RESEARCH ARTICLE

Estimation of annual average daily traffic (AADT) data for low-volume roads: a systematic literature review and meta-analysis [version 1; peer review: 2 approved]

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v1 **First published:** 11 Mar 2022, **4**:13
https://doi.org/10.35241/emeraldopenres.14515.1
Latest published: 11 Mar 2022, **4**:13
https://doi.org/10.35241/emeraldopenres.14515.1

Abstract

Background: The annual average daily traffic (AADT) data from road segments are critical for roadway projects, especially with the decision-making processes about operations, travel demand, safety-performance evaluation, and maintenance. Regular updates help to determine traffic patterns for decision-making. Unfortunately, the luxury of having permanent recorders on all road segments, especially low-volume roads, is virtually impossible. Consequently, insufficient AADT information is acquired for planning and new developments. A growing number of statistical, mathematical, and machine-learning algorithms have helped estimate AADT data values accurately, to some extent, at both sampled and unsampled locations on low-volume roadways. In some cases, roads with no representative AADT data are resolved with information from roadways with similar traffic patterns.

Methods: This study adopted an integrative approach with a combined systematic literature review (SLR) and meta-analysis (MA) to identify and to evaluate the performance, the sources of error, and possible advantages and disadvantages of the techniques utilized most for estimating AADT data. As a result, an SLR of various peer-reviewed articles and reports was completed to answer four research questions.

Results: The study showed that the most frequent techniques utilized to estimate AADT data on low-volume roadways were regression, artificial neural-network techniques, travel-demand models, the traditional factor approach, and spatial interpolation techniques. These AADT data-estimating methods' performance was subjected to meta-analysis. Three studies were completed: R squared, root means square error, and mean absolute percentage error. The meta-analysis results indicated a mixed summary effect: 1. all studies were equal; 2.

Open Peer Review

Approval Status ✓ ✓

	1	2
version 1 11 Mar 2022	✓	✓

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all studies were not comparable. However, the integrated qualitative and quantitative approach indicated that spatial-interpolation (Kriging) methods outperformed the others.
Conclusions: Spatial-interpolation methods may be selected over others to generate accurate AADT data by practitioners at all levels for decision making. Besides, the resulting cross-validation statistics give statistics like the other methods' performance measures.

Keywords
AADT, Low-Volume Roads, Rural Roadways, Estimating Techniques, Meta-Analysis

This article is included in the Sustainable Cities gateway.

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Author roles: Baffoe-Twum E: Writing – Original Draft Preparation, Writing – Review & Editing; **Asa E**: Supervision; **Awuku B**: Data Curation, Writing – Original Draft Preparation

Competing interests: No competing interests were disclosed.

Grant information: The author(s) declared that no grants were involved in supporting this work.

How to cite this article: Baffoe-Twum E, Asa E and Awuku B. **Estimation of annual average daily traffic (AADT) data for low-volume roads: a systematic literature review and meta-analysis [version 1; peer review: 2 approved]** Emerald Open Research 2022, **4**:13 https://doi.org/10.35241/emeraldopenres.14515.1

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Introduction

In 1994, Zegeer *et al.,* documented that the United States had about 3,082,001 miles of two-lane rural roads (Zegeer *et al*., 1994). Apronti *et al.* (2016) and Tsapakis *et al.* (2016) asserted that an estimated 69% of road miles in the United States of America are urban/local and low-volume roads. The manual on uniform traffic control devices (MUTCD) defined low-volume roads as lying outside the built-up areas of cities, towns, and communities. The annual average daily traffic (AADT) for low-volume roads was generally approximated as 400 vehicles per day (Apronti *et al.,* 2016). The Pennsylvania Department of Transportation (PennDOT) defined low-volume roads as having a maximum of 500 vehicles per day (PA Act 89 of 2013; PennDOT, 2014). The 2019 American Association of State Highway and Transportation Officials (AASHTO) guidelines for low-volume roads' geometric designs further outlined the classifications for low-volume roads. Low-volume roads are for movement and commerce in areas that are classified as 'local' for the regional transit areas (AASHTO, 2019).

Transportation engineers at the federal, state, and local levels are familiar with the importance of the AADT dataset (Sharma *et al.,* 2001). From the AADT data, roadway utilization is inferred; the planning and prioritizing is done for the needed and appropriate roadway improvements; and there is a source of information for planning new road-construction projects. Additionally, AADT data are utilized to assist with the development and implementation of traffic-control mechanisms and devices (managing congestion and ensuring safety); to serve as the basis for designing the roadways' pavements and geometry; to compare characteristics of road sections; to measure the development of land in the affected areas; a measure of air-quality compliance; to function as a means of validating travel modes; and to assist the process for decision making (Park, 2004; Shamo *et al.,* 2015; Sun & Das, 2015; Zhao & Chung, 2001). Therefore, transportation agencies commit a significant portion of their resources (finances and personnel) to various traffic-data collection programs. It is practically impossible to collect complete and extensive traffic data due to the associated cost (Zhao & Chung, 2001). However, an accurate determination or estimation of traffic volumes is important (Sun & Das, 2015; Sun & Das, 2019).

According to Albright (1991), traffic data collection and management have evolved since the 1930s. Summary statistics for traffic volumes served as an introductory AADT process for the transportation profession. In the 1930s, extensive manual-count activities characterized the AADT data collection. However, the mechanical measurement of traffic data was introduced in the 1940s. In the 1950s and 1960s, theoretical directions for annual traffic-summary statistics and calculations were provided. Occasionally, some uncertainties were encountered with the procedures, and until the late 1980s, the process was not challenged (Albright, 1991). Because the process was the only basis, reports were produced on the status of the roadways' traffic. Fekpe *et al.* (2004) and Tsapakis *et al.* (2016) noted that there are no universal methods to calculate the adjustment factors for the collected traffic data. Therefore, most states rely on the traffic management guide (TMG) to achieve corrected data. The transportation department uses its discretion to select sampling and AADT estimation techniques. Estimates of roadways with similar characteristics are used when it is impossible to access some road segments to conduct a traffic count.

Because there are fewer vehicles per day for the average daily traffic (ADT), Sharma *et al.* (2001) state that it may not be feasible to install automatic traffic recorders (ATR) for collecting continuous traffic data at set time intervals on low-volume roadways. These isolated locations with ATRs may not be reliable to determine AADTs. Furthermore, some ATRs may break down or become faulty, and they may need time to be fixed or replaced. As a result, vital data for the documentation and determination of AADT on the roadways may be lost. On low-volume roads, data-collection processes may be impeded by the high expense and time constraints (Apronti *et al.,* 2016; Tsapakis *et al.,* 2016). Due to scarce resources (human, capital, and equipment), it is uneconomical to collect consistent and systematic traffic data about low-volume roads.

The methods used to collect AADT data for low-volume roads involve counting traffic with a hand tally and/or video recording for two consecutive hours between 3 pm and 6 pm, or via automated traffic counter for either a period of two or 24 hours (PennDOT, 2014). Regardless of the vehicle's type and direction at the selected road segment, the vehicle is counted (PennDOT, 2014). Data-collection activities are completed to avoid seasonal activities (fluctuations) or circumstances that may lead to an artificially low average daily traffic count. Seasonal times may include summer recess periods for schools and temporarily or partially restricted road-segment areas (PennDOT, 2014).

Other methods for AADT data collection are non-traffic count-based and travel-demand models. The non-traffic count-based and travel-demand models use data such as socioeconomics, the census, land uses, road networks, and temporal variables (Tsapakis *et al.,* 2016). Furthermore, existing traffic count data may be validated or extrapolated to estimate AADT data. Although travel-demand models are used to estimate AADT for low-volume roads, the development and implementation cost compared to non-traditional models is high (Tsapakis *et al.,* 2016). In addition, travel-demand models are more challenging to implement than regression models (Tsapakis *et al.,* 2016). Much time is needed to create a transportation-analysis zone, which, likewise, requires information about the theory behind the travel-demand model's implementation and calibration for large rural areas (Tsapakis *et al.,* 2016).

Wang and Tsai (2013) emphasized that not much has been done about cost-effective data-collection plans. Therefore, Wang and Tsai (2013) recognized the need for finding cost-effective techniques for AADT data estimation, reducing data-collection locations, and maintaining data accuracy with a constrained budget. Despite the high costs associated with traffic-data collection, over-dependence on some of these datasets may be misleading, thus resulting in imprecise AADT data estimates, which affects the ultimate goal of planning and development.

Therefore, Tsapakis and Schneider (2015) suggested an integrated data-collection and estimation approach to achieve the desired accuracy.

Researchers in academia and some transportation officials have committed to techniques that ensure that the AADT data obtained for low-volume roads are accurate. For example, regression models and existing counts may accurately estimate an uncounted segment. The process also utilizes socio-economic data, network connectivity, and other information that is needed to predict AADT (Tsapakis *et al.,* 2016). For example, suppose an uncounted segment falls within a group of roads with similar characteristics. In that case, the AADT values for these roads are used for the uncounted segments (Tsapakis *et al.,* 2016). Researchers utilized regression methods to estimate some road segments in Alabama, Florida, Indiana, Kentucky, Minnesota, and Wyoming (Apronti *et al.,* 2016; Cheng, 1992; Deacon *et al.,* 1987; Lu *et al.,* 2007; Mohamad *et al.,* 1998; Raja *et al.,* 2018; Shon, 1989; Xia *et al.,* 1999). Others adopted logistic-regression methods (Apronti *et al.,* 2016), artificial neural networks (Sharma *et al.,* 2001), a traditional factor approach (Sharma *et al.,* 2000), the smoothly clipped absolute deviation (SCAD) penalty (*Yang et al.,* 2011; *Yang et al.,* 2014), geographically weighted regression (GWR) (Zhao & Park, 2004), Support Vector Regression (SVR) (Castro-Neto *et al*., 2009) geographical information system-based travel demand models (Zhong & Hanson, 2009), satellite imagery (Yang *et al.,* 2014), and spatial interpolation (Shamo *et al.,* 2015). Eom *et al.* (2006) considered spatial trends and spatial-correlation (geostatistical Kriging) methods for AADT estimates. A review conducted by Tsapakis *et al.* (2016) suggested substantial differences in the structure for these methods when estimating AADT on low-volume roads. The authors noted the differences with the techniques and error levels that resulted from data inaccuracies and input.

Staats (2016) also identified problems associated with several AADT estimating methods. For example, in the author's assertion, none of the methods could be directly applied to estimate the AADT on local roads in Kentucky. As a result, the models were modified before use, or new models, which were suitable for the purpose, had to be built. Therefore, Staats (2016) concluded that the models were created with conditions and characteristics to fit the areas for which they were developed. In addition, all the identified and documented estimating techniques asserted different levels of accuracy for AADTs that were determined or predicted at different locations (Park, 2004).

Further, some models (travel-demand models) were biased toward major roads and omitted most minor road networks (Tsapakis *et al.,* 2016). Therefore, although Staats (2016) suggested that these methods are acceptable for estimating AADT, some cautions and restrictions were advised. Otherwise, the resulting output may be associated with errors ranging from low to very high levels.

Tsapakis *et al.* (2016) suggested that these errors result when some estimators utilize adjustment factors from high-functional roads in low-volume road areas. These road types are expressively dissimilar in terms of characteristics and travel patterns when used for the estimating processes. In addition, low-volume roadways are homogenous compared to higher-classified roadways. As a result, the AADT values for low-volume roads are skewed due to high-count outliers (Wang & Kockelman, 2009). However, it is worth noting that models that are suitable for groups of counted roads which have similar features may be adopted for groups of uncounted roads (Tsapakis *et al.,* 2016). The disadvantage is the increased complexity, computing assumptions, and the needed knowledge about the statistical processes for non-traffic data (Tsapakis *et al.,* 2016). Some issues that limit the estimates' accuracy are the complications associated with segmenting roadways, the overwhelming experience required for data collection and the use of these estimating techniques, the process of inputting data from the several influencing factors for traditional methods, and the nonexistence of or inadequate AADT data (Tsapakis *et al.,* 2016). However, Park (2004) contended that some methods could not explain the influence of the independent variables' spatial variability on the dependent variables. However, geostatistics interpolate values at unmonitored geo-spaces of interest (Kethireddy *et al.,* 2014). Eom *et al.* (2006) and Wang and Kockelman (2009) indicated that Kriging is a better option for spatial extrapolation and the prediction of AADT when based on the points' nearest sampling site. Wang and Kockelman (2009) proposed using the Kriging techniques to make better predictions for decisions on pavement conditions, traffic speeds, population densities, land values, household incomes, and trip-generation rates.

The Federal Highway Administration (FHWA) (2015) strategic plan of anticipated improvements for traffic records (21st Century Act-MAP-21 and Fixing America's Surface Transportation Act [FAST Act]) requires the departments of transportation (DOTs) to report AADT data from all levels or functional classes of roadways within a state to the United States Department of Transportation. We intend to investigate and to select the best AADT estimating technique in order to support the agenda for this strategic plan. The best predictive method(s) is(are) intended to establish and to produce useful reports about low-volume roads while addressing the following issues: cost-effectiveness; time constraints; fewer staff requirements; reducing the difficulty with data input, least error(s); and unrestricted applicability. Also, the predictive model will combine local and global trends as well as spatial correlation and will be able to generate optimized data-collection locations from the model's output. The combined systematic literature review (SLR) and meta-analysis (MA) approach was utilized to document a list of peer-reviewed articles about estimating AADT for low-volume roads. The articles were quantitatively and qualitatively analyzed. Each AADT estimating methods' performance was considered and meta-analyzed in order to generate forest plots for the best method.

Methods

A combined SLR and MA were utilized for this study.

The SLR enabled the compilation of several published techniques that researchers used to estimate the annual average daily traffic (AADT) for low-volume roadways. Emphasis was placed on low-volume, local, and rural roads. In recent times, several researchers in different fields of study have utilized the combined SLR and MA approach to make inferences and to make better decisions. For example, Adebowale and Agumba (2021) adopted the combined SLR and meta-data analysis approach to investigate challenges undermining labor productivity growth in construction. Their findings resulted in workers' skills, inadequate training, rework, management style, and incentive to labor as the significant factors impacting construction labor productivity negatively. "To review trends of evolution, pinpoint strengths and gaps in the literature, and identify potential future directions for decision-making research in highway construction projects," to do away with subjective decision-making processes, a systematic review was conducted by Radzi *et al.* (2021) using systematic reviews and meta-analysis technique. According to Radzi *et al.* (2021), their reach finding shows four areas: feasibility, conceptual, detailed scope, and detailed design as existing decision-making tools in improving targets in highway construction projects.

Furthermore, Pansare *et al.* (2021) used a systematic literature review and analysis of RMS-related research papers from 1999 to 2020. In their research, Neale and Gurmu (2021) and Chellappa *et al.* (2021) adopted the systematic review of the literature approach. In addition, Neale and Gurmu (2021) investigated the impacts of production pressures in the building sector and proposed mitigation strategies accordingly. In contrast, in India, Chellappa *et al.* (2021) investigated construction workers' health and safety using a science mapping approach. Finally, Edwards *et al.* (2021) performed "a systematic review of the extant literature on the application of driverless technologies in civil engineering."

In this study, the systematic literature review attempted ''to identify, appraise, and synthesize all the empirical evidence that meets pre-specified eligibility criteria to answer a given research question'' (The Cochrane Library, 2013). The research was designed to complete the procedures proposed by Membah and Asa (2015), Hong *et al.* (2012), and Chan *et al.* (2020). The research articles were found using Boolean operators (AND, OR, and NOT), truncation (* and - symbols), and wildcards (a different word with similar meaning). Peer-reviewed journals, conference publications, technical reports, theses, and dissertations helped to critically conceptualize the concepts discussed in this study. The content analysis of publications about estimating the articles' methods was based on Tsai and Wen's (2005) publication. The critical review of the selected publications was based on Yi and Chan (2014). Finally, the quality assessment, data collection, and analysis were completed by adopting Kitchenham *et al.'s* (2009) processes.

The search procedure started with an all-inclusive search of the available, authoritative electronic databases. These databases included the American Society of Civil Engineering (ASCE); Transportation Research International Documentation (TRID, Transportation Research Board); Scopus; the Web of Science (WoS); and other sources through Yahoo, Google, and Google Scholar. A total of 370 articles associated with AADT were retrieved from these databases. The selected publications reviewed for this research were published between 1999 and 2020. Other articles falling outside of the years (1999–2020) also presented relevant information to guide the write-up. This vital information in the publications outside the stated period was only used to help emphasize the objectives or to introduce the research question. The articles were also selected by the source journal, the methods of AADT estimation used for low-volume roads in the publication, and the number of times a method has been used to explicitly answer the question of estimating AADT on low-volume and rural roads. The selected articles mainly concentrated on single or multiple AADT estimation techniques. The numerous AADT estimation techniques allowed for comparing the performance methods for low-volume and rural roads or for local roads. The final characterization of the publications was based on 19 articles (Table 1) directly related to the estimation of AADT and the evaluation methods for the low-volume and rural roads or the local roads. Figure 1 shows the flow of events for the systematic literature search. The collected articles were analyzed qualitatively and quantitatively to establish the number of techniques available for the low-volume rural or local roads' AADT estimation.

Several questions based on the analysis of the level of performance of each method employed and the adequacy of information in resolving the AADT estimates in the articles reviewed helped generate the understanding of the concepts and factors that affect the AADT estimation for low-volume roads. In addition, of interest and to better understand the processes, the following research areas were addressed with four compact questions:

1. What are the methods used for estimating AADT on low-volume roads?
2. What methods have been used most to estimate AADT on low-volume roads?
3. What are the shortcomings with the estimation techniques for AADT on low-volume roads?
4. What are the advantages and disadvantages of the estimation methods used on low-volume roads?

Meta-analyzing results from the 19 articles helped in selecting the AADT estimating methods. Kossmeier *et al.* (2020) adopted a combined meta-analysis and systematic reviews for their research. Schriger *et al.* (2010), Neyeloff *et al.* (2012), Liu *et al.* (2016), Li *et al.* (2020), and Tamilmanil *et al.* (2020) completed their studies using meta-analyses to understand the performance of the methods they explored. According to Li *et al.* (2020), "systematic literature reviews and meta-analysis are increasingly being used to summarize available evidence, develop guidelines, aid in decision-making, and direct future research." According to Neyeloff *et al.* (2012), a meta-analysis is essential to synthesize data from primary research. Simultaneously, the forest plot is a graphical

Table 1. **List of articles reviewed for AADT estimation methods associated with local, low volume, and rural roads.**

Author(s)/ Year	Title of Paper	Method used	Journal/Source
Sharma *et al.* (2001)	Application of Neural Networks to Estimate AADT on Low-Volume Roads	Artificial Neural Networks Short Applied Period Traffic Counts.	Journal of Transportation Engineering, 127(5): PP. 426-432
Sharma *et al.* (2000)	Estimation of Annual Average Daily Traffic on Low-Volume Roads	Traditional Factor Approach Versus Neural Networks Applied Short-Period Traffic Counts.	Transportation Research Record: Journal of the Transportation Research Board 1719, Paper No. 00-0125, PP. 103-111
Apronti *et al.* (2016)	Estimating Traffic Volume on Wyoming Low Volume Roads Using Linear and Logistic Regression Methods	Linear Regression Model and Logistic Regression Model	Journal of Traffic and Transportation Engineering, 3 (6): PP. 493-506
Raja *et al.* (2018)	Estimation of Average Daily Traffic on Low-Volume Roads in Alabama	Linear Regression, Known AADTs, And Collection of Socio-Economic and Location Variables	Transportation Research Board 97th Annual Meeting, Washington DC, United States
Doustmohammadi & Anderson (2019)	A Bayesian Regression Model for Estimating Average Daily Traffic Volumes for Low Volume Roadways	Bayesian Regression model	International Journal of Statistics and Probability; Vol. 8, No. 1
Zhong & Hanson (2009)	GIS-Based Travel Demand Modeling for Estimating Traffic on Low-Class Roads	Geographical Information System-based Travel Demand Models	Transportation Planning and Technology, 32:5, 423-439, DOI:10.1080/03081060903257053
Yang *et al.* (2011)	Efficient Local AADT Estimation via SCAD Variable Selection Based on Regression Models	Smoothly Clipped Absolute Deviation Penalty (SCAD) Variable Selection Based on Regression	Chinese Control and Decision Conference, IEEE Transactions on Intelligent Transportation System
Yang *et al.* (2014)	New Efficient Regression Method for Local AADT Estimation via SCAD Variable Selection	Smoothly Clipped Absolute Deviation Penalty (SCAD) with Satellite Image	IEEE Transactions on Intelligent Transportation Systems, 15 (6), PP. 2726 - 2731
Wang *et al.* (2013)	Estimating Annual Average Daily Traffic for Local Roads for Highway Safety Analysis	Travel Demand Modeling Method	Transportation Research Record: Journal of the Transportation Research Board, No. 2398, Transportation Research Board of the National Academies, Washington, D.C., PP. 60–66. DOI: 10.3141/2398-07
Pan (2008)	Assignment of Estimated Average Annual Daily Traffic Volumes on All Roads in Florida	Linear Regression and Social Economy	Graduate Theses and Dissertations
Xia *et al.* (1999)	Estimation of Annual Average Daily Traffic for Nonstate Roads in a Florida County	Multiple Regression Model, GIS	Transportation Research Record: Journal of the Transportation Research Board, https://doi.org/10.3141/1660-05
Khan *et al.* (2018)	Development of Statewide Annual Average Daily Traffic Estimation Model from Short-Term Counts: A Comparative Study for South Carolina	Support Vector Regression (SVR) and Artificial Neural Network (ANN).	Transportation Research Record, Vol. 2672(43) 55–64, DOI: 10.1177/0361198118798979

Emerald Open Research 2022, 4:13 Last updated: 27 JUL 2023

Author(s)/ Year	Title of Paper	Method used	Journal/Source
Chen *et al.* (2019)	Estimating Traffic Volume for Local Streets with Imbalanced Data	Combined Synthetic Minority Oversampling Technique (SMOTE) And Generalized Linear Mixed Model (GLMM)	Transportation Research Record Vol. 2673(3) 598–610, DOI: 10.1177/0361198119833347
Zhao & Chung (2001)	Contributing Factors of Annual Average Daily Traffic in a Florida County: Exploration with Geographic Information System and Regression Models	Geographic Information System and Multiple Regression Models	Journal of the Transportation Research Board, Transportation Research Record 1769, Paper No. 01-3440, PP 113-122
Eom *et al.* (2006)	Improving the Prediction of Annual Average Daily Traffic for Nonfreeway Facilities by Applying a Spatial Statistical Method	Spatial Regression	Journal of the Transportation Research Board, No. 1968, Transportation Research Board of the National Academies, Washington, D.C., PP. 20–29.
Klatko *et al.* (2017)	Addressing the Local-Road VMT Estimation Problem Using Spatial Interpolation Techniques	Kriging, Inverse distance weighting (IDW), natural neighbor (NN), and trend techniques.	Journal of Transportation Engineering, Part A: Systems, 143(8): 04017038-1 - 04017038-13, ASCE, ISSN 2473-2907.
Sun & Das (2019).	Estimating Annual Average Daily Traffic for Low-Volume Roadways: A Case Study in Louisiana	Support Vector Regression (SVR)	Transportation research circular Number E-C248, 12th International Conference on Low-Volume Roads, Kalispell, Montana
Staats (2016)	Estimation of Annual Average Daily Traffic Only Traffic on Local Roads in Kentucky	Nonlinear Regression	Theses And Dissertations--Civil Engineering, 36, https://uknowledge.uky.edu/ce_etds/36, http://dx.doi.org/10.13023/ETD.2016.066
Sfyridis & Agnolucci (2020)	Annual average daily traffic estimation in England and Wales: An application of clustering and regression modeling	standard multivariate linear regression, Random Forests (RF) and Support Vector Regression (SVR)	Journal of Transport Geography, 83, 102658

Emerald Open Research 2022, 4:13 Last updated: 27 JUL 2023

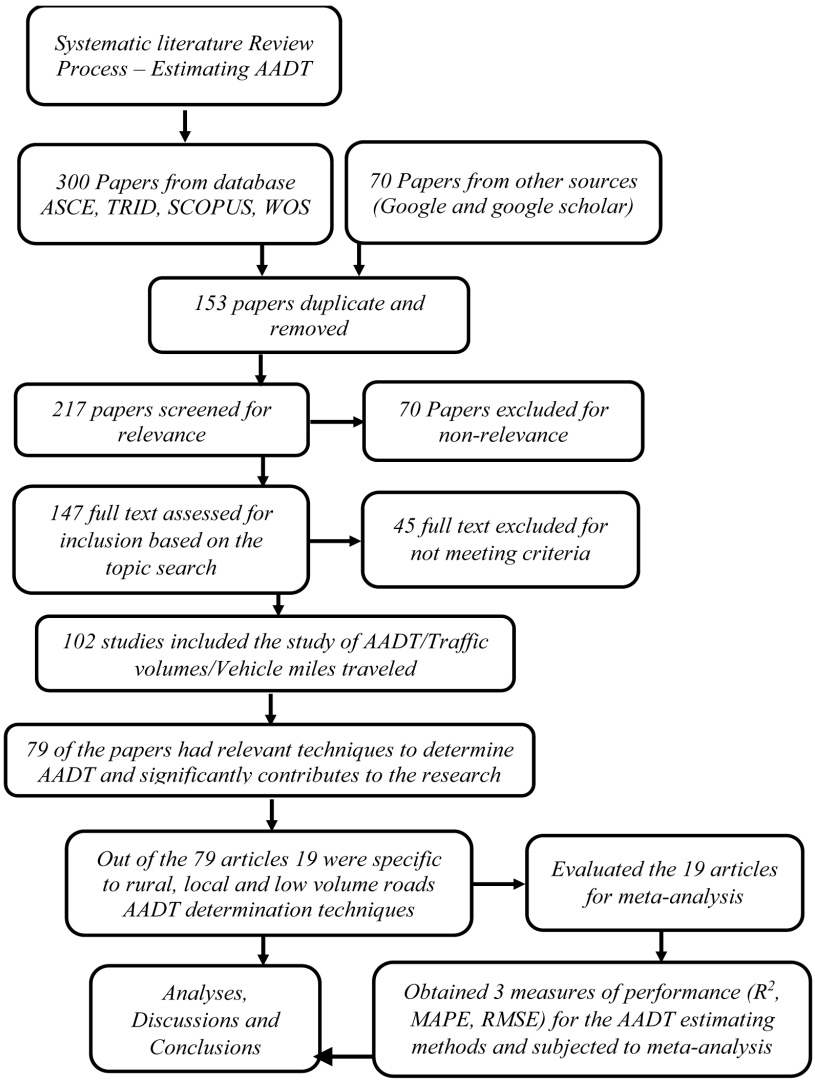

Figure 1. Flow chart of the systematic literature review process.

representation of the systematic and meta-analysis output (Li *et al.,* 2020). The forest plot makes it easier to view variations with different study results. The graphical representation shows the effect estimates and the confidence intervals. After reviewing the papers, the estimation methods were grouped into three categories based on their performance measures. These performance measures were methods of R squared (R^2), root means square error (RMSE), and mean absolute percentage error (MAPE). Because some performance measures differed and departed from these three, not all estimation methods could be placed in these three groups. Thus, the individual means to measure performance were not evaluated in the meta-analysis and the subsequent forest plots.

Each of the groups' analysis was completed based on the stated hypothesis: the null hypothesis assumed that all studies were equal. In contrast, the alternative hypothesis assumed that all studies were not equal or not of the same effect. To examine the null hypothesis that all studies evaluated the same effect may not be possible. Therefore, it was necessary to combine and to consider the heterogeneity of these test results with qualitative assessment studies in a systematic review. However, the summary effect was analyzed on fixed and random-effect models in order to test for the studies' homogeneity and heterogeneity. The fixed effect assumed that the parameter population and the effect size are the same, wherein assessments were considered to have been conducted under similar settings. Therefore, the error in the sampling process was attributed to the differences in studies. However, the random-effect samples assumed that the sample population can differ (Neyeloff *et al.,* 2012). The decision to use either a random effect or a fixed effect was dependent on the critical values associated with the number of degrees of freedom in the chi-square distribution when compared with the classical measure of heterogeneity (Cochran's Q). According to

Gavaghan *et al.* (2000), when the number of studies was small, Q had a low power as a comprehensive heterogeneity test. In contrast, Higgins *et al.* (2003) asserted that Q has too much power to test heterogeneity if the number of studies is large. Besides, each of the studies' mean effect in comparison was different and varied with the population. Because the literature search was a product of various studies, different evaluation paths and effects were analyzed with the search. In a study with nonsimilar means from a universe of population, Neyeloff *et al.* (2012) recommended using the random-effect model to enable meta-analysis for a dataset. It was assumed that the sampling error and the population effect contributed to the variability. According to Higgins and Thompson (2002), the percentage of variation across studies due to heterogeneity is described using the I^2 statistic. The inconsistency with the studies' results is expressed with an intuitive I^2. $I^2 = 100\% \times (Q\text{-}df)/Q$. I^2 contrasting Q does not characteristically depend upon the number of studies considered. The forest plots depict the results as a universal path of measures.

Results

This subsection discusses the results of the systematic literature review and the meta-analysis. 300 papers were initially download from ASCE (51), TRID (38), SCOPUS (85), and WOS (126). 70 others were obtained from Yahoo, Google, and Google Scholar. However, most of these publications were cross-referenced. The resulting articles are based on the methods used when gathering articles from the electronic databases, the research questions, and the measure of model performance. In this section, five steps are developed. The first step is aligned with research question 1. Step 1 is identified and outlined from the 19 articles reviewed the methods used in estimating AADT for low-volume roads. The second step is determined from the listed techniques and their frequency of being mentioned in the journals. Step three looks at the reasons for the shortcomings. The fourth step compiles the reviewed papers and other sources' advantages and disadvantages for some estimating methods in order to ensure accurate conclusions. Finally, step five assesses the performance measure using meta-analysis and forest plots.

Research question one

What are the methods used for estimating AADT on low-volume roads?

This question is to help describe the techniques used when estimating AADT for low-volume roads. Table 2 provides an example of the summary techniques extracted from various publications. Table 2, therefore, depicts the methods that the 19 articles' authors identified for AADT estimation on low-volume roads. The sources for the 19 documents are presented in Figure 2. Besides the sources, the number of documents per source is highlighted. Therefore, Figure 2 illustrates the sources and the number of publications.

The *Journal of Transportation Research Records* had the most with seven articles. Three publications were obtained from conference proceedings. Two publications were found in the *Journal of Transportation Engineering* and graduate theses and dissertations. The *Journal of Geography*, the *Journal of Traffic and Transportation Engineering*, and the *International Journal of Statistics and Probability* each had one article. Figure 3 displays the number of publications and the years. The most publications about low-volume roads' AADT, per the inclusion criteria, in a year, were in 2019 (three articles). The years 2001, 2016, and 2018 each had two publications. There were no publications relating to the subject in 2002, 2003, 2004, 2005, 2007, 2010, 2012, and 2015. Besides these dates and the ones mentioned earlier, each year was only associated with a single publication. Although researchers are making efforts, there seems to be much room for more work due to the lack of significant publications.

Table 2. List of AADT estimation methods found in the publications reviewed.

AADT estimation methods for low-volume roads
Artificial neural networks
Traditional factor approach
Regression methods
Geographical information system-based
Smoothly clipped absolute deviation (SCAD) penalty
Satellite-based Imagery
Travel-demand modeling method
Synthetic minority oversampling technique (SMOTE)
Generalized linear mixed model (GLMM)
Kriging (Geostatistics)
Inverse distance weighting
Natural neighbor (NN) and trend techniques
Random Forest

Research question two

What methods have been used most to estimate AADT on low-volume roads?

This subsection discusses the number of times that a method has been utilized. The methods were tallied using the 19 papers that met the inclusion criteria. Figure 4 displays the number of times, or the frequency, that a technique was counted. Although 19 articles were used in the study, the number of estimating methods was 30. Some authors utilized more than one method to enable comparison. The process showed the shortfalls for the techniques' performance. From the compiled methodology, the regression methods were utilized the most, a total number of 13 times, thus representing 43.33% of the methods tallied. The artificial neural network (ANN) model was explored three times (10%); smoothly clipped absolute deviation (SCAD), Geographical Information System (GIS), and the travel-demand model were each used twice (7% each).

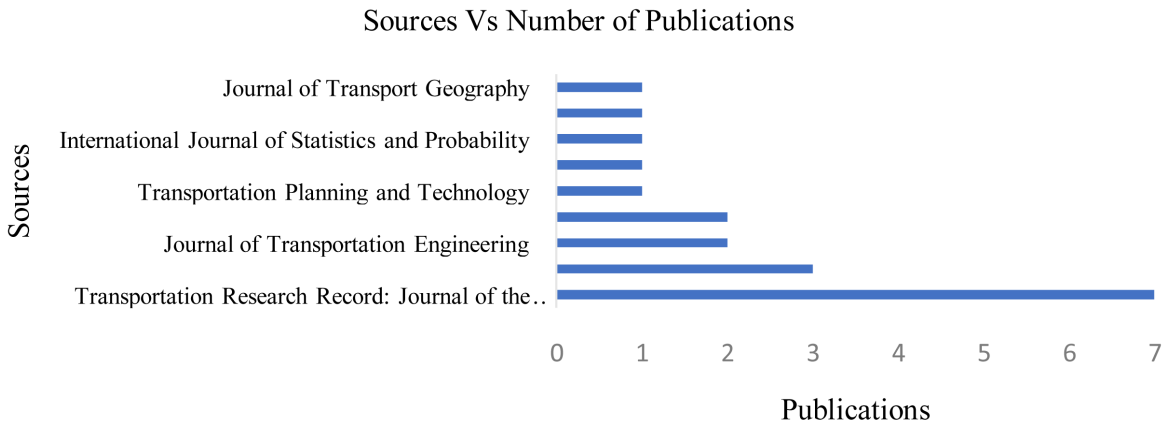

Figure 2. **Sources versus the number of publications.**

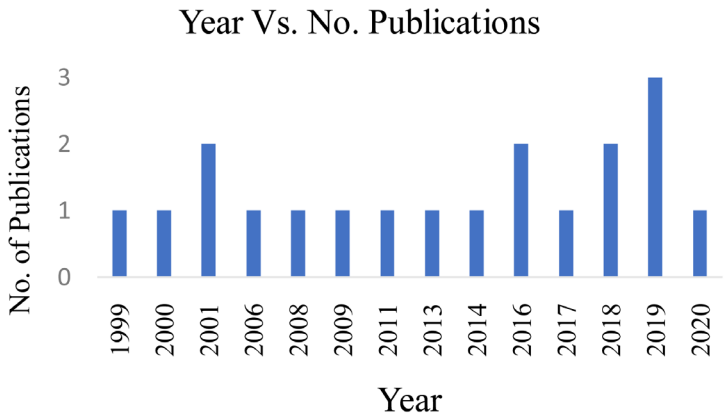

Figure 3. **The number of publications versus the year of publication.**

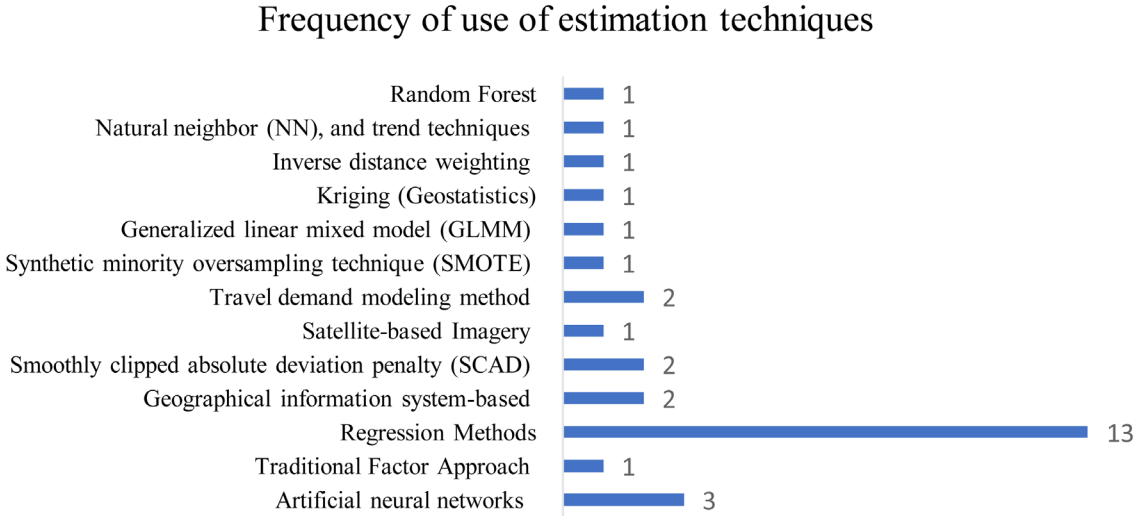

Figure 4. **Consolidated methods and the number of times they were counted.**

The rest of the techniques were employed once. Figure 5 represents the breakdown of the regression method into various types. Support-vector (23%), linear (23%), and multiple (23%) regressions were utilized three times. In contrast, spatial, non-linear, Bayesian, and logistic regressions were used once (about 8% for each technique).

Research questions three and four

What are the shortcomings with the estimation techniques for AADT on low-volume roads?

What are the advantages and disadvantages of the estimation methods used on low-volume roads?

Table 3 is a brief review of the selected articles and illustrates some of the authors' conclusions. Table 3 also has some factors that influence the AADT estimation accuracy.

This section outlines the advantages and disadvantages for the methods used to estimate AADT on low-volume roads. Analyzing these advantages and disadvantages (examples in Table 4) helps to explain and to comprehend the reasons why researchers have utilized these regression techniques. The easy-to-use and apply regression techniques allow for quick AADT estimates.

PennDOT (2014) notes that, because most counts on low-volume roads are for short intervals, are short-duration counts, and have minimal data points, the regression technique becomes ideal for estimators. The regression technique is utilized most because the other techniques have some bottlenecks to overcome in order to make exploration possible. Therefore, most of the techniques have not been explored much. However, the

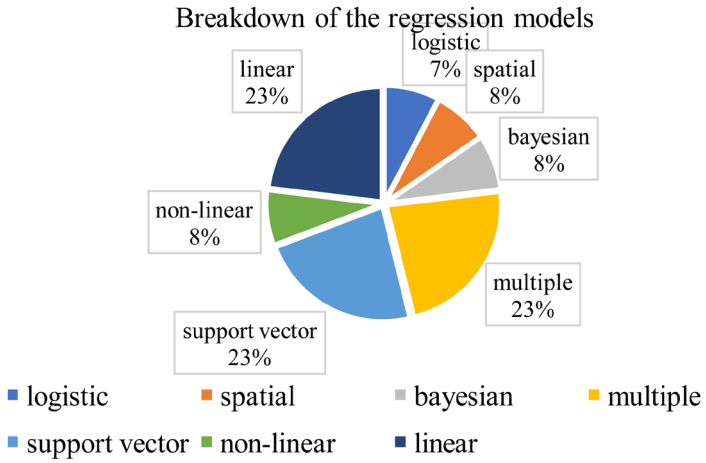

Figure 5. Percentages for the most-used regression techniques.

Table 3. Observations from published papers utilized for qualitative and quantitative analysis, highlighting the importance, shortfalls, and applicability on the various road segments.

Author(s)	Comments
Wang & Kockelman (2009)	AADT values for low-volume roads tend to be skewed due to high-count outliers that result from inadequate data collection in the process.
Apronti *et al.* (2016)	Linear-regression methods are prone to errors compared to logistic regression, especially "when there is a need to identify roads impacted by industrial activities for road maintenance scheduling."
Raja *et al.* (2018)	The linear-regression technique used for AADT determination is subjectively completed for low-volume or off-system roads when there is a need to compare and rely on similar roads. Thus, the estimates are probably characterized with errors.
Wang *et al.* (2013)	The authors compared the travel-demand modeling method and the regression-based method for AADT estimation and found that the travel-demand method had expressively lower mean absolute percentage errors.
Khan *et al.* (2018)	Support-vector regression (SVR), an artificial neural network (ANN), a regression-based model, and a factor-based model were compared to predict AADT by using short-term counts. Support-vector regression (SVR) provided superior and accurate results over all the methods to estimate AADT for the different functional classes of roadways. The errors for estimating AADT were minimal compared to the ANN, regression, and factor-based models.
Zhao & Chung (2001)	Geographic information system technology and multiple linear regression models were used for low-volume road AADT estimation. The models may not be applicable to other urban areas.

Table 4. **Estimation techniques: advantages and disadvantages.**

Methods	Advantages / Disadvantages
Regression (compiled from Apronti *et al.*, 2016 & others)	**Advantages:** Easy to group; highly aggregated; easy in application and use; linear regression of daily short-count volumes give more accurate results than the factoring method; In theory, a minimum of data points is sufficient to complete linear regression analysis. **Disadvantages:** Ignores the difference among roadways in the saved classification group; ordinary linear regression techniques are commonly used for purposes of future-year AADT estimation; to ensure a robust correlation, a maximized and significant data points are required; require a minimum number of days for count validation; Site visits of two or more needed to obtain needed minimum data; regression-analysis approach matches short-term counts to permanent counters based on the actual variation in the short-term count; regression methods require significantly more computational resources, which is more complex
Travel demand (compiled from Bassolas *et al.*, 2019; Wang *et al.*, 2013; & others)	**Advantages:** Needs data update at least annually, which makes it possible to update the AADTs in response to lane use changes; Consistently represents time, persons and households, time-dependent routing; The fundamental assumption is activity-based, which originates from persons executing their daily activities. **Disadvantages:** Need several parcels to be pre-processed to improve the model's efficiency; Needs microsimulation of travel demand and traffic; Practical application is still limited; Huge amount of very detailed input data is hard to get with surveys; Travel demand models do not account for spatial dependence, thus serves as a potential cause of inaccurate and flawed predictions; There is only a little literature addressing the accuracy of their predictions; The literature existing raises serious doubts regarding the accuracy of travel demand prediction.
Traditional Factor Approach (Sharma *et al.*, 2000; & others) Robichaud & Gordon (2003)	**Advantages:** Short-term counts are assigned to a group by reviewing functional classification characteristics, seasonal patterns, geography, and surrounding development levels. The determination of seasonal and daily factors requires a minimum dataset to ensure statistical validity. Factors can be developed to estimate AADT volumes from less than 1 day in length counts. Grouping the permanent counters according to functional class or region helps to assign the short-term counters to a defined class and the matching of short-term counters to the most appropriate factor group. **Disadvantages:** It is essential to have a firm understanding of all the traffic characteristics to ensure an adequate number of groups are developed to describe each seasonal pattern; high errors are associated with estimates of the annual traffic summary statistics from less than 24 hours of traffic data; Short-term counter classification into factor groups requires significant professional judgment and local knowledge; it is necessary to redefine the factor groups according to highway functional classifications or geographic regions to aid matching if traffic is sampled only once; the accuracy of the factors is reduced when group variability increases; a subjective approach resulting in less-than-ideal average group factors.
Stratification method	**Advantages:** Better results than the traditional sampling Methods **Disadvantages:** Not useful when the population cannot be exhaustively partitioned into disjoint subgroups
Clustering and regression trees	**Advantages:** Analyzing AADT for roadways with similar characteristics **Disadvantages:** No specific models
Support vector regression with data-dependent parameters (SVR-DP) – Modified version of a pattern recognition technique known as Support vector regression	**Advantages:** Highly aggregated at county by rural and urban with good results, SVR-DP reduces uncertainties relating to the selection of parameters and time for computations; SVR-DP achieves better predictors; The foundational theories of SVR-DP are ideal for predicting traffic volume; The SVR-DP technique accurately predicts when no external explanatory variable is used; Smaller support vector parameter values are guaranteed, and a less complicated model is obtained with data-dependent parameters. **Disadvantages:** Ignores the difference inside a large geographic area or roadway class; Not appropriate for future-year AADT estimation studies because the external variables needed to be predicted into the future may introduce significant error to the model
Fuzzy theory and artificial neural network Mahanta (2019) and Mijwil (2018)	**Advantages:** The algorithms model intricate patterns and predict problems. The processes of generating the algorithm are based on the brain process. ANN is best used in forecasting and image processing, and character recognition. Considers uncertainty, Learns and models non-linear and complicated relationships, Stores information on the entire network, not on a database. Therefore, the loss of some information does not prevent the network from running; Can generalize relationships unseen and an unseen date can be inferred, or able to work with incomplete knowledge; No restriction imposition on input data, and fault tolerance; Better models heteroskedasticity (data with high volatility and non-constant variance); Able to make machine learning. **Disadvantages:** Uses pre-defined aggregated roadway grouping; Depends on hardware – processors with parallel processing power make its realizations equipment dependent; Network behavior cannot be explained, it means solutions produced does not indicate why and how, thus, less trusted in the network; There is not a laid down rule for specific determination proper network structure of ANN. ANN is achieved through trial and error and experience; the network's performance is influenced by the process of transforming information into numerical values before use in ANN; The duration of the network is unknown, and thus results obtained may not be optimum.

Emerald Open Research 2022, 4:13 Last updated: 27 JUL 2023

Methods	Advantages / Disadvantages
GIS-based -(Paramasivam, 2019)	**Advantages:** Highly supportive in all kinds of environments; easy to visualize the spatial information in output maps with groups in different colors, patterns, and clear legends; supportive of all database operations (creation, updating, and manipulation); map accuracy depends on the quality of input data; offers an influential decision-making tool in its administration, policy-making, and instructions; monitoring safety; mapping and surveilling infrastructures; routing; planning; present patterns; interpret spatial correlation targeting potential resources; use for efficient management of resources; for site selection, zoning, planning, and conservation measures; combined GIS and geostatistical technologies incorporated with spatial data and interpolation techniques can be applied to the exploration, assessment, and prediction; integrates spatial and nonspatial data to enable better understanding; refine datasets, data models, and the relation between attributes; allows for existing attributes to be linked with newly defined dataset. **Disadvantages:** Expensive; complex setup; training cost; errors in results are due to the frequency of updating of datasets or data models; deals with real-time parameters; overall challenge arising from handling growing datasets; increase with larger-scale data results in geographical errors; data quality directly affects the accuracy; net results are affected by geographic errors; relative loss of resolution; positional accuracy and precision are the functions of the scale of paper or digital map created; any nonspatial data linked to location may also be inaccurate or imprecise; inaccuracies result from mistakes; nonspatial data vary greatly in precision; l privacy violation as is not limited to authorized persons; interpretation is error-prone; failures in initiating or additional effort is required to implement fully; lack of trained persons in the domain and has not been taught to the fullest extent
Kriging Methods (Arfaoui & Inoubli, 2013)	**Advantages:** Less error and statistically significant; used to fill-in missing spatial values of satellite-derived data; allows for estimating the unknown; no dependence on the functional classification to estimate AADT effectively, minimal interactive modeling; Standard errors of prediction are more accurate; Spatial and nonspatial variability of random variables can be studied; the determination of the weights is based on the unbiased and optimality conditions; the unbiased condition shows the exactness of the kriging interpolator; works on both stationary and non-stationary data; kriging is controlled by variance estimation which locates the sector of significant error; the semivariogram explains the relationship and difference between the measured and predicted values with the help of spatial auto-correlation and distance measurement; the techniques enhances the distribution of spatial data; techniques offer convenient management of resources; expert interpretation; model-based approach of these techniques optimizes the accuracy of the obtained result; techniques have the ability to reproduce the trend and provide continuity which allows for precise interpretation. **Disadvantages:** Ignores the difference within each roadway classification; it estimates the value for the center of each unmeasured grid cell with prediction assumption; points location may be a problem with sampling distribution being random; requires user proficiency; dataset used in the interpolation process might have errors; Spatial interpolation evaluates physical data in a continuous domain; result depends on data input the correctness

Emerald Open Research 2022, 4:13 Last updated: 27 JUL 2023

geostatistics (Kriging) method has proven (in other disciplines) to be accurate with minimal errors compared to the associated errors with the regression methods. The regression methods require significantly more computational resources, which, in turn, is more complicated. The Kriging method requires minimal interactive modeling; standard errors of prediction are more accurate; the random variables' spatial and nonspatial variability can be studied; the weights are based on the unbiased and optimality conditions, and the terrain has no influence on the output. The techniques can reproduce the trend and provide continuity, allowing for precise interpretation.

Meta-analysis

Table 5, Table 6, and Table 7, together with Figure 6, Figure 7, and Figure 8, characterize the output from these meta-analyses. The tables depict the resulting analysis while the figures present the pictorial forest plots representing the outcomes. Table 5 shows a summary output for the meta-analysis of AADT estimation methods with R^2 as a measure of model performance. Table 5 provides the authors/publication years, methods, sample sizes, model performance measures, standard errors, and confidence intervals (lower and upper). The table also lists the study's hypothesis and other essential model parameters for the meta-analysis. These parameters explain the value of the heterogeneity test (Q) for the variables and the results' statistical significance.

Ten studies were evaluated (Table 5). The resulting heterogeneity test for both the fixed-effect and random-effects models suggested a random-effect model for model validation. We failed

Table 5. Summary of the meta-analysis generated by using the AADT estimation methods with R^2 as a measure of performance.

Authors	Methods	Events	R^2	(SE)	CI Lower	CI Upper	CD	R^2(%)	CI Lower	CI Upper
Zhao & Chung (2001)	Regression Models	49	0.74	0.12	0.50	0.98	11	74.00	24.09	172.09
Yang *et al.* (2011)	SCAD	200	0.65	0.06	0.54	0.76	10	65.00	11.17	141.17
Khan *et al.* (2018)	Support-Vector Regression	7	0.92	0.36	0.21	1.64	9	92.40	71.21	256.01
Apronti *et al.* (2016)	Linear-Regression Model	13	0.64	0.22	0.21	1.08	8	64.00	43.49	171.49
Xia *et al.* (1999)	Multiple Regression, GIS	450	0.63	0.04	0.56	0.70	7	63.00	7.33	133.33
Raja *et al.* (2018)	Linear Regression	205	0.84	0.06	0.72	0.97	6	84.00	12.55	180.55
Raja *et al.* (2018)	Quadratic	205	0.82	0.06	0.70	0.94	5	82.00	12.40	176.40
Raja *et al.* (2018)	Logarithmic	205	0.53	0.05	0.43	0.63	4	53.00	9.97	115.97
Zhong & Hanson (2009)	GIS-Based Travel Demand	55	0.54	0.10	0.35	0.74	3	54.14	19.45	127.73
Yang *et al.* (2014)	SCAD with Satellite Image	200	0.66	0.06	0.55	0.77	2	65.94	11.25	143.13
Effect Summary			0.67	0.04	0.60	0.75	1	67.50	7.42	142.41

SE= Standard Error, CI = 95% Confidence Interval, CD = Countdown, SCAD = Smoothly Clipped Absolute Deviation Penalty, and GIS = Geographic Information Systems.

H_o:	All studies are equal.					
H_1:	All studies are not equal.					
K (Number of studies)	**10**		Scaling Factor (c)	**611.56**		
df (Degrees of freedom)	**9**		Q	**8.27**	< Critical value 16.919, fail to reject H_o	
			I^2	**-8.90**	Low	
Q (Test of heterogeneity)	**23.90**	> Critical value 16.919	T2	**-0.001**		
I^2 (Quantify heterogeneity)	**62.34**	High	es (Random effect)	**0.68**		
			SEes (Random)	**0.04**		
es (Effect summary: fixed effect)	**0.66**		CI (Random) 95%	**0.60**	**0.75**	Random has a broader CI than fixed.
SEes (Fixed)	**0.02**		Z-Value	**17.84**		
CI (Fixed) 95%	**0.62**	**0.70**	P-Value	**0.00**		
Z-value	**32.42**					

Table 6. Summary of the meta-analyses generated from the AADT estimation methods with MAPE as a measure of performance.

Authors	Methods	Sample Size	MAPE %	SE	CI Lower	CI Upper	CD	MAPE	CI Lower	CI Upper
Sfyridis & Agnolucci (2020)	SMLR	19,000	15.69	0.03	15.63	15.75	10	1,569	5.63	3,143.63
Sfyridis & Agnolucci (2020)	Random Forests (RF)	19,000	14.48	0.03	14.43	14.53	9	1,448	5.41	2,901.41
Sfyridis & Agnolucci (2020)	SVR	19,000	14.47	0.03	14.42	14.52	8	1,447	5.41	2,899.41
Pan (2008)	Linear Regression	2	46.79	4.84	37.31	56.27	7	4,679	948.02	10,306.02
Khan *et al.* (2018)	SVR	7	12.00	1.31	9.43	14.57	6	1,200	256.62	2,656.62
Khan *et al.* (2018)	ANN	7	23.50	1.83	19.91	27.09	5	2,350	359.12	5,059.12
Khan *et al.* (2018)	Factor-based model	7	16.40	1.53	13.40	19.40	4	1,640	300.01	3,580.01
Wang *et al.* (2013)	TDM (78 counting)	10	52.00	2.28	47.53	56.47	3	5,200	446.95	10,846.95
Wang *et al.* (2013)	Regression models	10	211.00	4.59	201.99	220.00	2	21,100	900.32	43,100.32
Effect Summary			**20.00**	**0.55**	**18.93**	**21.08**	**1**	**2,000**	**107.46**	**4,107.94**

SMLR= Standard Multivariate Linear Regression, SVR = Support Vector Regression, ANN= Artificial Neural Network, and TDM = Travel Demand Modeling.

H_o:	All studies are equal.				
H_1:	All studies are not equal.				
K (Number of studies)	**9**		Scaling Factor (c)	**2.73**	
df (Degrees of freedom)	**8**		Q	**1900.84**	> 15.507 @ 95 CI, reject H_o, studies are not equal
			I^2	**99.58**	high heterogeneity
Q (Test of heterogeneity)	**3383.50**	> 15.507 @ 95 CI	T2	**692.67**	
I^2 (Quantify heterogeneity)	**99.76**	high heterogeneity	Es (Random)	**20.00**	
			SEes (Random)	**0.55**	
es (Effect summary: fixed effect)	**14.86**		CI (Random)	**18.93**	**21.08**
SEes (Fixed)	**0.02**		Z-Value	**36.48**	
CI (Fixed) 95%	**14.83**	**14.90**	P-Value	**0.00**	
Z-Value	**920.79**				

to reject the studys' null hypothesis with the random-effect model because the critical chi-square value for nine degrees of freedom was more significant than the Q value. The critical chi-square was at a Q value of 8.287 for the random-effects model compared to the 16.919 critical chi-square value. The Q value of 23.90 for the fixed-effect model could not be used because it was more significant than the critical chi-square value. I^2, quantifying the heterogeneity, had a value of -8.90 with the random-effects model, showing low heterogeneity variability between the studies. With the fixed-effect model, the value was 62.34,

Table 7. Summary of meta-analyses generated from the AADT estimation methods with RMSE as a measure of performance.

Authors	Methods	Events	RMSE (%)	SE	CI Lower	CI Upper	CD	RMSE	CI Lower	CI Upper
Doustmohammadi & Anderson (2019)	Linear Regression	205	32.81	0.40	32.03	33.59	5	3,281	78.41	6,640.41
Doustmohammadi & Anderson (2019)	Bayesian Regression	205	31.09	0.39	30.33	31.85	4	3,109	76.33	6,294.33
Apronti *et al.* (2016)	Linear Regression	13	73.40	2.38	68.74	78.06	3	7,340	465.73	15,145.73
Apronti *et al.* (2016)	Logistic Regression	13	83.50	2.53	78.53	88.47	2	8,350	496.74	17,196.74
Effect Summary			**54.54**	**5.13**	**44.48**	**64.61**	**1**	**5,454**	**1006.17**	**11,914.87**

H_o:	All studies are equal.				
H_1:	All studies are not equal.				
K (Number of studies)	4		Scaling Factor (c)	0.03	
df (Degrees of freedom)	3		Q	20.97	> 7.815 @ 95 CI, reject Ho, studies are not equal
			I^2	85.69	high heterogeneity
Q (Test of heterogeneity)	710.28	> 7.815 @ 95 CI	T2	631.42	
I2 (Quantify heterogeneity)	99.58	high heterogeneity	Es (Random)	54.54	
			SEes (Random)	5.13	
es (Effect summary: fixed effect)	33.09		CI (Random)	44.48	64.61
SEes (Fixed)	0.28		Z-Value	10.63	
CI (Fixed) 95%	32.55	33.63	P-Value	0.00	
Z-Value	120.12				

indicating a high variability among the studies. Therefore, confidence intervals (lower and upper) with a broader range for random effects were used.

This corresponds to the random-effect model with a CI between 0.60 and 0.75 instead of the fixed effects of 0.6 to 0.70. The P-value at 0.00 was less the 0.05, making it statistically significant. Figure 6 is the forest plot for Table 4. The plot was generated using Microsoft Excel and followed what was described in Neyeloff *et al.* (2012). The graph has scatter markers of different colors and shapes, horizontal lines running through the markers, and a vertical line representing the central tendency. The large, black diamond marker corresponds with the studys' effect summary.

In contrast, the length of each horizontal line corresponds with the spread of that studys'95% confidence intervals. The horizontal lines are, conceivably, the essential part of the graph. A line crossing the vertical line (line of null effect) indicates no difference in the studies.

In contrast, if the horizontal line does not cross the vertical line, then there is evidence of statistical differences between the evaluated studies. If all horizontal lines cross the vertical line, there is evidence that all of the studies are in agreement. However, the vertical line is the central tendency in the forest plot. Therefore, the proximity of each studys' markers to the central tendency gives the agreement associated with the summary effect. Figure 6 illustrates that all evaluated studies agree, thus similar. All markers are also close to the vertical line despite the slight separation for some markers. Khan *et al.*'s (2018) AADT estimating method is a little widespread from all other studies.

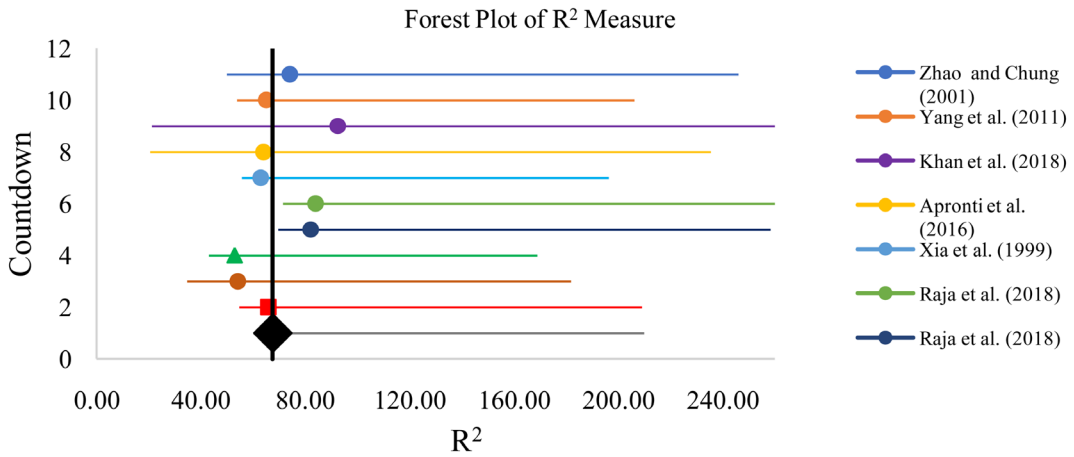

Figure 6. **Forest plot for the R2 measure of the AADT estimation's performance.**

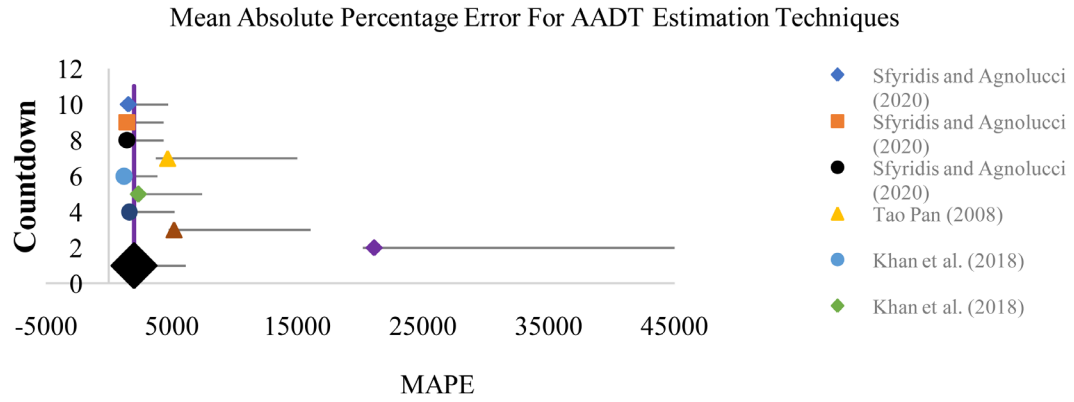

Figure 7. **Forest plot for the MAPE measure of the AADT estimation's performance.**

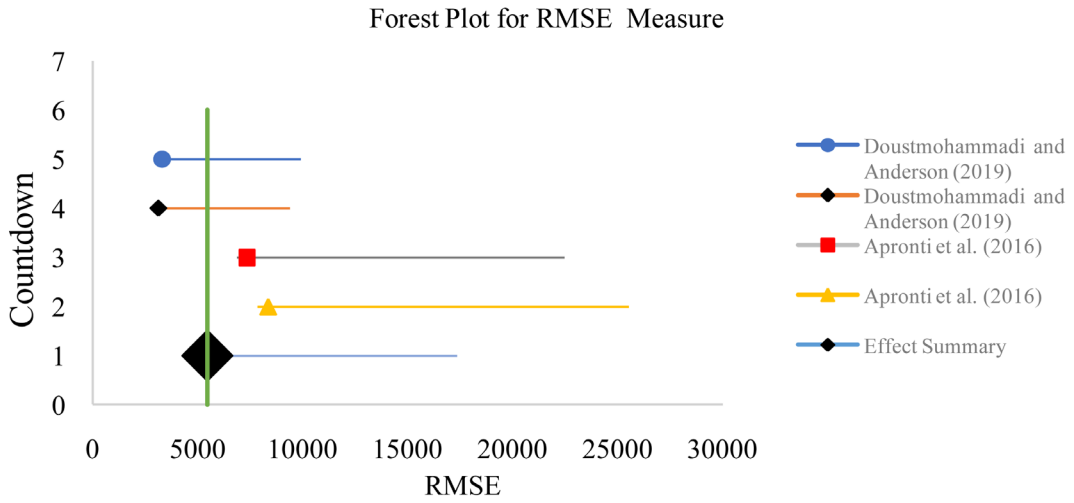

Figure 8. **Forest plot for the RMSE measure of the AADT estimation's performance.**

Similarly, Table 6 and Table 7 display a summary of the meta-analysis for the measure of model performance when using the mean absolute percentage error (MAPE) and root means square error (RMSE). Nine and four AADT estimating methods, respectively, were meta-analyzed based on the MAPE and RMSE performance measures. In both cases, the evaluation utilized the random-effects model. The studies indicated high heterogeneity for each case when the Q values were compared to the critical chi-square value for the associated degrees of freedom. I^2 values for the two studies were high, indicating high heterogeneity for the studies variability. However, P-values at 0.00 for both outputs indicated statistical significance at a 95% confidence level. Nonetheless, the null hypothesis was rejected in both cases, suggesting that the evaluated studies were not the same. Figure 7 displays the forest plot for the MAPE measure of the AADT estimation's performance with heterogeneity. All the studies except one were similar to the summary effect. This exception corresponded with Wang *et al.*'s (2013) regression models. In Figure 8, the forest plot for the RMSE measure of the AADT estimation's performance depicted high heterogeneity. The studies from the Wang *et al.* (2013) exhibited similar characteristics. For example, the two studies of Doustmohammadi and Anderson (2019) had similar characteristics. Apronti *et al.*'s (2016) two studies were also the same. However, both of their studies were plotted on opposite sides of the central tendency.

Discussion

Several estimating techniques evolved after the literature search was conducted. Utilizing the authors' knowledge in specialty areas, other methods were established. However, further studies are in progress to improve the output. These techniques are believed to bring about dynamics in the industry and help solve estimation precision. The annual average daily traffic (AADT) dataset is required for roadways throughout the United States. Thus, estimation is done at the federal, state, and local levels (Jessberger *et al.*, 2016). Chen *et al.* (2019) acknowledge the importance of AADT data estimation for traffic engineering. Chen *et al.* (2019) suggest that AADT data are essential for transportation planning and traffic monitoring and guarantee cost savings to data collection.

Chen *et al.* (2019) stressed the limitation of allocating automatic traffic recorders (ATRs) to collect AADT data. The ATRs are mostly installed on arterial roads, not local streets or low-volume roads, because of the associated cost. Chen *et al.* (2019) noted that arterial road capacity is gradually becoming inadequate for the growing traffic demand; thus, local street traffic continues to grow in terms of traffic volumes. As a result, there is a need to predict AADTs for the local streets to avoid skewed and under-representing the services that these road networks deliver. There is no specific convention adopted globally except to modify existing models. However, there is some guidance from the federal highway authority. Nonetheless, Jessberger *et al.* (2016) asserted the AASHTO's AADT estimation formula as, typically, the most generally used method. The AASHTO estimation formula can be adopted and used in many circumstances, but not without issues. A characteristic example of a possible issue is the common measurement issue associated with permanent traffic-counting sites where there are missing observations for the hourly traffic volume. An additional limitation with the AASHTO's AADT estimation formula is the inability to interpret disparities in the numbers of the day of the week in a month or discrepancies in the days of a month (Jessberger *et al.*, 2016). The regression analysis, traditional factor approach/seasonal adjustment factors, travel-demand modeling method, artificial neural networks, cluster analysis, satellite-based imagery, and Kriging, to mention a few, are some models identified. These techniques may be utilized for AADT estimation on low-volume roads. However, there have also been counterarguments about the shortfalls, except under conditions where the techniques are combined.

Consequently, additional validation may be needed to confirm the model's appropriateness. Staats (2016) affirmed that, in a bid to adopt the ordinary linear regression model developed by Zhao and Chung (2001), which was based on Florida's road-network conditions, it was only possible to use the model when modifications were made in order to suit the characteristics of Kentucky. The model that was suitable in Florida was not appropriate for direct use on Kentucky's roads. Notwithstanding, Zhao and Chung's' (2001) models presented R-squared values that ranged from 0.66 to 0.82. Mohamad *et al.'s* (1998) ordinary linear regression model could only be applied to estimate AADT for areas with existing AADT data. Mohamad *et al.* (1998), when comparing their model to real, existing AADT data, estimated errors from approximately 1.6% to 34.2%. According to Raja *et al.* (2018), linear-regression techniques were subjective when employed to estimate AADT. Corresponding to Zhao and Park (2004), the geographically weighted regression models accounted for spatial variability in the transportation network. The model generated high R-squared values and minor estimation errors. Utilizing Zhao and Chung's (2001) data showed that the model outperformed the ordinary linear regression models introduced by Zhao and Chung (2001). Thus, the geographically weighted regression model generally estimates AADT better than ordinary linear regression models.

Furthermore, Apronti *et al.* (2016) cautioned users about the errors associated with linear-regression methods. However, those authors developed two effectual, cost-effective, and easy-to-use models (linear and logistic regression) to predict traffic volumes for low-volume roads in Wyoming. The linear-regression model gave an R^2 value of 0.64 and a root mean square error of 72.34%. The logistic-regression model was completed by classifying the road percentages into five thresholds. These thresholds resulted in a correctly classified range from 79% to 88%. Doustmohammadi and Anderson (2019) utilized the Bayesian regression model to generate ADT estimates for low-volume rural and local roads in 12 of Alabama's counties. Doustmohammadi and Anderson (2019) asserted that linear regression is not always optimal for developing prediction models. Although wildly understood, linear regression cannot account for data distribution or the variability of point estimates.

Aside from regression models, artificial neural network (ANN) models, in multiple arrays, have also been explored extensively to estimate AADT (Khan *et al.,* 2018; Sharma *et al.,* 2000; Sharma *et al.,* 2001). The ANN advantage is the capability to model nonlinear correlations. Also, the ANN is not defined by any specific mathematical equation. The ANN's strengths have been affirmed by Sharma *et al.* (2000); Sharma *et al.* (2001), yet Sharma *et al.* (2001) suggest a percentage error of 25 from the model at an even 95% confidence interval. The travel-demand model is an estimation technique that has been explored with several predictions of future traffic patterns and volumes. The travel-demand model is based on network modeling, trip generation, trip distribution, and trip assignment. Zhong and Hanson (2009) and Wang *et al.* (2013) explore the travel-demand model on low-volume and local roads. According to Zhong and Hanson (2009), the travel-demand model may be adopted to reduce the cost associated with traffic volume and parameter estimation. The travel-demand model may be used to identify high-volume road segments and funding prioritization. However, Wang *et al.*'s (2013) travel-demand model has a 52% mean absolute error. The percent mean absolute error from Wang *et al.*'s (2013) travel demand model seems high; their model performs better than Zhao and Chung's (2001) ordinary linear regression model. The state of Florida's turnpike models and the origin-destination centrality-based model are techniques that have been developed and used for AADT estimates. Florida's turnpike models and the origin-destination centrality-based models rely on several factors that affect AADT. These factors are used as the models' input to estimate AADT. Florida's turnpike models require a statewide shapefile, an existing AADT shapefile, employment data, appropriate traffic analysis for the selected zones, and the HERE street network (HERE traffic analytics from HERE technologies use historical road-traffic data). Despite the high R-squared values and the low percent mean absolute error from the origin-destination centrality-based model, the model requires the availability of known AADT data as well as information about the use of the land parcels, the street networks, and the associated boundaries in order to articulate the required prediction. Jessberger *et al.* (2016) evaluated four estimation methods (simple average; AASHTO; AASHTO with a day of the week or the month-of-year adjustment factors; and Highway Policy Steven Jessberger Battelle- HPSJB) for AADT. In the evaluation, some days did not have all of the hourly observations available. Therefore, the authors had to adjust the weeks' traffic volume per day and the days per month. However, the authors asserted that there was a remarkable improvement with the accuracy and precision. The comparison was based on the estimations' bias and precision. Accordingly, Jessberger *et al.* (2016) successfully evaluated their estimating techniques.

Estimates with geostatistics present the least errors when compared to known, conventional estimating methods (Staats, 2016). The spatial interpolation approach allows for AADT estimates of values for sampled and unsampled locations (Eom *et al.,* 2006; Wang & Kockelman, 2009). Toblers' first law of geography is the basis for the spatial interpolation (Geostatistics-Kriging) estimation approach.

Although extensively explored and successfully used for prediction in other scientific disciplines, geostatistical methods have barely been used in the transportation industry. Eom *et al.* (2006) explored spatial statistics to estimate AADT on non-freeway facilities. Wang and Kockelman (2009) and Selby and Kockelman (2011) studied spatial interpolation and the universal Kriging model when estimating AADT for Texas roads. Shamo *et al.* (2015) investigated AADT estimation using linear spatial interpolation. Klatko *et al.* (2017) utilized Kriging, inverse distance weighting (IDW), natural neighbor (NN), and trending techniques to address the estimation of vehicle miles traveled on local roads. Apronti *et al.* (2016) suggested using the travel-demand modeling and spatial interpolation methods more accurately when estimating AADT results. The outcome will help compare methods and, at the same time, select an easy-to-implement, cost-effective AADT prediction technique which is best for low-volume roads (Apronti *et al.,* 2016).

Eom *et al.* (2006) suggested using a geostatistical (Kriging) approach when estimating AADT. Geostatistical models incorporate the spatial dependency of the traffic volume monitored at one station and are correlated with the volumes at neighboring stations. The process allows for the accurate prediction of unknown or unsampled locations. In addition, the process accounts for the spatial trend (mean) and spatial correlation. Eom *et al.* (2006) proposed that, even with budgetary constraints at all levels of the transportation department, the technique may help to estimate AADT accurately. Wang and Kockelman (2009) noted that pavement conditions, traffic speeds, population densities, land values, household incomes, and trip generation are areas that make up transportation evaluation. Therefore, the application of Kriging techniques may be applied to aid in better decision-making. Wang and Kockelman (2009) encouraged the exploration of Kriging as a better option than other techniques, based on the points closest to the sampling site, for accurate spatial extrapolation and prediction of AADT. Eom *et al.* (2006) noted that using the geostatistical approach in urban areas has a much better prediction than in rural areas. The assertion was based on data adequacy and availability. However, other literature sources suggested sophisticated geostatistical techniques besides simple Kriging; therefore, data adequacy can be resolved. Thus, spatial interpolation techniques were seen as useful techniques for transportation researchers to obtain accurate estimates. A typical sophisticated geostatistical technique is the empirical Bayesian Kriging (EBK), which can resolve the drawbacks and uncertainties with the datasets' classical Kriging models. According to Gribov and Krivoruchko (2020), the EBK technique can efficiently interpolate small to large datasets up to a billion data points. Also, EBK can outperform all other predictors with even an ever-increasing complexity in dataset (Gribov & Krivoruchko, 2020).

Limitations and implications

The study is limited to systematically analyzing secondary data related to AADT estimation methods published between 1999 and 2020.

Departments of Transportation decision-makers can adopt the study's findings to help in selecting appropriate methods for AADT data estimation. This presents an overview of existing research into AADT estimation methods collected from previously published documents. In addition, it provides a valuable suggestion that may be used to validate other methods not included in this document.

Conclusions

Researchers have proven that AADT estimation methods work for the tested locations. Scholars argue that some techniques for AADT estimates have performed better than others. Various authors also claim that several assertions about the AADT data estimation methods could be validated, whereas others cannot be confirmed. Some AADT estimation techniques are only applicable in specific locations. Others require significant data to provide accurate estimates. Several processes to adjust models for a location may be needed for other locations. Some authors discuss techniques that are not applicable at every location of interest. Nordback *et al.* (2019) caution that certain models serve the purpose of minimizing the errors when estimating AADT for nonmotorized or low-volume roads. Therefore, those models may serve as guides to better the estimation and AADT monitoring programs. 30 AADT estimating methods were obtained by counting methods from each article with the systematic literature review; however, some appeared to have been repeated as some authors compared two or three methods in a single paper. The AADT estimating methods were meta-analyzed based on the measure of performance of the methods. The performance measures utilized were R squared (R^2), root means square error (RMSE), and mean absolute percentage error (MAPE). Forest plots were generated with the results of the meta-analysis. Generally, the results were mixed, indicating a measure of similar effects but under different conditions. Challenges exist when estimating ADDT for planning and development, especially when data-collection methods and data acquired are inadequate or are considered rough estimates (Wang & Kockelman, 2009). For example, the reduction-effectiveness ratio method adopted by Wang and Tsai (2013) cannot generate the much-needed cost-effectiveness. The model was intended to reduce data collection, especially in rural areas, on low-volume roads, and in areas with high variability in the dataset. Generally, the authors of the various AADT data estimation techniques aim to generate an accurate and reliable method that all users may adopt for every location. The models were to possibly incorporate spatial and temporal variability and to generate data for unsampled locations. The qualitative evaluation of the advantages and disadvantages in Table 4 places Kriging methods (geostatistical approaches) above all other methods. The result for the Kriging techniques was consistent with generating accurate and precise AADT estimates with fewer errors. Besides, this method is a statistically significant technique. The Kriging methods (geostatistical approach) incorporate both Spatio-temporal variabilities and unsampled locations in the final outputs and are applied to every location. There are no boundaries and restrictions when using the geostatistical methods. The methods are significantly affected by terrain/ geographical locations, skewness, randomness, and stationarity in the dataset. A stand-alone Kriging method may be preferred to complete the estimation using two or more methods. The normal score transformation to apply the simple Kriging method can approximate non-symmetric data to symmetrical. Recently, the geostatistical approach was proven to be a better option for estimates. The geostatistical approach outperformed many of the methods in use today. Wang and Kockelman (2009) suggested that "Kriging is a promising way to explore spatial relationships across a wide variety of dataset."

Furthermore, there is an opportunity to produce a much-enhanced form of the Kriging technique. The enhanced geostatistical methods incorporate the ordinary Kriging capabilities while solving additional complexities in the dataset. None of the evaluated techniques were superior to the geostatistics Kriging method. Therefore, the Kriging method may be adapted to generate a universally accepted approach for estimating AADT data values. Other scientific fields, such as environmental research, ore reserve estimation, groundwater quality, health surveys, etc., have successfully employed Kriging geostatistical Kriging methods, such as simple Kriging and other Kriging methods, empirical Bayesian Kriging, geostatistical simulations, and coKriging. These techniques have been confirmed as the potentially preferred methods. These approaches are robust, precise at predicting, and have improved other techniques' predictive capabilities in practice and applicability. Therefore, the scientific disciplines have confirmed the effectiveness of the geostatistical tools in many publications. To conclude, it is expected that this literature study will serve as a guide for all AADT-data users, especially for local, low-volume, and rural roads, to fill in the gaps and factors that affect AADT estimation when solving with inadequate data-collection and budget issues.

Data availability statement

All data underlying the results are available as part of the article and no additional source data are required.

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Open Peer Review

Current Peer Review Status: ✔ ✔

Version 1

Reviewer Report 27 July 2023

https://doi.org/10.21956/emeraldopenres.15612.r29126

✔ **MOYA IGNACIO MANUEL**
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In my opinion, the paper is of great interest to determine the state of the art of the different techniques developed to estimate the AADT. The literature review is wide enough and fully updated. The objectives are clear, and the results and discussion section is well shown and explained as well.

From my point of view, the conclusion section could be a little bit shorter. Some paragraphs in this section are of great extension and they could be better synthesized. In some cases, they seem more a dissertation than a conclusion properly providing information not too relevant that has been previously exposed at the discussion section. It could be enough citing the different techniques and to conclude their adequacy to the type of roads and/or circumstances, so that other researchers can consider their application or not in each case.

Is the work clearly and accurately presented and does it cite the current literature?
Yes

Is the study design appropriate and is the work technically sound?
Yes

Are sufficient details of methods and analysis provided to allow replication by others?
Yes

If applicable, is the statistical analysis and its interpretation appropriate?
Yes

Are all the source data underlying the results available to ensure full reproducibility?
Yes

Are the conclusions drawn adequately supported by the results?

Yes

Is the argument information presented in such a way that it can be understood by a non-academic audience?
Yes

Does the piece present solutions to actual real world challenges?
Yes

Is real-world evidence provided to support any conclusions made?
Yes

Could any solutions being offered be effectively implemented in practice?
Yes

Competing Interests: No competing interests were disclosed.

Reviewer Expertise: Low-volume roads.

I confirm that I have read this submission and believe that I have an appropriate level of expertise to confirm that it is of an acceptable scientific standard.

Reviewer Report 27 June 2023

https://doi.org/10.21956/emeraldopenres.15612.r28954

Sam Ricord
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This paper conducts a systematic literature review on AADT estimation of rural roads. To do this a systematic literature review and meta-analysis using R-squared, RMSE, and MAPE were used. It was found that Kriging methods perform best for AADT estimation.

I do have one comment for the authors to consider: At the beginning of the Discussion section, the authors mention "further studies are in progress to improve the output". Please elaborate on these studies further so the readers can understand what further work is being done in the field. Also, this idea can be discussed further in the limitations section to highlight what areas need further improvement.

Is the work clearly and accurately presented and does it cite the current literature?
Yes

Is the study design appropriate and is the work technically sound?

Yes

Are sufficient details of methods and analysis provided to allow replication by others?
Yes

If applicable, is the statistical analysis and its interpretation appropriate?
Yes

Are all the source data underlying the results available to ensure full reproducibility?
Yes

Are the conclusions drawn adequately supported by the results?
Yes

Is the argument information presented in such a way that it can be understood by a non-academic audience?
Yes

Does the piece present solutions to actual real world challenges?
Yes

Is real-world evidence provided to support any conclusions made?
Yes

Could any solutions being offered be effectively implemented in practice?
Yes

Competing Interests: No competing interests were disclosed.

Reviewer Expertise: Rural Road Transportation Safety and Equity, Data Equity

I confirm that I have read this submission and believe that I have an appropriate level of expertise to confirm that it is of an acceptable scientific standard.