetLight	**Streetlytics**
Permanent Data	18.93	25.55
Full-Month Data	93.82	57.17
24-Hour Specific Day Data	70.43	64.33
24-Hour Typical Day Data	70.54	59.03
Weighted MAPE	70.04	57.68

From Table 8, it is evident that Streetlytics had an overall better weighted MAPE, and hence better accuracy for the validation effort, when MAPE is used as the primary metric.

On the other hand, if %RMSE had been used as the primary metric, it can be seen from Table 9 that StreetLight would have outperformed Streetlytics for all the 24-hour counts (both typical and specific) and the full-month counts assessment, while performing similarly on the permanent (continuous) data assessments. As previously, a weighted %RMSE was computed using the %RMSEs obtained for each data type as well as the number of data points used in its computation. Through this method, StreetLight slightly outperformed Streetlytics with a weighted %RMSE of 64.41 against 68.58 computed for Streetlytics.

Table 9. Illustration of weighted %RMSE

	Percent Root Mean Square Error (%RMSE)	
	StreetLight	**Streetlytics**
Permanent Data	27.61	24.23
Full-Month Data	75.22	75.59
24-Hour Specific Day Data	68.70	74.79
24-Hour Typical Day Data	64.00	69.56
Weighted %RMSE	64.41	68.58

While this study's preference of a primary metric is MAPE, it does not in any way prescribe MAPE as superior metric over %RMSE since different agencies choose either, and there is currently no consensus in the scientific body of knowledge on which metric is better. While MAPE gives a uniform assessment of the errors, %RMSE applies bigger weights to bigger errors in the data and hence may give a different result and conclusions than MAPE. Both MAPE and %RMSE are normalized with the reference data (traditional count data/ground truth data). It is for this reason that results of %RMSE are presented in addition to those of MAPE.

While the study analyzed different data types (i.e., AADT, full-month volume, and 24-hour counts), a weighted metric was computed to represent the overall prediction accuracy of the estimating tool since it is the same single tool that estimates data points for all three data types.

Furthermore, following on the limitations of the previous LTRC Project 16-3SA [4], the monthly and 24-hour data were further stratified to undertake a comparative analysis for roadways with volumes under 300 vpd. Because the emphasis of this study is on low-volume roads (less than 500 vpd), the traditional count data were segmented into two bins: ≤ 300 vpd, and 300 vpd-500 vpd.

Table 10 shows values of MAPE and %RMSE obtained for the full-month data comparative analysis undertaken for the stratified data.

Table 10. Summary of accuracy metrics for stratified full-month data validation

Traditional Count Data	Number of Locations		MAPE		%RMSE	
	StreetLight	Streetlytics	StreetLight	Streetlytics	StreetLight	Streetlytics
≤ 300 vpd	18	18	128.69	59.17	117.37	80.10
301-500 vpd	10	11	31.05	53.90	32.32	67.40

From the results, Streetlytics performed better for both MAPE and %RMSE for locations under 300 vpd, while StreetLight performed better for volumes above 300 vpd, also for both MAPE and %RMSE.

Table 11 shows results for the 24-hour specific day analysis stratified as in previous table. Results show similar trend as observed for the full-month stratification, in that, Streetlytics performed better for both MAPE and %RMSE for locations under 300 vpd, while StreetLight performed better for volumes above 300 vpd, also for both MAPE and %RMSE.

Table 11. Summary of accuracy metrics for stratified 24-hour specific day validation

Traditional Count Data	Number of Locations		MAPE		%RMSE	
	StreetLight	Streetlytics	StreetLight	Streetlytics	StreetLight	Streetlytics
≤ 300 vpd	8	11	159.47	98.07	126.72	88.86
301-500 vpd	15	15	84.16	92.63	99.47	139.67

Lastly, similar stratification was done for the 24-hour typical day analysis and results presented in Table 12. As before, similar results were obtained but Streetlytics, additionally, showed a slightly better MAPE score for roadways with volumes over 300 vpd.

Table 12. Summary of accuracy metrics for stratified 24-hour typical day validation

Traditional Count Data	Number of Locations		MAPE		%RMSE	
	StreetLight	Streetlytics	StreetLight	Streetlytics	StreetLight	Streetlytics
≤ 300 vpd	10	11	144.15	86.66	112.76	80.65
301-500 vpd	15	15	85.75	83.33	116.62	131.23

The data can be further segmented into additional bins for the 24-hour counts but since the emphasis was on low-volume roadways, the bins were capped at 500 vpd, which is the limit defined for low-volume roadways for this study. Interestingly, the results showed that in general terms, Streetlytics outperformed StreetLight for volumes under 300 vpd; while StreetLight outperformed Streetlytics for volumes over 300 vpd for low-volume roadways.

Completeness of Data

Calculations for completeness of data are based on equation [7] with $n_{available}$ and $n_{expected}$ being respectively deduced from the number of valid data points from StreetLight and Streetlytics volume data, and the number of valid points from the traditional count data, that were used in the accuracy estimation. The results for each data type are presented below.

Permanent Data

StreetLight provided 14 StreetLight AADT 2018 V3 data points, and Streetlytics likewise provided 14 Streetlytics 2018 AADT data points to match the 14 permanent traditional count data provided from DOTD's MS2 TCDS platform [5]. Therefore, the completeness score is 100% for each estimating tool.

Full-Month Data

Data was collected at 30 stations by Quality Counts LLC and used to represent DOTD's full-month traditional count data. However, M30 was removed from further analysis because of the exceptionally large volume. For the full-month StreetLight volume, station M18 was considered an outlier and removed from the accuracy computations. Therefore, StreetLight had 28 valid points out of 29 total stations, and Streetlytics had 29 valid data points out of the total 29 stations. These translated to completeness scores of 96.55% for StreetLight and 100% for Streetlytics.

24-Hour Specific Day Data

DOTD's MS2 TCDS platform [5] was used to generate 24-hour counts throughout 2018 and 2019 for 60 locations. However, H49 was discarded as data were collected for the wrong location. Therefore, 59 24-hour traditional count data represented the total number of expected data points to be used for the accuracy assessment. Data provided by both StreetLight and Streetlytics contained a number of outliers that were removed from the accuracy computation. Altogether, data points not included in StreetLight's data were H12, H25, H34, and H47, while for Streetlytics, only H47 was removed. In summary, StreetLight had data available for 55 out of 59 stations, translating to a completeness score of 93.22%; while Streetlytics had data available for 58 out of the 59 locations, translating to a completeness score of 98.31%.

24-Hour Typical Day Data

Similar to the 24-hour specific day data, DOTD had 60 24-hour traditional count data for the validation of the 24-hour typical day data assessment but H49 was discarded, leading to 59 valid data points. Altogether, StreetLight had two data points removed as outliers, i.e., H25 and H47; and Streetlytics had only H47 removed as an outlier. Therefore, StreetLight had 57 valid points out of a total of 59, translating to a completeness score of 96.61%; while Streetlytics had 58 valid points out of 59, translating to a completeness score of 98.31%.

Summary of Completeness of Data

Table 13 provides a summary of the completeness scores for each of the data types assessed for both StreetLight and Streetlytics. It also provides a composite score which was computed as a weighted average of all the scores reported for each estimating tool using equation [9]:

$$Composite\ Score = \frac{(Completeness\ Score) * (n_{available})}{\sum n_{available}} \quad [9]$$

where,

$Completeness\ Score =$ the completeness score as previously calculated

$n_{\text{available values}} =$ the number of StreetLight or Streetlytics data points used in estimating the completeness score.

For example using equation [9], weighted completeness score for StreetLight can be estimated as $\frac{100*14+96.55*28+93.22*55+96.61*57}{14+28+55+57} = \frac{147,37.27}{154} = 95.70.$

Table 13. Summary of completeness score

	Completeness Score (%)	
	StreetLight	**Streetlytics**
Permanent Data	100	100
Full-Month Data	96.55	100
24-Hour Specific Day Data	93.22	98.31
24-Hour Typical Day Data	96.61	98.31
Composite Score	95.70	98.76

From Table 13, it is evident that even though both had high scores, Streetlytics had an overall better score for the completeness of data used for the validation effort.

Timeliness of Data

Timeliness of data was determined by reviewing, for each data type, StreetLight Data and Bentley System's ability to readily provide their corresponding estimated volumes and how far back they are able to produce the data. Thus, two time periods were of significance, namely:

1. How far back can data be estimated, i.e., historical data?
2. What is the lag time required to produce the data?

Both were considered important attributes because it shows how readily the data can be made available to DOTD if required, and what historical data can be made available for trend generation or any other assessments requiring an historical perspective. The comparison for each data type is presented next.

Permanent Data

Permanent data refers to the generation of AADT. For traditional count data, DOTD annually publishes factors such as axle-factors, K-factors, and seasonal factors for agencies to be able to estimate AADTs. Alongside the factors, for the current year, DOTD publishes AADTs for select roadway locations within the first quarter of the subsequent year. AADTs can be provided for as far back as the year 2000 for most of these locations.

Both StreetLight and Streetlytics have AADTs available for 2017, 2018, and 2019. StreetLight indicated they have a lag time of up to 3 months to produce AADTs i.e. 2020 AADT will probably be available by March 2021. Streetlytics indicated a lag time of 5 months. So similarly, 2020 AADT will be available by May 2021. With the pace of developments in data analytics, both could be available sooner than the dates currently stated.

Full-Month Data

Full-month traditional count data is quite expensive to obtain and takes a lot of effort. For this study, a contractor was hired to undertake the data collection at a cost. However, data are readily available immediately after it has been collected. Besides the data collected by DOTD's continuous counters at permanent locations, no monthly data are available. The limitations with the full-month traditional count data is the quality of counts being undertaken by the continuous counter and the fixed locations of these counters. For monthly data needed for other locations, the traditional way of data collection will have to be undertaken by manually installing devices on the field and continuously collecting data for the month of interest.

StreetLight noted they are able to develop monthly volumes for any data period going back to January 2016 with a typical lag time of 3-4 weeks even though this can be shortened under extenuating conditions. For instance, during the COVID-19 stay-at-home-orders, StreetLight reported they were able to generate half-month volumes within 2 weeks. Streetlytics noted they are able to generate monthly volumes for any data period going back to January 2018 with a typical lag time of 12 weeks.

Both StreetLight and Streetlytics have noted that, with rapid developments in data analytics, the generation of monthly volumes will gradually become more spontaneous and require a much shorter lag time. It is worth noting that for the November 2019 monthly volumes requested for this study, StreetLight was able to provide in 12 weeks, while Streetlytics provided in 15 weeks.

24-Hour Data

DOTD's Traffic Data Collection Unit maintains a systemic data collection program where short duration counts of 24-hours or 48 hours are undertaken throughout the state annually. Generally, for state-maintained roadways, data are collected at about 1,400 locations across a third of the state such that within 3 years, data will be collected at about 4,200 locations across the entire state. For local roadways, data are collected on a 10-year cycle but at limited locations. Some local agencies and MPOs also maintain their own data collection program. Additionally, consultants working on behalf of the state or local agency do sometimes collect short duration counts for locations not included in the routine DOTD collection program. All such data are currently being compiled on DOTD's MS2 TCDS platform [5] for easy query and retrieval.

Similar to the full-month volumes, StreetLight noted they are able to generate daily volumes from January 2016 with a typical lag time of 3-4 weeks while Streetlytics reported a typical lag time of 12 weeks to generate daily volumes from January 2018.

Summary of Timeliness of Data

Table 14 provides a summary of the timeliness of data assessments undertaken in the previous sections for StreetLight and Streetlytics. The information in this table were reported by the respective vendors and could not be verified, so the table is provided for easy reference rather than for evaluation purposes.

Table 14. Summary of timeliness of data

	StreetLight		Streetlytics	
	Earliest Available Date	Lag Time for Data Availability	Earliest Available Date	Lag Time for Data Availability
Permanent Data (AADT)	2017	12 weeks	2017	20 weeks
Full-Month Data	1/2016	4 weeks	1/2018	12 weeks
24-Hour Data	1/2016	4 weeks	1/2018	12 weeks

Validity

Validity has a number of definitions depending on how it is used and for what concept. However, for this study, it refers to two things:

- Do the estimated volumes represent what they are supposed to estimate?
- Do the results of the accuracy evaluations agree with established metrics criteria?

Each of the above is further discussed below for StreetLight and Streetlytics in how they relate to the three data types validated for this study.

Representativeness of Estimated Volumes

For this study, the traditional count data was considered to be the ground-truth data, against which the estimated volumes were compared. The ground-truth data was therefore assumed to be with no errors and 100% accurate in order to compare the estimated volumes against. While the full-month traditional count data and 24-hour traditional count data are likely to satisfy this assumption, the same cannot be said for the permanent traditional count data or AADTs. Data was collected from 14 continuous counters at permanent stations to calculate the AADT to be considered as the ground-truth. For this to be with no error and 100% accurate, it required data to be collected for every day in 2018, thus 365 days. However, due to a combination of factors (e.g., weather, maintenance, malfunctioning, etc.), none of the continuous counters were able to meet this criterion. Table 15 shows the break-down of the number of stations with their respective count coverages. Count coverage refers to the percentage of days in 2018 when the station was collecting data. To be assumed to be with no error and 100% accurate, count coverage should be 100%.

Table 15. Count coverage at permanent stations

Number of Stations	Count Coverage (%)
1	50-59
3	60-69
4	70-79
5	80-89
1	90-100

As can be seen from the table, the distribution of count coverage varied for the 14 stations used to generate the ground-truth AADT, without satisfying the 100% count coverage criteria for the majority of them. For this reason, even though there were differences between the permanent traditional count data and StreetLight AADT 2018 V3/Streetlytics 2018 AADT estimated volumes, it is impossible to tell which of the three data types was closest to the ground-truth.

Comparison to Established Metrics Criteria

The primary metric used for this study is the MAPE, even though results for MdAPE, MaxAPE, and %RMSE were also provided. Table 16 shows a summary of some validation studies that used prediction models to predict AADT and used MAPE as the measuring metric for accuracy. Results show that MAPE varied from 11% to 79%, providing some published ranges for which the MAPEs obtained for this study can be compared against. The research team was unable to determine an exact MAPE threshold that will render the data valid because no such publication was retrieved from the literature search. However, it is common knowledge that lower MAPEs signify more accurate data estimate. MAPEs obtained for the validation of StreetLight varied from 18.93% to 93.82% while that for Streetlytics varied from 25.55% to 64.33%.

Table 16. Research studies showing MAPE for AADT estimation

Research Studies	MAPE for AADT estimation
[6], [19], [20], [21]	16% to 79%
[21]	11.30%
[28]	21%
[41]	29 to 69%
[42]	26%

In a bid to obtain a single metric to represent each estimating tool, Table 8 provides the composite MAPE metric for StreetLight and Streetlytics to be 70.04% and 57.68%, respectively. Based on Table 16, these are within the observed ranges from published studies.

While %RMSE was provided, but not as a primary metric of measure, the values obtained were compared to published studies that used %RMSEs for validation studies pertaining to AADT. Generally, the closer the %RMSE is to zero, the better the estimated data. Wegmann and Everett [48] referenced that Montana Department of Transportation

(MDOT) suggests a maximum %RMSE of 30% for their traffic studies. More so, %RMSE of 28% to 48% for AADT prediction [49] were tabulated across different metropolitan areas within the United States. The Florida Standard Urban Transportation Model Structure [50] suggests an allowable %RMSE range of 35% to 50% though it shows allowable %RMSE largely dependent on the volume counts, with larger volumes associated with lower %RMSEs. Ohio Design Traffic Forecasting Manual [51] estimated a desired %RMSE of 12% to 100% for different volume groupings ranging from 250 vpd to 97,500 vpd. From Table 9, %RMSEs obtained for StreetLight varied from 27.61% to 75.22% with a weighted mean of 64.41% while that for Streetlytics ranged from 24.23% to 75.59% with a weighted mean of 68.58%. These values indicate both data's estimation power are within acceptable ranges.

A third validity factor that was not evaluated was whether the estimated volumes generated by StreetLight and Streetlytics were reproducible. It was concluded that both StreetLight Data and Bentley Systems already have systems in place to reproduce any of the data type used for the validation study because these constitute the core of their business functions.

Accessibility

This section was meant to assess the ease of using StreetLight and Streetlytics and report on the accessibility of the user interface. However, the research team was unable to explore at first-hand the data platforms of the respective tools as part of this study. Instead, researchers reached out to provide their own write-ups on how accessible their data is. Below is a summary from their individual submissions as well as a summary of how other agencies have used these tools.

StreetLight

StreetLight helps planners, modelers, and engineers to collect real-world transportation data in unchallenging ways with their interactive transportation online platform, StreetLight InSight®. Users can easily access information like origin-destination, travel time, routing, link selection, etc. Key solutions that make the StreetLight InSight® platform outstanding are:

- Instant access to on-demand analytics
- Running of granular analysis into interested study areas

- Access to mobility-relevant sources of Location-Based Service (LBS) data
- Processing of big data for transportation related purposes

By using their machine-learning algorithms, StreetLight helps planners and engineers to run on-demand parameters like (i.e., type of day, time of data, commercial or personal vehicle trips, etc.). Most analytics are ready in minutes, and more complex studies are available in hours—enabling users to focus more time and energy on planning and problem-solving than data-crunching.

StreetLight Data understands changes in mobility patterns in specific neighborhoods by running zone analysis, which gives an idea of traveler attributes like trip purpose and demographics. One of the many things unique to StreetLight InSight® is the ability to create zones on any road, road segment, or geographical area of interest anywhere in the US. Zone designation can be done in two ways on StreetLight InSight® by uploading a standard shapefile or by drawing zones in the interactive “Add Zone Set.” Module zones can be standard geographies (e.g., ZIP codes) or unique customized shapes created by the user. StreetLight InSight® supports two types of zones: polygon and line zones.

Streetlytics

Streetlytics can be accessed in three different ways: desktop application, on-premises data, and data API (application program interface). The desktop application is an interface that allows users to view, query, and run analysis on volume maps, driver demographics, and trip pattern. The on-premises data uses software like Bentley Cube or ArcGIS to access the data provided as a geodatabase or shape file. The data API grants users access to integrate Streetlight InSights (on-premises data attributes) into their own transportation, retail, etc.

Streetlytics is available for all roadway segments within an area, from controlled access freeways to major arterials, neighborhood streets, and country roads. Streetlytics travel patterns are aggregated to represent travel between US Census block groups. The analysis produces data that are stratified into four typical daily patterns: Monday-Thursday, Friday, Saturday, and Sunday. Streetlytics delivers six core data products for all four-day types within each analysis period:

- Volumes of vehicle and pedestrian on roadway segment
- Speeds of vehicles on roadway segment
- Demographics of people traveling on roadway segment by vehicle

- OD trip flows of people traveling between or within a census block group
- Home locations of people traveling on segment
- Trip paths of vehicles traveling through network

Other Functionalities of StreetLight Data and Streetlytics

Table 17 shows a summary of organizations/institutions that have used StreetLight and Streetlytics and what they used the tools for. While the list is not exhaustive, it shows that certain agencies have already begun utilizing big data analytics to supplement their traffic data sources. It is also worth noting that either estimating tool (StreetLight or Streetlytics) can be used to perform any of the functions listed in the table, but the table is only showing how each organization has reported utilizing the tool. Because of the self-reporting nature of the content, information has only been provided but not used to rate the estimating tools. It is recommended that staff from DOTD experience both platforms for a hands-on demonstration of the user friendliness of each tool's interface.

Table 17. Summary of StreetLight Data and Streetlytics products used by other institutions

Estimating Tool	Project/Objective	Organization	Metrics Provided	Year
StreetLight	Downtown Congestion Study	City of Lafayette, CA	Origin/Destination	2015
	Develop active transportation plan for Sarasota	Sarasota/Manatee MPO, Florida	Origin/Destination	NA
	Filling Traffic Count Gaps	Tulsa MPO, Oklahoma	AADT	2018
	California Department of Transportation's pilot study in partnership StreetLight	California Department of Transportation	Multiple metrics provided	2018

Estimating Tool	**Project/Objective**	**Organization**	**Metrics Provided**	**Year**
Streetlytics	Provide a complete picture of nationwide population movement	Geopath	Volume, speed, and vehicle paths	2017/Ongoing
	Provide a complete picture of population movement	Canadian Out of Home Marketing and Measurement Bureau	Volume, speed, and vehicle paths	2018/Ongoing
	Support travel demand model development in the state of Alabama	Alabama Department of Transportation	Origin-destination matrices	2018/Ongoing

Conclusions

The primary objective of this study was to validate data generated by StreetLight and Streetlytics against ground-truth data provided by DOTD and make a recommendation on whether each tool can be adopted by DOTD to provide supplemental traffic volume data for its operations. Three types of data were validated: permanent data (AADT), full-month data, and 24-hour data (further broken down to specific day counts and typical day counts). The ground-truth data for each data type were respectively obtained as follows: AADT generated from DOTD's continuous counters at permanent locations and retrieved from the MS2 TCDS platform; full-month data collected by Quality Counts LLC using pneumatic tube counters at designated locations; and 24-hour counts generated by DOTD's short duration counters and retrieved from the MS2 TCDS platform [5]. Five measures of effectiveness were evaluated, namely, accuracy, completeness, timeliness, validity, and accessibility. Each is further discussed below.

Accuracy was evaluated using MAPE as the primary metric, and %RMSE as a secondary metric. To provide information on the distribution of the errors (deviations from the ground-truth), the median (MdAPE), and maximum (MaxAPE) absolute percentage errors were also provided. %RMSE was used to provide information on the effect of the larger errors. This is because %RMSE penalizes larger errors more by assigning heavier weights to them while MAPE penalizes errors linearly. So, while MAPE is the primary metric used to compare the accuracy of the data, %RMSE provides context as to which model has more weighted large errors. Lower values of MAPE and %RMSE are indications of good estimating tools. There is currently no consensus in the body of knowledge as to which should be the primary metric, and agencies generally choose one as a matter of preference and not as an indication of one being superior to the other. For this study, because the emphasis was on low-volume roadways, MAPE was the preferred primary metric as it weights all errors in same manner. Nevertheless, results obtained for both metrics are presented for completeness and for alternative conclusions by those who prefer to use %RMSE as their preferred primary metric.

For the permanent data type (AADT), StreetLight performed better with a MAPE of 18.93% compared to Streetlytics' 25.55%. StreetLight also had lower MdAPE and MaxAPE suggesting that its data distribution was more identical to that of the ground-truth data. However, StreetLight's slightly larger %RMSE of 27.61% compared to Streetlytics' 24.23% suggests that StreetLight had some data points with larger errors than Streetlytics. The study also acknowledges the small sample size used for the permanent count data analysis may not present an accurate assessment of each tool's AADT prediction capability.

For the full-month data, Streetlytics performed better with a MAPE of 57.17% compared to StreetLight's 93.82%. Similarly, MdAPE and MaxAPE were lower for Streetlytics suggesting a more identical distribution to the ground-truth data. However, %RMSEs were identical at 75.59% and 75.22% for Streetlytics and StreetLight, respectively. Furthermore, when the data was segmented into two bins, roadways under 300 vpd and roadways over 300 vpd, the results showed that in general terms, Streetlytics outperformed StreetLight for volumes under 300 vpd; while StreetLight outperformed Streetlytics for volumes over 300 vpd for low-volume roadways. This was evident in both the MAPE and %RMSE results.

The 24-hour data were broken down to specific day and typical day counts, with the former referring to data corresponding to the particular day of the week for which the ground-truth data was collected, and the latter referring to either a weekday or weekend count. For both data types, Streetlytics performed better with MAPEs of 64.33% and 59.03% compared to StreetLight's of 70.43% and 70.54%, respectively. All values of MdAPE and MaxAPE were also lower for Streetlytics, suggesting a more identical distribution to the ground-truth data. %RMSEs were slightly higher for Streetlytics for both data types, i.e., 74.79 and 69.56 % compared to 68.70 and 64.00%, respectively. Again, this suggests that Streetlytics had some data points with larger errors than StreetLight. However, the study would like to acknowledge that 24-hour specific day volumes are not readily produced by StreetLight but were generated specifically for the study. Once again, stratifying the data into two bins showed that, generally, Streetlytics outperformed StreetLight for volumes under 300 vpd, while StreetLight outperformed Streetlytics for volumes over 300 vpd for low-volume roadways. However, all these results must be considered in reference to the completeness of the data and its validity.

Some of the data points had to be removed from the analysis either because they were considered outliers, or they were just not provided for lack of enough background data to generate the estimates. The completeness score was computed to represent the percentage of useful data points that each estimating tool generated for the validation exercise. Even though both scored very high completeness scores, Streetlytics had a slightly better composite completeness score of 98.76% compared to the 95.70% for StreetLight.

Validity of the data referred to whether the StreetLight and Streetlytics data represented what they were supposed to be measuring, how the accuracy metrics compared to established thresholds, and whether the estimated volumes are reproducible. It was determined that for the permanent data (AADT), it was impossible to determine which of the data estimated was closer to the ground-truth data, as the DOTD data representing the ground-truth data was in itself not a fully accurate data. However, the full-month and 24-hour data (both specific and typical day count) from DOTD represented ground-truth data and could be considered fully accurate for the comparative analysis. In considering MAPEs for the comparative analyses undertaken for only these data types, a weighted score of 70.04% and 57.68% was computed when all the data types, including permanent data, are considered. In all cases, the MAPEs compared favorably to what other studies had reported, i.e., a range of 11.3% - 79.0% from Table 16. Both StreetLight Data and Bentley Systems have structures in place to continue reproducing StreetLight and Streetlytics volumes, respectively, for any of the data types used for the validation studies.

Timeliness of the data was evaluated on how far back each data type can be reproduced and the lag time required to generate the data. Both StreetLight and Streetlytics reported AADT availability from 2017 with a lag time of 12 weeks and 20 weeks, respectively, after the end of a current year to make available its corresponding AADT. Monthly and 24-hour volumes can be made available when needed with StreetLight reporting data availability from January 2016 and up to 4 weeks' notice to produce, and Streetlytics reporting from January 2018 and up to 12 weeks to produce. Since these dates are all reported and cannot be verified, they have been presented in the report for information, and not to be used for comparative assessments.

Likewise, the data on accessibility of StreetLight and Streetlytics have been presented for information and not to be used for comparative assessments. Both products boast of friendly user interfaces with various tools to provide solutions to any transportation agency. The study has documented few agencies using these tools and for what purpose. However, in order to properly evaluate the accessibility of each product, it is recommended that select users from DOTD (including planners, engineers, technicians, and policy makers) be allowed exposure to use each data platform for a specified brief period. Both StreetLight Data and Bentley Systems view it favorably to engage in such pilot demonstration at no cost to DOTD.

Recommendations

Based on the observations and findings from this research, the recommendations to DOTD are detailed in the following sections. These will include recommendations on ground-truth data required for validation and the choice of estimating tool to be adopted to provide supplemental traffic data.

Need for Maintaining Ground-Truth Data

For every traffic validation study, it is imperative to have accurate real-world data to be used for the comparative analysis. The use of existing infrastructure to obtain ground-truth data is both quick and cost-effective, but this requires the existing infrastructure to be maintained. Tools such as StreetLight and Streetlytics still rely on traditional counts from published sources as one of their data sources for input into their models. Besides, they are unable to generate important information such as heavy vehicle percentages, crosswalk volumes, etc. More importantly, they may require recent counts in a project vicinity for calibration purposes. During data collection for this study, it was noted that none of the continuous counters from DOTD's permanent stations had collected volumes throughout the year (2018 was the study year). In fact, only 14 counters out of the 65 permanent counters had been able to collect continuous volumes for more than six months out of the year. A recommendation emerging from this study is for these counters to be maintained to be able to properly collect volumes all year round.

Preferred Estimating Tool (StreetLight or Streetlytics)

Five measures of effectiveness were used to compare the traffic volumes generated by StreetLight and Streetlytics to traditional ground-truth data. For timeliness and accessibility, the study provided information mainly provided by the vendors and so could not use this to evaluate the tools. However, for accuracy, completeness, and validity, even though Streetlytics generally scored higher than StreetLight, both tools had acceptable score ranges. This is complicated further in that when considering low-volume roadways, Streetlytics outperform StreetLight in estimating for roadways with volumes under 300 vpd, while StreetLight generally outperforms Streetlytics for roadways with volumes between 300 to 500 vpd.

Since both tools show valid and acceptable range of results, the research team recommends a hands-on demonstration by select DOTD personnel from various departments, who can then report on the user-friendliness of the individual interfaces as well as the ease of use of the various tools on each platform. Both vendors are open to offer this demonstration at no cost to DOTD.

Even though this study focused on traffic volumes, both vendors offer solutions to traffic congestion studies, origin-destination studies, transportation demand management, travel demand modeling, project performance evaluations, performance measures analysis, detour planning, and public transit design. It is recommended that DOTD's personnel, selected for the hands-on demonstration, be drawn from a wide pool of expertise area that encompasses all these disciplines.

Acronyms, Abbreviations, and Symbols

%RMSE	Percent Root Mean Square Error
3SG	Three-Approach Signalized Intersections
4SG	Four-Approach Signalized Intersections
AADT	Annual Average Daily Volume
AAHV	Average Annual Hourly Volume
ADT	Average Daily Traffic
ANN	Artificial Neural Network
APE	Absolute Percentage Error
API	Application Program Interface
ATC	Annual Traffic Census
ATR	Automatic Traffic Recorders
DOT	Department of Transportation
DOTD	Department of Transportation and Development
ESRI	Environmental Systems Research Institute
FHWA	Federal Highway Administration
GAM	Generalized Additive Model
GIS	Geographical Information System
GML	Gaussian Maximum Likelihood
GPS	Geospatial Positioning System
GT	Geospatial Technologies
GWR	Geographically Weighted Regression
DOTD	Department of Transportation and Development
LBS	Location-Based Services
LLC	Limited Liability Company
LTRC	Louisiana Transportation Research Center
MADT	Monthly Average Daily Traffic
MAPE	Mean Absolute Percentage Error
MaxAPE	Maximum Absolute Percentage Error
MdAPE	Median Absolute Percentage Error
MDT	Montana Department of Transportation
M-F	Monday to Friday
MLR	Multiple Linear Regression
MnDOT	Minnesota Department of Transportation
MOE	Measures of Effectiveness

MPE	Mean Percentage Error
MPO	Metropolitan Planning Organization
OLR	Ordinary Least Squares
PLNB	Piecewise Linear Negative Binomial
PRC	Project Review Committee
RSME	Root Mean Square Error
SDAPE	Standard Deviation of Absolute Percent Error
SP&R	State Planning and Research
STC	Seasonal Traffic Count
SVR	Support Vector Regression
SVR-DP	Support Vector Regression technique with Data-Dependent analysis
TCDS	Traffic Count Database System
TMC	Turning Movements Counts
TPF	Transportation Pool Fund
TTSD	Traffic and Transport Survey Division
VEH	Vehicles
VPD	Vehicles per Day
VPM	Vehicle Per Month
VPY	Vehicle Per Year
WAC	Work Area Characteristic

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Appendix A

Details of 2018 Permanent Data (AADT)

Station ID	Latitude	Longitude	Traditional	StreetLight	Streetlytics
P01	29.9243	-90.1683	31785	48293	41585
P02	32.051427	-92.122881	2006	1850	2389
P03	30.474421	-90.756599	49080	57514	53387
P04	30.052656	-90.459014	19967	23485	21189
P05	31.656879	-92.089537	3224	2454	4343
P06	32.21913	-91.733051	8297	7355	10169
P07	30.782845	-91.348434	16399	11549	17485
P08	30.820252	-91.000773	4862	5141	7189
P09	30.204755	-90.920289	15274	12301	12707
P10	30.709799	-91.511899	5138	4788	8359
P11	31.269918	-92.692935	2577	1633	1087
P12	30.236967	-93.237026	60825	56331	79029
P13	30.368153	-91.046951	96468	78269	107951
P14	30.442802	-91.223508	65968	58803	64667

Appendix B

Details of Full-Month Count from November 2019

Station ID	Latitude	Longitude	Traditional	StreetLight	Streetlytics
M01	30.8271	-92.073	8285	10650	1500
M02	31.1766	-92.1308	7328	9360	1620
M03	31.1941	-93.0632	10942	12660	18630
M04	31.9458	-93.1143	3421	9240	1500
M05	31.7439	-93.4156	11790	14070	12000
M06	31.84	-92.7	3186	10620	4170
M07	31.833	-92.3071	15448	12660	17400
M08	31.9982	-92.2065	3611	9690	3660
M09	32.3068	-92.3635	5336	9480	4290
M10	32.3925	-92.4152	8203	13470	7140
M11	32.1707	-93.0564	13519	16500	19740
M12	32.5071	-93.9029	11860	16470	29940
M13	32.8191	-93.6313	8495	20730	11400
M14	32.8505	-93.2032	3784	11250	5490
M15	32.2988	-91.7981	8096	12930	4290
M16	32.7949	-91.3892	6366	13260	20760
M17	32.6116	-91.2983	6159	9720	7260
M18	30.1039	-91.0849	12594	151500	10350
M19	30.8081	-91.2782	9405	14220	14760
M20	30.7652	-90.6236	9501	15330	2370
M21	30.4998	-90.7503	5559	12840	1500
M22	30.8688	-90.389	12639	18180	1500
M23	29.7803	-90.3988	3211	11010	8610
M24	30.1307	-92.5829	8804	14970	5880
M25	30.3307	-92.3534	8139	13650	12540
M26	30.3554	-92.6021	3804	11760	3210
M27	29.8159	-93.1054	11667	13860	19410
M28	30.6696	-92.4835	4801	17220	8160
M29	30.5841	-92.2831	10584	12840	11160
M30	30.4121	-92.0314	167084	154890	107100

Appendix C

24-hour Volume for Specific Days of the Week (2018 and 2019)

Station ID	Latitude	Longitude	Date	Traditional	StreetLight	Streetlytics
H01	29.87	-90.0137	5/8/18	4803	13084	7924
H02	32.6116	-93.8628	2/26/18	2819	10183	8571
H03	30.9367	-90.6967	8/7/18	473	843	627
H04	30.9356	-91.9814	3/27/18	825	849	2099
H05	30.9183	-91.991	3/27/18	257	338	399
H06	31.047	-92.0598	10/2/18	290	511	498
H07	30.922	-92.1656	7/24/18	326	755	111
H08	31.3375	-93.1675	4/16/19	141	407	259
H09	31.7611	-93.0843	5/14/19	4210	4688	4337
H10	31.9249	-92.6332	8/14/18	10553	11256	10693
H11	32.0202	-92.3977	8/7/18	175	280	119
H12	32.08	-92.4872	8/7/18	60	NA	91
H13	32.1638	-91.6911	4/24/18	3885	1644	3287
H14	32.0829	-92.0926	8/15/18	13619	9144	10976
H15	32.2297	-92.2672	4/18/18	260	601	482
H16	32.278	-92.7218	4/17/18	10119	8869	10901
H17	32.3562	-93.5625	1/30/19	5641	4720	5762
H18	32.4858	-93.7724	9/18/18	7222	10921	6609
H19	32.6721	-93.8314	6/12/18	303	328	290
H20	33.0195	-93.8911	1/31/18	368	303	298
H21	32.4791	-93.7195	5/8/18	19037	20627	16516
H22	32.5347	-93.4622	7/9/19	3530	4323	4783
H23	32.6111	-92.92	6/4/19	74	614	270
H24	32.788	-92.7918	6/4/19	456	1044	553
H25	32.8983	-91.7981	10/16/18	89	2053	340
H26	32.79	-91.9358	11/28/18	366	1013	197
H27	32.6337	-91.7711	10/30/18	2694	1944	2585
H28	32.9719	-91.4402	2/12/19	236	252	282
H29	32.3269	-91.0257	4/24/18	467	321	791
H30	30.4518	-91.2029	7/23/19	301	483	59
H31	30.5113	-91.2076	1/23/19	387	769	49
H32	30.3796	-91.2448	1/23/19	1037	1676	280
H33	30.3542	-91.2647	1/23/19	377	842	1500
H34	30.1457	-91.1826	3/20/18	133	NA	60

Station ID	Latitude	Longitude	Date	Traditional	StreetLight	Streetlytics
H35	30.5012	-90.9549	6/5/18	5521	8051	5361
H36	30.4121	-90.7398	1/10/18	5984	4595	2930
H37	30.8384	-90.175	2/5/19	9458	6652	6752
H38	30.5631	-90.0056	1/31/18	1648	669	1136
H39	30.4291	-90.1538	1/31/18	13258	7788	8929
H40	30.3434	-90.0236	2/27/18	480	795	1622
H41	30.3799	-89.7436	3/13/18	238	115	53
H42	29.8218	-90.4635	5/7/19	1431	2590	1770
H43	30.0055	-90.7293	4/4/18	4792	4868	2581
H44	29.5872	-90.371	8/15/18	346	749	56
H45	29.7329	-90.6099	7/31/18	370	931	1421
H46	29.6948	-90.6222	9/11/18	924	1280	511
H47	29.8586	-90.9777	3/13/18	383	4448	7782
H48	30.2086	-91.998	7/31/18	14243	10509	25161
H49	30.1836	-91.9906	4/17/18	332	NA	4028
H50	30.2642	-92.0687	7/10/18	1464	1497	1944
H51	30.4064	-92.2004	1/15/19	857	643	984
H52	30.4813	-92.6616	6/26/18	6515	6570	6066
H53	30.2321	-92.655	7/10/18	21420	7924	8034
H54	30.2513	-92.7405	7/10/18	3590	1759	1201
H55	30.246	-93.0158	5/22/19	2555	3714	2544
H56	30.2311	-93.2044	7/30/19	9471	11264	18256
H57	30.1811	-93.3761	2/6/19	13759	13392	17243
H58	30.8483	-92.4213	5/15/19	325	464	435
H59	30.5403	-91.7633	1/24/18	15757	10319	13094
H60	29.8622	-91.1067	3/13/18	313	217	233

Appendix D

24-hour Volume for Typical Days of the Week (2018 and 2019)

Station ID	Latitude	Longitude	Date	Traditional	StreetLight	Streetlytics
H01	29.87	-90.0137	5/8/18	4803	11812	6602
H02	32.6116	-93.8628	2/26/18	2819	10513	9622
H03	30.9367	-90.6967	8/7/18	473	1173	540
H04	30.9356	-91.9814	3/27/18	825	983	1986
H05	30.9183	-91.991	3/27/18	257	440	364
H06	31.047	-92.0598	10/2/18	290	562	472
H07	30.922	-92.1656	7/24/18	326	408	121
H08	31.3375	-93.1675	4/16/19	141	373	280
H09	31.7611	-93.0843	5/14/19	4210	4668	3712
H10	31.9249	-92.6332	8/14/18	10553	12163	9507
H11	32.0202	-92.3977	8/7/18	175	487	110
H12	32.08	-92.4872	8/7/18	60	279	71
H13	32.1638	-91.6911	4/24/18	3885	1867	3003
H14	32.0829	-92.0926	8/15/18	13619	10272	9827
H15	32.2297	-92.2672	4/18/18	260	429	448
H16	32.278	-92.7218	4/17/18	10119	8780	10097
H17	32.3562	-93.5625	1/30/19	5641	4864	5712
H18	32.4858	-93.7724	9/18/18	7222	11277	5816
H19	32.6721	-93.8314	6/12/18	303	359	248
H20	33.0195	-93.8911	1/31/18	368	342	327
H21	32.4791	-93.7195	5/8/18	19037	20367	14864
H22	32.5347	-93.4622	7/9/19	3530	4474	4084
H23	32.6111	-92.92	6/4/19	74	348	213
H24	32.788	-92.7918	6/4/19	456	777	484
H25	32.8983	-91.7981	10/16/18	89	2199	311
H26	32.79	-91.9358	11/28/18	366	631	220
H27	32.6337	-91.7711	10/30/18	2694	2103	2471
H28	32.9719	-91.4402	2/12/19	236	268	343
H29	32.3269	-91.0257	4/24/18	467	269	774
H30	30.4518	-91.2029	7/23/19	301	643	50
H31	30.5113	-91.2076	1/23/19	387	769	50
H32	30.3796	-91.2448	1/23/19	1037	1567	228
H33	30.3542	-91.2647	1/23/19	377	815	1296
H34	30.1457	-91.1826	3/20/18	133	203	52

Station ID	Latitude	Longitude	Date	Traditional	StreetLight	Streetlytics
H35	30.5012	-90.9549	6/5/18	5521	8160	4716
H36	30.4121	-90.7398	1/10/18	5984	4943	3077
H37	30.8384	-90.175	2/5/19	9458	6566	8186
H38	30.5631	-90.0056	1/31/18	1648	1044	1248
H39	30.4291	-90.1538	1/31/18	13258	8415	9468
H40	30.3434	-90.0236	2/27/18	480	1289	1849
H41	30.3799	-89.7436	3/13/18	238	398	50
H42	29.8218	-90.4635	5/7/19	1431	2470	1513
H43	30.0055	-90.7293	4/4/18	4792	4568	2364
H44	29.5872	-90.371	8/15/18	346	675	50
H45	29.7329	-90.6099	7/31/18	370	1349	1084
H46	29.6948	-90.6222	9/11/18	924	1528	482
H47	29.8586	-90.9777	3/13/18	383	4768	6954
H48	30.2086	-91.998	7/31/18	14243	10868	20565
H49	30.1836	-91.9906	4/17/18	332	NA	3950
H50	30.2642	-92.0687	7/10/18	1464	1663	1630
H51	30.4064	-92.2004	1/15/19	857	679	981
H52	30.4813	-92.6616	6/26/18	6515	6281	5432
H53	30.2321	-92.655	7/10/18	21420	9533	7148
H54	30.2513	-92.7405	7/10/18	3590	2114	1070
H55	30.246	-93.0158	5/22/19	2555	3482	2209
H56	30.2311	-93.2044	7/30/19	9471	11526	15174
H57	30.1811	-93.3761	2/6/19	13759	13557	19448
H58	30.8483	-92.4213	5/15/19	325	435	407
H59	30.5403	-91.7633	1/24/18	15757	10572	14013
H60	29.8622	-91.1067	3/13/18	313	276	223

Appendix E

Instructions on Replicating Research Efforts

1. The basic equation to estimate mean absolute percentage error (MAPE) and percent root mean square error (%RMSE) is as follows. See equations (1)-(6) in the report for more detail.

$$MAPE\ (\%) = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{Volume_{traditional} - Volume_{estimated}}{Volume_{traditional}}\right|$$

$$RMSE = \sqrt{\frac{\sum_{1}^{n}(Volume_{estimated} - Volume_{traditional})^2}{n}}$$

$$\%RMSE = \frac{RMSE}{Average\ of\ Traditional\ Count} = \frac{RMSE}{\frac{1}{n}\sum_{i=1}^{n} volume_{traditional}}$$

2. Arrange traditional volume data and StreetLight or Streetlytics volume data in two separate columns. The sample table is as follows.

Station (A)	Traditional Volume Count (B)	StreetLight or Streetlytics Volume Count (C)
1	2200	2100
2	2050	2000
3	1850	1900
4	2500	2500

3. The study used three different types of volume data types: permanent data (AADT), full-month data and 24-hour data. The table in Step 2 should be created separately for the three types of data to estimate MAPE and %RMSE.

Permanent Count

4. Add all 14 stations ID (P01, P02…P14) and their traditional permanent volume count in Column B as shown in the table in step 2. Include the count data received from either StreetLight or Streetlytics depending on which source is being analyzed.
5. Estimate the difference of Column B and Column C as (Column B-Column C). The order of volume count during difference does not affect the estimate as absolute of the difference will be taken at the end. So, it can either (Column B-Column C) or (Column C-Column B). Name it the Column D.

Estimation of MAPE

6. Divide Column D from step 5 by traditional permanent volume count, i.e., Column B and take an absolute of it. Then divide it by 100 to convert it to percentage error. The outcome in Column D at each station is called Absolute Percentage Error. Name it as Column E.

7. Take the mean of Column E, i.e., the mean of Absolute Percentage Error or divide the sum of all the values in that column by total number of station (n = 14), which is the Mean Absolute Percentage Error (MAPE). In addition, take the median and maximum of the Absolute Percentage Error.

Estimation of RMSE

8. Take square of Column D from Step 5. Name it Column F.
9. Take a mean of Column F or divide the sum of total from Column F by total number of station (n = 14).
10. Take a square root of mean from Step 9, which is the Root Mean Square Error (RMSE).
11. Divide RMSE from step 10 by the mean of traditional volume count, i.e., mean of Column B. Multiply it by 100% to convert it to percentage. The outcome is Percent Root Mean Square Error (%RMSE).
12. Repeat steps 4 to 11 to get MAPE and %RMSE separately for StreetLight and Streetlytics count data. It should match Table 4 in the report.

Full-month count

13. In step 2, use full-month count data from all 60 stations. In Column B, traditional full count data are manually collected data in the month of November 2019. In Column C, StreetLight and Streetlytics provided data in terms of average daily traffic. Multiply it by 30 to convert it to full-month data so that it is comparable to Column B. Do not use outliers mentioned in the report for the analysis.
14. Follow the procedure from steps 4 to 12 to estimate MAPE and %RMSE for StreetLight and Streetlytics separately. It should match Table 5 in the report.

24-hour count

15. Similarly, in step 2, use 24-hour count data from all 30 stations. In Column B, use traditional 24-hour count data. In Column C, StreetLight and Streetlytics provided data in terms of specific day and typical day 24-hour count data. Two separate analysis (one for specific day and another for typical day) needs to be done separately. Do not use outliers mentioned in the report for the analysis.
16. Repeat steps 4 to 12 to estimate MAPE and %RMSE for StreetLight/Streetlytics (specific and typical day) volume count. It should match Tables 6 and 7 in the report.

Weighted MAPE

17. Use the following equation to estimate weighted MAPE. For detail please see Equation (8) in the report.

$$Weighted\ MAPE(\%) = \frac{(MAPE)*(n_{available})}{\sum n_{available}}$$

18. Arrange the outcome from above steps in the following format

Volume Type	Number of available locations from StreetLight/Streetlytics (G)	StreetLight or Streetlytics Volume Count (H)
Permanent Count	14 (both)	MAPE from Step 7
Full-Month Count	28 (StreetLight) 29 (Streetlytics)	MAPE from Step 14
24-Hour Specific Day Data	55 (StreetLight) 58 (Streetlytics)	MAPE from Step 16
24-Hour Typical Day Data	57 (StreetLight) 58 (Streetlytics)	MAPE from Step 16

19. Multiply Column G and Column H to get the product of available locations and MAPE. Name it Column I.
20. Take the sum of Column I and divide it by the sum of Column G which is weighted MAPE. Use StreetLight and Streetlytics MAPE separately in Column H to estimate weighted MAPE separately. The outcome should match with Table 8 in the report.

Completeness

21. The basic equation to estimate percentage complete (%) is as follows. See Equation (7) in the report for the detail. $\text{Percentage Complete (\%)} = \frac{n_{available\ values}}{n_{total\ expected}} * 100$
22. Arrange the outcome from above steps in the following format.

Volume Type	Total Count (Column J)	Number of available locations (G) for StreetLight or Streetlytics (excluding outliers)
Permanent Count	14	14
Full-Month Count	29	28 (StreetLight) 29 (Streetlytics)
24-Hour Specific Day Data	59	55 (StreetLight) 58 (Streetlytics)
24-Hour Typical Day Data	59	57 (StreetLight) 58 (Streetlytics)

23. Divide Column G by Column J and multiply it by 100% to estimate percentage complete. Do separate analysis for StreetLight and Streetlytics. It should match with Table 9 in the report.
24. To estimate the composite or weighted score, multiply Column G and outcome from step 24. Name it Column K. Divide sum of Column K by sum of Column G, which gives the composite score for the completeness. It should match with Table 9 in the report.

Timeliness

25. Timeliness for both StreetLight and Streetlytics as tabulated in Table 10 was summarized based on the information available from them. No separate analysis was done for this metrics.

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