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JASA ARTICLE

Toward a dynamic national transportation noise map: Modeling temporal variability of spectral traffic noise emission levels

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ABSTRACT:
The National Transportation Noise Map predicts time-averaged road traffic noise across the continental United States (CONUS) based on annual average daily traffic counts. However, traffic noise can vary greatly with time. This paper outlines a method for predicting nationwide hourly varying source traffic sound emissions called the Vehicular Reduced-Order Observation-based Model (VROOM). The method incorporates three models that predict temporal variability of traffic volume, predict temporal variability of different traffic classes, and use Traffic Noise Model (TNM) 3.0 equations to give traffic noise emission levels based on vehicle numbers and class mix. Location-specific features are used to predict average class mix across CONUS. VROOM then incorporates dynamic traffic class mix data to obtain dynamic traffic class mix. TNM 3.0 equations then give estimated equivalent sound level emission spectra near roads with up to hourly resolution. Important temporal traffic noise characteristics are modeled, including diurnal traffic patterns, rush hours in urban locations, and weekly and yearly variation. Examples of the temporal variability are depicted and possible types of uncertainties are identified. Altogether, VROOM can be used to map national transportation noise with temporal and spectral variability.
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I. INTRODUCTION

Road traffic noise comprises a significant amount of total anthropogenic noise in many developed areas and can have a large impact on diverse acoustic environments. Increased noise levels are correlated with anything from mild annoyance to an increase in violent crime.[1–3] Not only humans are adversely affected by loud traffic noise,[4,5] but many other species are as well.[6,7] Whereas studies typically look at 24-h averaged overall sound pressure levels, traffic noise exhibits significant spectro-temporal variability. Traffic noise cannot be effectively measured along every roadside in the country, and long-time-averaged levels are seldom accurate for particular times of day, therefore, accurate modeling of vehicular noise is necessary for improving traffic noise characterization.

Because overall road traffic noise is directly related to traffic volume—the number of vehicles per time period—road traffic noise characterization depends heavily on the characterization of traffic volume itself, along with other parameters such as vehicle class mix, vehicle speed, pavement type, and road inclination.[8,9] The National Transportation Noise Map (NTNM), published by the Bureau of Transportation Statistics, uses annual average daily traffic (AADT) counts to predict annually averaged *A*-weighted 24-h equivalent sound levels near major roads across the continental United States (CONUS), Alaska, and Hawaii.[10] Although this map is useful for determining average sound levels, it lacks temporal and spectral variability and so may not reflect the actual sound level for a particular time period.

Cook *et al.*[11] recently outlined a method to represent traffic volume dynamics. This traffic volume model is the first part of the Vehicular Reduced-Order Observation-based Model (VROOM), a flow chart of which is displayed in Fig. 1. The traffic volume model used principal component analysis on reported traffic volume to find a compact way to represent traffic volume concisely. By using a combination of road data (e.g., speed limit, through lanes, and road classification) and geospatial data (e.g., combinations of features like nighttime light brightness, land cover, and population), the VROOM traffic volume model enables prediction of dynamic traffic volume across CONUS. Further developments of the traffic volume model with expected sound level errors in decibels based on total traffic volume were published alongside a comparison with expected errors when using time-averaged traffic volume in Cook *et al.*[12] The VROOM-based predictions were revealed to have much smaller errors than those obtained from time-averaged traffic volume. This paper is a direct continuation of Cook *et al.*[12] on the traffic volume model and, hence, the interested reader is encouraged to consult that publication for additional information.

The traffic volume model incorporated in VROOM is an important step toward modeling characteristic dynamic sound levels of road traffic. Another important step is to

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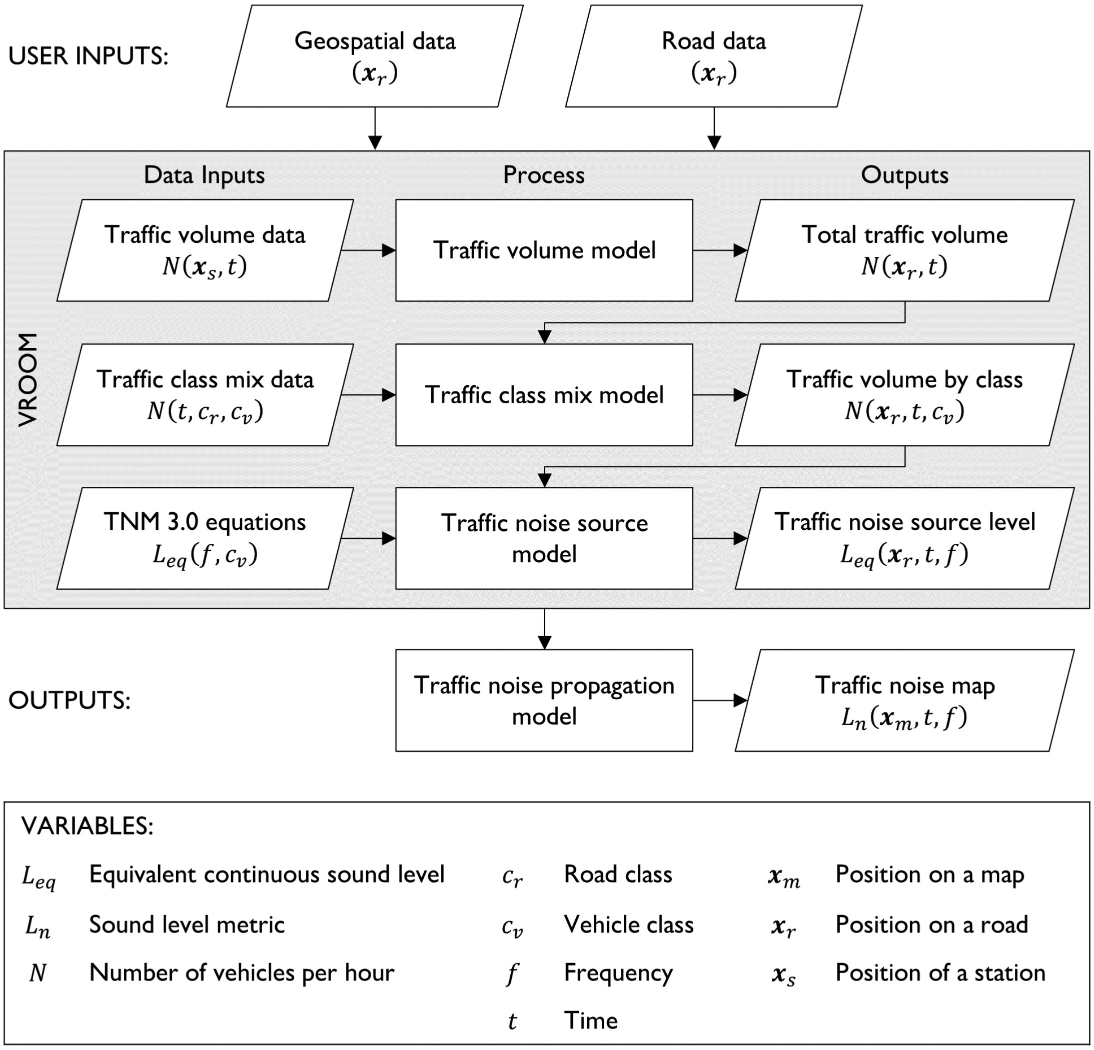

FIG. 1. Flowchart outlining the steps toward creating a dynamic national road traffic noise map. For further information on the traffic volume model incorporated in VROOM, see Ref. 12. The traffic class mix model and traffic noise source model are presented in this paper. VROOM, which consists of all three models, can then be used to create traffic noise maps that include spectro-temporal variability.

characterize traffic class mix or the different types of vehicles that compose the total traffic volume. Heavy trucks generally produce much higher sound pressure levels than smaller vehicles, and their characteristic sound spectra also differ.[13] This paper outlines the traffic class mix model and traffic noise source model used by VROOM. As shown in Fig. 1, these are the second and third models that, together with the traffic volume model, comprise VROOM. By combining modeled hourly class mix with modeled total traffic volume, hourly vehicle numbers for each traffic class type are modeled.

When vehicle class numbers are known, either reported or modeled by VROOM, the Traffic Noise Model (TNM) 3.0 equations of the Federal Highway Administration (FHWA) can be used to predict hourly spectral traffic noise source levels.[13] Spectral traffic noise source levels or traffic noise emission levels are the predicted one-third octave band *A*-weighted equivalent levels, or LAeq, produced by a given number of vehicles of each traffic class type. As defined by the TNM 3.0 equations,[13] the traffic noise emissions give an estimate of the spectral levels that would be measured 15 m (50 ft) from a road segment at a height of 1.5 m (5 ft), dependent on vehicle traffic class numbers, speed, and road type.

By incorporating the TNM 3.0 equations,[13] VROOM uses road data and geospatial data to predict traffic noise source levels across CONUS. As depicted in Fig. 1, the predicted traffic noise source levels can then be used in conjunction with traffic noise propagation models to predict traffic noise across the continent with spatial, spectral, and temporal variation. VROOM-predicted noise levels do not include propagation of sound to acoustic receivers at different distances from roadways but instead give predicted traffic noise source levels for individual road segments. Obtaining complete spatially varying traffic noise maps requires propagating source levels from road locations, which remains a topic for future consideration and, therefore, is not discussed in this paper.

VROOM can be useful for many different applications beyond the noise applications mentioned previously. Urban planning uses traffic congestion and, thus, can benefit from additional insights into traffic dynamics.[14,15] Similarly, freight analysis framework forecasting could be aided by the VROOM framework.[16–18] Beyond characterizing noise emissions, VROOM could also be helpful for traffic planning in reducing greenhouse gas emissions.[19] Many health and annoyance studies use daily average sound levels with possible penalties for nighttime hours, but with VROOM, hourly levels can be obtained directly from predicted traffic volume and traffic class mixes. This enables predictions specific to the hour or hours of interest for such studies rather than adjusting daily averages to target those hours.

II. GEOSPATIAL AND ROAD DATA

VROOM uses a combination of geospatial and road data to predict temporal variability of traffic volume. In this section, these input variables are considered. Although the geospatial data values are available everywhere across CONUS, road data may or may not be reported for all locations, hence, VROOM accounts for missing road data by using default values employed by TNM based on road characteristics and predicts AADT when it is not reported.

A. Geospatial data

The geospatial data used by VROOM comprise 13 values for each location and are available everywhere across CONUS. One type is a Boolean value that indicates whether a location is classified as urban (including suburban) or rural. The other 12 values are known as diffusion coordinates (DCs) and are further described in Pedersen[20] Diffusion mapping, sometimes called geometric harmonics, is a method used to reduce the dimensionality of high-dimensional data or graphs.[21] The DCs are a reduced-order representation of a larger dataset of 51 geospatial features, including brightness of nighttime lights, population density, land use, etc. The DCs are ordered nonlinear combinations of these 51 geospatial features, the details of which are beyond the scope of this paper.[22–25] The merits for the first DC values are shown across CONUS at road locations in Fig. 2. Values for the first DC are positively correlated with more populated areas, which are positively correlated with a higher traffic volume. The supplementary material includes maps of these 13 geospatial values at roads across CONUS. Important variations, such as constructing housing in land previously used as farmland, cause changes in DC values and, therefore, in VROOM predictions.

B. Road data

Whereas publicly available FHWA hourly traffic counts are only reported at a few thousand locations across CONUS (which will be discussed further in Sec. V), FHWA road data are reported for millions of road segments across CONUS.[10] However, for locations where road data are unknown, TNM default values can be used for the number of through lanes, the *f*-system (which distinguishes interstates from highways or other types of roads), pavement type, and speed limit. Additionally, VROOM limits these values in computation to avoid unnecessary complexity, such as limiting the maximum number of through lanes to eight. To see the reported values alongside the values used by VROOM, see the supplementary material.

1. AADT

Dealing with missing AADT values and also missing average class mix data is more difficult because default values are not available. Instead, values must be predicted.

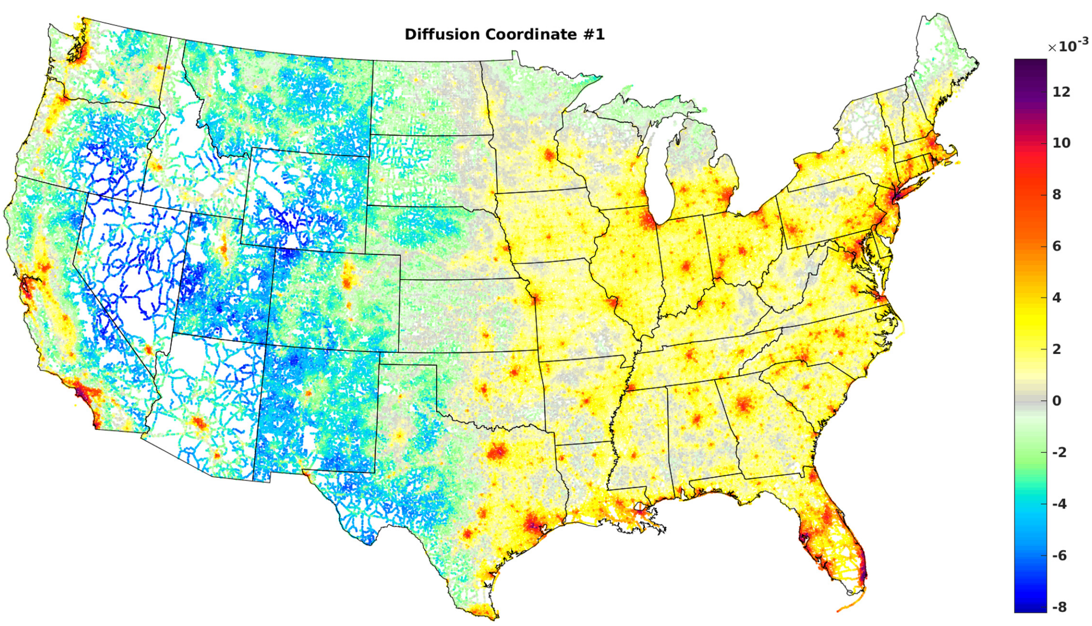

FIG. 2. (Color online) Values for the first DC are depicted geographically. For all 12 DC values used by VROOM, see the supplementary material.

Several methods were investigated for predicting the AADT. Ultimately, separate models were created for different f-system values, urbanizations (urban or rural), and each individual state because states tend to have very different reported AADT values, even when other road and geospatial values are similar. For each model, a least squares fit of the logarithmic value of the AADT, with the DCs as the predictive variables, was found to be more accurate than using unscaled AADT values. Mathematically, let D_{s_i,u_i,f_i} be the DCs for all roads in a particular state with the same urbanization and f-system values and A_{s_i,u_i,f_i} be the logarithm of the known AADT. The predicted logarithmic AADT values, $\tilde{A}_{s_i,u_i,f_i}$, for other locations in the same state with the same urbanization and f-system values can be found using the DCs at those locations, $\tilde{D}_{s_i,u_i,f_i}$, by

$$\begin{aligned} X_{s_i,u_i,f_i} &= \min_X \|D_{s_i,u_i,f_i}X - A_{s_i,u_i,f_i}\| \\ &= \left(D^T_{s_i,u_i,f_i}D_{s_i,u_i,f_i}\right)^{-1}\left(D^T_{s_i,u_i,f_i}A_{s_i,u_i,f_i}\right), \\ \tilde{A}_{s_i,u_i,f_i} &= \tilde{D}_{s_i,u_i,f_i}X_{s_i,u_i,f_i}, \\ u &= \{\text{urban, rural}\}, \quad s = \{\text{US states}\} = \{\text{AL}, \ldots, \text{WY}\}, \\ f &= \{\text{interstate, other freeway, principal arterial, other}\}. \end{aligned} \tag{1}$$

Then, the matrix X_{s_i,u_i,f_i} is the transformation from DCs to the predicted logarithm of the AADT for a particular state, urbanization, and f-system. Because a matrix X_{s_i,u_i,f_i} is created for every combination, a value for the AADT can be predicted at every road across CONUS using the DCs.

The AADT for each reported location is shown alongside the AADT used by VROOM in Fig. 3. By design, predictions are constrained to be nonnegative. Although many locations do report AADT values, VROOM can predict the AADT at locations where values are not given. In Fig. 3, the locations with predicted AADT values are more easily observed in the Western states, where road density is less than that in Eastern states. Whereas the accuracy at small-scale locations, such as individual cities, is not discussed herein, this approach minimizes errors across CONUS. Possible prediction biases are considered in Sec. V.

2. Average traffic class mix

Like the AADT values, average traffic class mix, which gives the percentage of combination trucks, single-unit trucks, and other vehicles, is not reported along all road segments. Before a dynamic class mix can be predicted, the average class mix must be predicted when it is unknown. A similar method to the AADT prediction method is used but with a few additional constraints.

To be physically meaningful, individual traffic class mix percentages must always be between 0% and 100%. Additionally, the sum of all traffic class mix predictions must be equal to 100%. Although these constraints can be met in various ways, such as ensuring non-negativity and regularizing predictions, another option is to consider traffic class mix percentages as an n-dimensional spherical coordinate on a hyperplane.[26] For a particular traffic class mix of the three main FHWA traffic class types (combination trucks, single-unit trucks, and other vehicles), this can be represented as a point on the plane $x + y + z = 1$, which is characterized by the two angular coordinates θ_1 and θ_2, where $0 \leq \theta_i \leq \pi/2$. This approach is particularly useful as it is generalizable to any number of traffic class types (e.g., buses and motorcycles) and not limited to just the main three traffic class types.

Average traffic class mix is predicted in the same manner as the AADT but by way of predicting angular coordinates rather than values or percentages directly. The angular coordinates predicted using the least squares approach outlined in Eq. (1) are then converted to percentages for each traffic class type. Figure 4 shows the reported percentages of single-unit and combination trucks alongside the percentages used by VROOM. The stark differences observed at state borders are a result of differences in traffic characteristics reported by each state. A nationwide predictive model is simple to implement, but as states can and do report very different traffic characteristics, VROOM predicts missing data using unique models for each state. This serves to make results consistent within individual states such that discontinuities occur at state borders instead of within a state at locations where values are and are not reported.

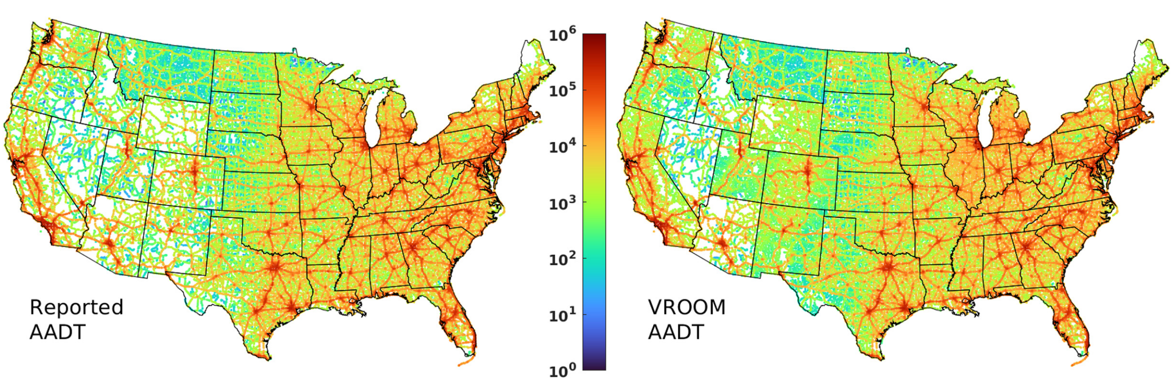

FIG. 3. (Color online) Reported AADT values are displayed alongside AADT values used by VROOM. VROOM can predict logarithmic AADT values at locations where the values are unknown.

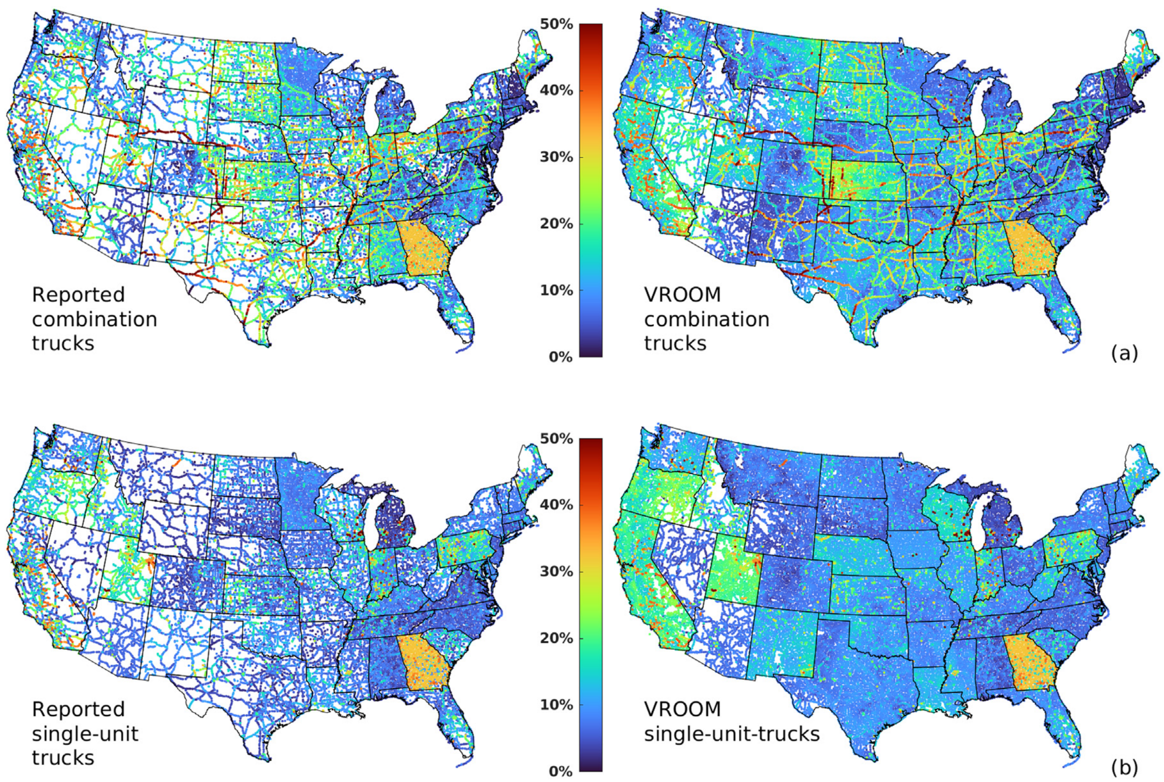

FIG. 4. (Color online) Reported percentage of traffic that is (a) combination or (b) single-unit trucks depicted alongside the percentages used by VROOM. Predicted percentages are only needed at locations where traffic class mixes are not reported. Differences in reported values by different states, as observed along state lines, explain the need for creating models for each state separately.

III. TRAFFIC CLASS MIX MODEL

With either reported or predicted average traffic class mix values, VROOM then models temporal variation in traffic class mix numbers using a traffic class mix model (see Fig. 1). In 1997, a FHWA report was published by Hallenbeck *et al.*[27] This report includes observed characteristic temporal variation of the three main traffic class types for urban and rural locations and, despite its age, is still used by the FHWA for traffic volume by vehicle classification. For improved fidelity, more modern traffic class mix studies could be considered but are not publicly used by the FHWA and, therefore, are not considered herein. The results of Hallenbeck's report can be used together with VROOM's traffic volume model[12] to predict temporal variation in each traffic class type on roadways across CONUS. Yearly variation is predicted separately from weekly variation as outlined below.

A. Yearly variation

Observed yearly traffic characteristics of different traffic class types from Hallenbeck *et al.*[27] are reported on a month-by-month basis for urban and rural locations (see Table 7 therein). The monthly resolution described is a discrete representation of just 12 values. However, using VROOM's traffic volume model, smooth yearly traffic variation can be represented with just three values. For further details, see Cook *et al.*[11] The three coefficients to represent the relative amount of combination trucks across a year (and three to represent single-unit trucks, and three more to represent other vehicles) are found by using a least squares fitting method, yielding the coefficients that create the yearly traffic flow pattern which most closely matches the stepwise reported yearly traffic variation of each traffic class type in the Hallenbeck data.

The Hallenbeck data represent the compilation of traffic counts at 99 geographic locations, and the reported values are given for each month of a year. The VROOM representation was obtained from traffic count data at thousands of geographic locations with values for each hour of a year. By finding a VROOM representation to approximate the Hallenbeck data, a smoothed traffic pattern based on nationwide reported traffic flow behavior is obtained. The Hallenbeck data are shown together with the fitted pattern in Fig. 5. Note that because the mean value is equal to one, the fitted value can be used as a yearly traffic class multiplier. When multiplied by the average traffic class percentage and predicted total traffic volume, the product gives the predicted traffic volume for that particular traffic class type (e.g., the number of combination trucks) at that time period.

B. Weekly variation

Observed weekly traffic characteristics of different traffic class types from Hallenbeck *et al.*[27] are reported on a day-of-week basis and an hour-of-day basis for urban and rural locations (see Table 3 and Fig. 6, respectively, in the

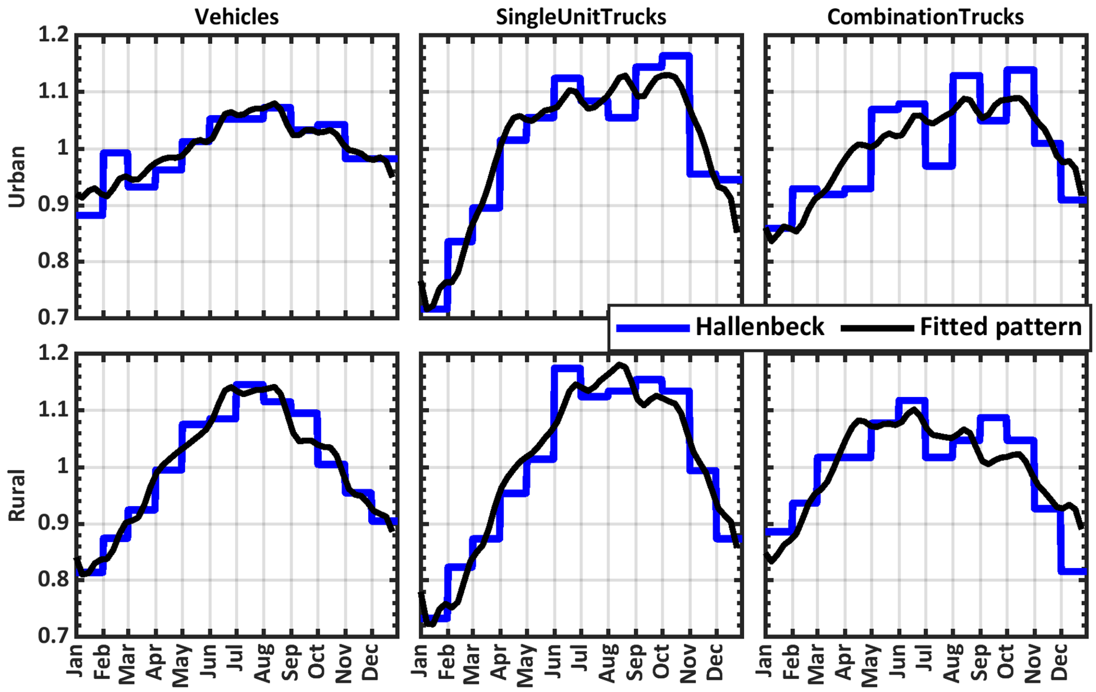

FIG. 5. (Color online) Average relative amount of each traffic class type on urban and rural roads as observed in Hallenbeck *et al.* (Ref. 27) and the fitted pattern using VROOM's yearly traffic volume model representation.

report). By combining the two, a total hour-of-week characteristic variation is obtained. Although this makes for a relatively smoothly varying representation, there is some discontinuity when transitioning to and from the weekends, most notably for heavy/combination trucks. Further refinements, such as accounting for the lack of rush hour traffic for urban vehicles on weekends, are made in Hallenbeck *et al.*[27]

Rather than refining each class type and time period, the approach taken in this paper is to use VROOM's traffic volume model[12] to find a similar VROOM representation for weekly traffic patterns of each traffic class type. Just as three coefficients were found by fitting the traffic pattern to the reported yearly data for heavy trucks (and three other coefficients for single-unit trucks and three coefficients for vehicles), five coefficients are found to represent the weekly variability for single-unit trucks and five coefficients are found to represent the weekly variability for vehicles.

For combination trucks, the five-coefficient representation for weekly traffic variability used in the VROOM traffic volume model does not accurately represent observed patterns (see the supplementary material for temporal representations of the weekly principal components). This is because the number of combination trucks reported in the Hallenbeck data does not decrease significantly during nighttime hours. This highlights a potential weakness of the VROOM weekly representation; because observed total traffic volume always decreases during nighttime hours, the VROOM representation cannot accurately represent traffic patterns that do not show diurnal variability. This is not a significant issue in predicting total traffic volume but does not work well for predicting combination truck numbers. Instead of using the VROOM representation for combination trucks, the transition to and from weekend combination truck numbers is simply smoothed by adjusting the hours around midnight, which removes the large discontinuities in reported numbers.

The reported and fitted weekly traffic patterns for each traffic class type are displayed in Fig. 6. The fitted patterns shown approximate the combined patterns of the Hallenbeck data on weekdays for all traffic class types. On weekends for single-unit trucks, and more obviously for vehicles, a more smoothly varying pattern is found, which does not include the artificial morning and evening rush hours. Whereas the Hallenbeck data are further refined using additional methods (to remove erroneous rush hour patterns on weekends), the VROOM representation is automatically able to remove such artifacts because the representation was created using observed traffic counts. The smoothed pattern exhibited for combination trucks does not entirely vary smoothly but does account for the temporal variation and removes discontinuities on weekday/weekend transitions.

Figure 4 shows time-averaged reported and modeled traffic class mix percentages without accounting for temporal variation. VROOM predicts the dynamic class mix percentage at any location by multiplying the predicted temporal variation with the average class mix at that location, explained further in Sec. III C. Mm. 1 shows an example of the temporal variability across the hours of a week by showing the predicted percentage of trucks (the sum of combination trucks and single-unit trucks). Urban locations often have a low percentage of trucks during day and night while freeways often have larger percentages, which is expected.

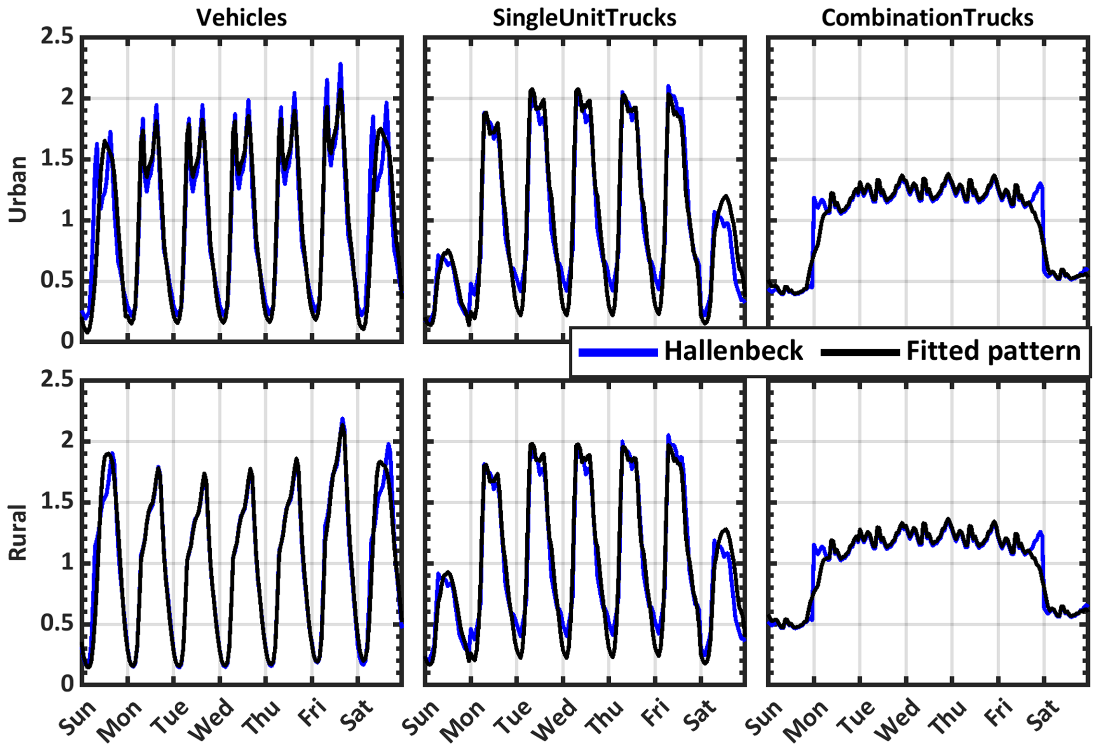

FIG. 6. (Color online) Observed and fitted hour-of-week traffic patterns for each of the three major traffic class types.

Mm. 1. The predicted percentage of trucks (combination and single-unit trucks) for hours across a week. Averaged hourly predictions across time match reported time-averaged percentages by design.

C. Combining with average predictions

Because the weekly and yearly traffic class predictions are normalized, combining them with the average traffic class for any time period desired requires only simple multiplication. The predicted number of heavy trucks for a particular time is calculated by multiplying the relative weekly prediction for that time, the relative yearly prediction for that time, the average percentage of combination trucks at that location, and the average predicted traffic volume at that location (the AADT divided by 24). Due to the constraints, the predicted number of vehicles of each class type is always nonnegative, and the sum of vehicles of each class type for any hour is the total number of vehicles predicted for that hour. In this manner, AADT values are maintained.

IV. SOUND EMISSION SPECTRA

With the predicted number of vehicles of each class type for any time period, calculating the predicted sound emission spectra requires use of the TNM 3.0 equations [see Appendix A in the technical manual, particularly Eq. (5)].[13] This is the traffic noise source model, which is displayed in Fig. 1. With these equations, the predicted number of vehicles of each class, the speed limit (whether this is a good indication of actual vehicle speed is beyond the scope of this paper), and pavement type at each location, sound emission spectral levels can be predicted for any time period with up to hourly resolution. The predicted overall sound pressure levels give a predicted 1-h *A*-weighted equivalent sound level, LAeq, at a distance 15 m (50 ft) from each road at a height of 1.5 m (5 ft), which is the predicted traffic noise source level.

Figure 7 shows the time-averaged predicted 1-h LAeq across CONUS. Interstates and other freeways are observed to be the dominant sources of traffic noise across the country, and on several freeways, sound levels exceed 85 dBA while smaller roads are much quieter, some with sound levels below 35 dBA.

Although the VROOM-predicted average sound levels are useful, the NTNM already gives time-averaged levels for geographic locations.[10] The utility of VROOM is that it can predict source levels for any time period and frequency of interest. Dynamic sound levels are more easily understood using multimedia such that results can be noticed spatially and temporally. Section IV A shows the weekly and yearly temporal variability of predicted sound levels across CONUS using multimedia. Section IV B shows predictions for two specific time periods, and Sec. IV C explains spectral variability of VROOM predictions.

A. Temporal variability

Mm. 2 shows the predicted levels for each hour across a week, where the time given is the local time for each location (traffic volume is reported in local time, therefore, all predictions are also in local time). Most locations, especially

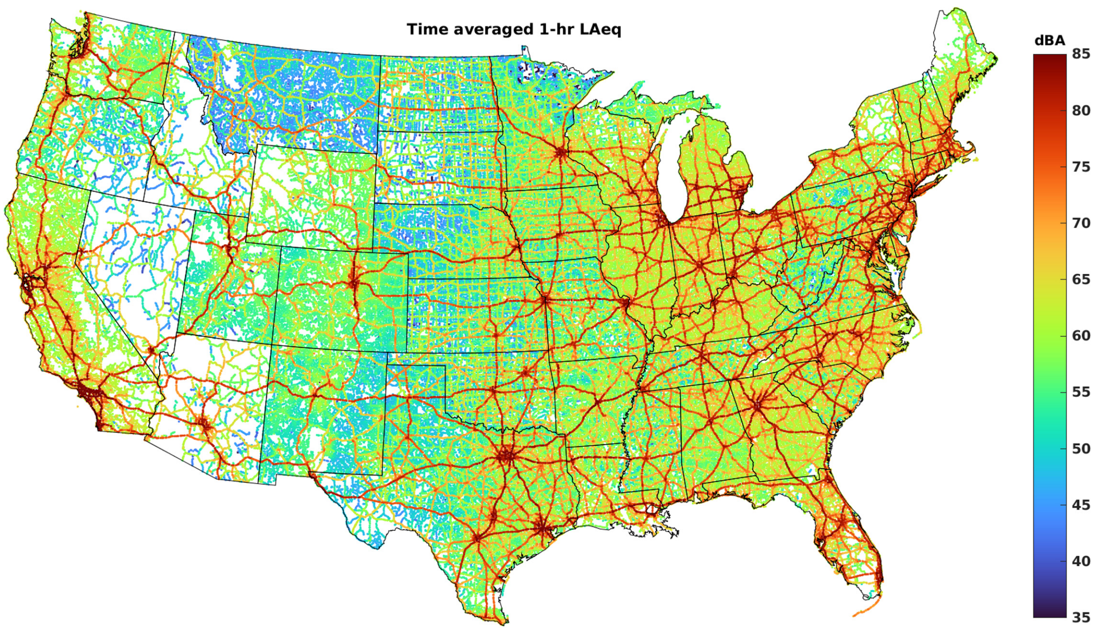

FIG. 7. (Color online) Time-averaged predicted traffic noise source levels across CONUS.

more rural locations, have a significant decrease in sound level during nighttime hours (see Sec. IV B for specific examples). For most locations, weekends show smooth increases and decreases in overall levels. Rural weekday locations show a similar pattern while urban weekdays show rush hours morning and afternoon, rather than smooth increases and decreases over the day. Friday evenings also show a more protracted decrease in sound levels.

Mm. 2. Predicted sound levels at locations across CONUS for each hour across a week in local time for each location.

In general, sound levels do not change as drastically across days of a year as they do across the hours of week. Instead of showing the predicted sound levels across the days of a year, Mm. 3 shows the predicted yearly levels relative to the time-averaged sound level for each location. A value of 3 dBA means that for that particular location, the noise level for that time period is 3 dBA larger than the time-averaged level at that location. Note that because some locations have higher sound levels than others, on average, a location with a value of –5 dBA may still have a higher overall level than a location with a value of –2 dBA. The differences revealed should not be confused with absolute levels. The changes across the year in different parts of the country are more easily seen in this manner. In the West, especially in locations where national and state parks are common, large changes can be observed from the summer to the winter. In more urban locations, there is less variation across the year. Adjacent locations show similar trends with smooth spatiotemporal variation.

Mm. 3. Predicted sound levels at locations across CONUS for each day across a year, shown relative to the average sound level for each location.

B. Examples of specific time periods

Predictions across CONUS for two different time periods are given in this subsection. Note again that in all results, local time is used. Additionally, as was performed in Mm. 3, levels are shown relative to the time-averaged LAeq (which was given in Fig. 7) and, hence, two locations with the same difference value do not necessarily have the same total level.

For the first example, Fig. 8 shows relative predicted levels for a weekday nighttime in December. Results, therefore, show a combination of the weekly behavior and yearly behavior for a location. Sound levels are observed to be lower than average for all locations, which is expected as nighttime hours are generally less busy than daytime hours and, therefore, lower than average. In many places in the Western states, levels are much quieter for this time period than on average, which is a result of the greater variation in yearly traffic for these locations, as noticed in Mm. 3. Although some urban areas show more variation at this time period than the surrounding areas, cities generally still have overall higher total sound levels at all times as they have much higher time-averaged levels. This shows that sound levels do not change in the same ways at all locations; some locations exhibit large changes in sound level while others show only small changes.

For the second example, Fig. 9 shows the relative predicted levels for a weekend afternoon in July. For many locations, sound levels are higher than average, most notably in the Rocky Mountain areas from Montana to New Mexico, as the mountainous areas are much more popular destinations during summer weekends than during wintertime. For some of the larger cities, sound levels are lower than on average. This could be a result of less traffic in cities because more people are outside of cities for summer

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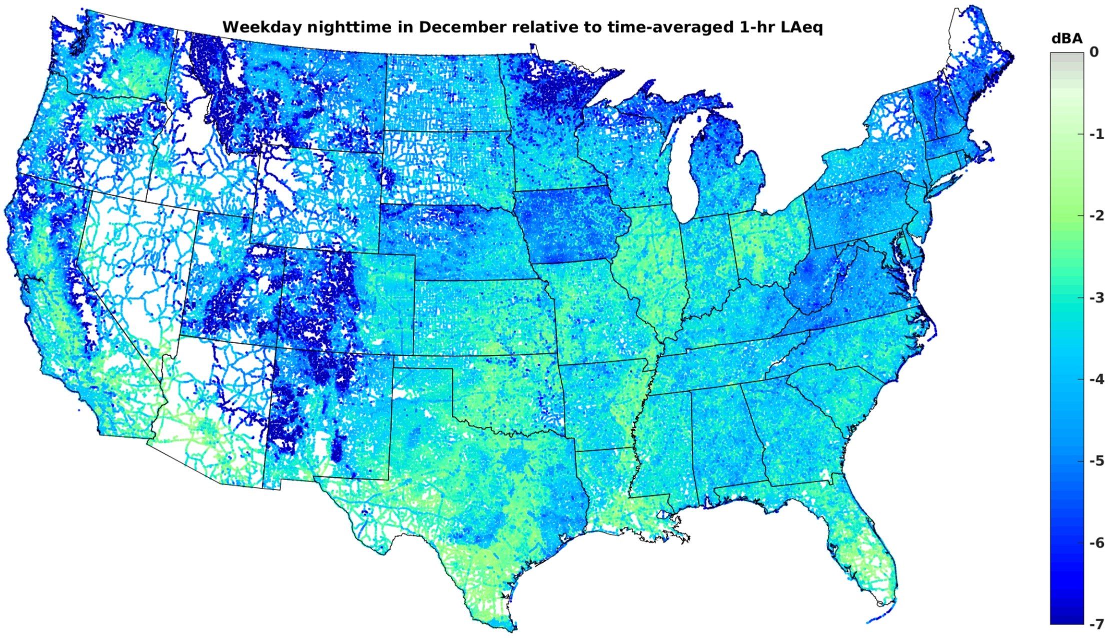

FIG. 8. (Color online) VROOM-predicted sound levels for a weekday nighttime in December relative to the time-averaged levels for each location.

vacations, although this would have to be validated by correlating with other studies on human movement.

C. Spectral variation

While consideration has been given, thus far, primarily to the spatiotemporal variability of traffic noise, its spectral variability is also important to consider. Not only do combination trucks produce higher sound levels than smaller vehicles, but they also have fundamentally different spectral characteristics. Predicted time-averaged spectral characteristics are observed in Mm. 4, which shows differences from the overall sound pressure level for each location and frequency. Differences in spectral characteristics noticed between interstates and small roads are mainly a result of different percentages of the vehicle class types, although the speed limit does contribute to spectral differences as well. This primarily shows that the spectral shape of noise near interstates differs from the spectral shape of noise near smaller roads. Mm. 4 shows only the time-averaged spectral characteristics while VROOM predicts spectral characteristics in a dynamic manner.

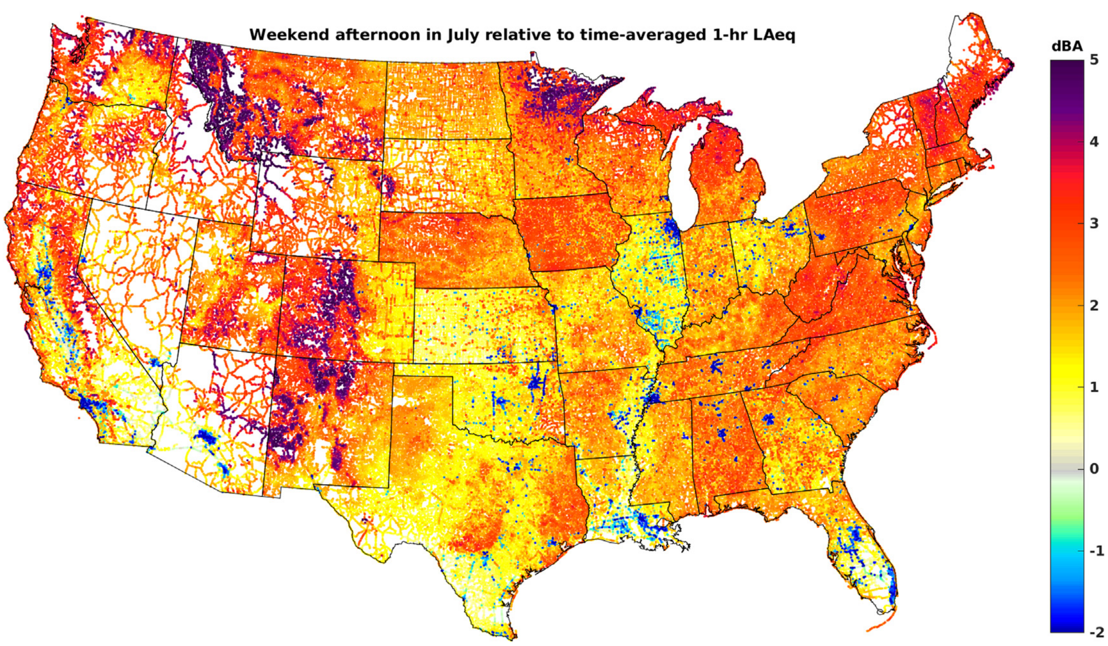

FIG. 9. (Color online) VROOM-predicted sound levels for a weekend afternoon in July relative to the time-averaged levels for each location.

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Mm. 4. Characteristic spectral differences from the overall sound pressure level for each location across third-octave bands.

V. UNCERTAINTY QUANTIFICATION

Whereas the NTNM gives a 24-h LAeq for traffic noise across CONUS, VROOM was created to address the temporal and spectral variabilities of road traffic noise. Consequently, the new model provides down to a 1-h LAeq traffic noise source level for individual road segments. To truly create a temporally and spectrally varying traffic noise map, source levels would need to be mapped to physical locations using sound propagation methods (see Fig. 1) as is performed in the NTNM. Additional adjustments caused by objects like sound barriers should also be considered. Thus, a direct comparison of NTNM to VROOM-predicted noise levels is not currently useful. However, the time-averaged 1-h LAeq displayed in Fig. 7 was calculated directly using the TNM 3.0 equations and, as such, gives the source levels such as those used to create the NTNM.

Instead of comparing predicted vehicle emission levels to time-averaged levels, the uncertainty of VROOM is considered regarding the location of traffic monitoring stations (TMSs). The VROOM traffic volume model was created using hourly vehicle counts from TMSs across CONUS. The locations of these stations are shown in Fig. 10. The VROOM coefficients, which represent the weekly and yearly traffic volume variability for any location, are calculated using the DCs for that location, and values are shown spatially in the supplementary material. Much of the uncertainty in VROOM comes from the dissimilarity of geospatial and road data values at TMSs compared to values found across CONUS.

A. Uncertainty based on road data

One form of uncertainty is caused by the bias of TMS locations relative to road data. Ideally, the distribution of any road data at TMS locations should match the distribution observed across CONUS. If the TMS distribution are unevenly weighted in comparison to the CONUS distribution, for example, containing larger AADT values, then that value will have more impact on VROOM, and other locations will be underrepresented. For categorical road data, such as urbanization, *f*-system, and pavement type, the distributions can be characterized simply by comparing what percentage of locations are in each category. These results are given in Table I.

The results in Table I show that there is some bias toward urban traffic patterns because TMS locations are more common in urban locations than there are urban roads across CONUS. To reduce bias, more TMSs could be placed along rural roads. Similarly, TMS locations are much more heavily weighted toward interstates, freeways, and principal arterial roads than CONUS and, as such, smaller roads are underrepresented as stations are often more interested in intercity travel rather than intracity travel. There are also some differences in pavement type distribution.

Other types of road data are numeric rather than categorical, such as the number of through lanes. Because VROOM uses a maximum number of only eight through lanes, this could still be summarized in table format.

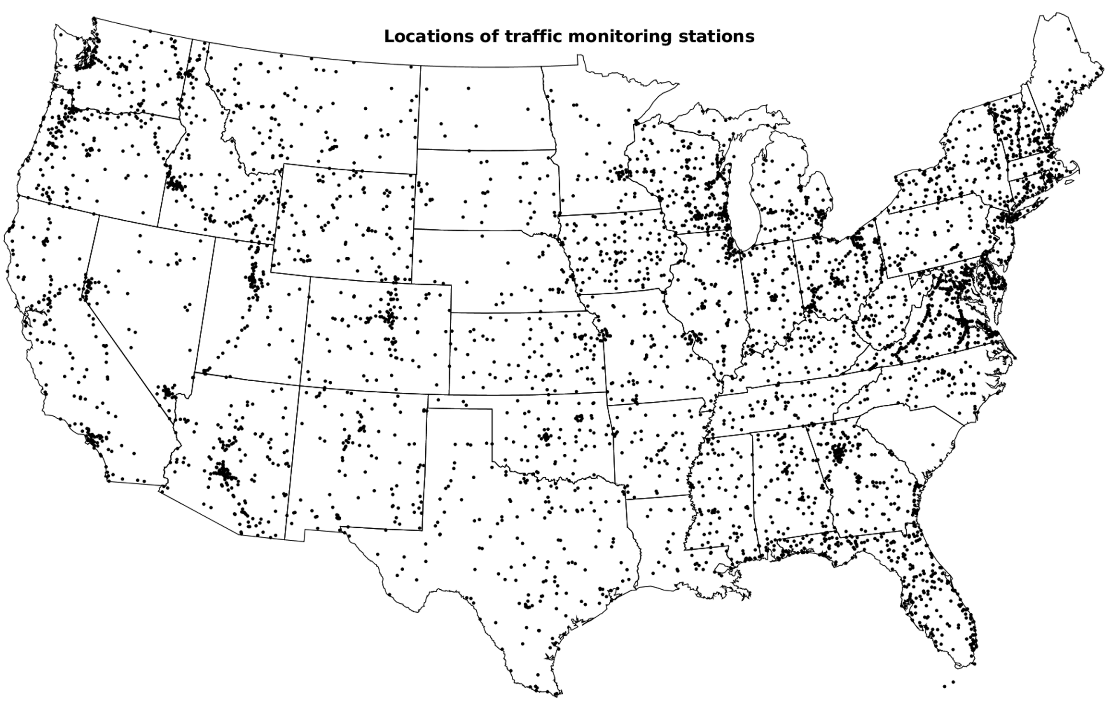

FIG. 10. TMS locations across CONUS.

https://doi.org/10.1121/10.0028627

TABLE I. Comparisons of the distributions of urbanization, f-system, and pavement type across TMS locations and across roads throughout all of CONUS.

	Distribution of urbanization			
TMS	46.2% urban		53.8% rural	
CONUS	38.8% urban		61.2% rural	
	Distribution of f-system			
TMS	26.6% interstate	9.3% other freeway	31.7% principal arterial	32.4% other
CONUS	4.0% interstate	1.7% other freeway	13.0% principal arterial	81.3% other
	Distribution of pavement type			
TMS	29.6% average	60.1% asphalt		10.3% concrete
CONUS	66.7% average	30.2% asphalt		3.1% concrete

However, when moving to a variable with more possible values, like the speed limit, a probability density plot can be used to show results more concisely. Therefore, comparisons for through lanes, speed limit, and logarithmic AADT are shown as probability densities in Fig. 11.

The distributions in Fig. 11 show that there is a bias toward a greater number of through lanes, higher speed limits, and higher AADT values. Although not surprising, as TMS locations are more likely to be located where there is more traffic, this does show that VROOM could be improved and uncertainty reduced by obtaining hourly traffic volume for locations where there is less total traffic.

B. Uncertainty based on DCs

VROOM's traffic volume model uses DCs to predict the temporal variability of traffic volume and is based on hourly counts taken at TMSs across CONUS. Therefore, in addition to comparing road data distributions at TMS locations to those for CONUS, the DC distributions should be

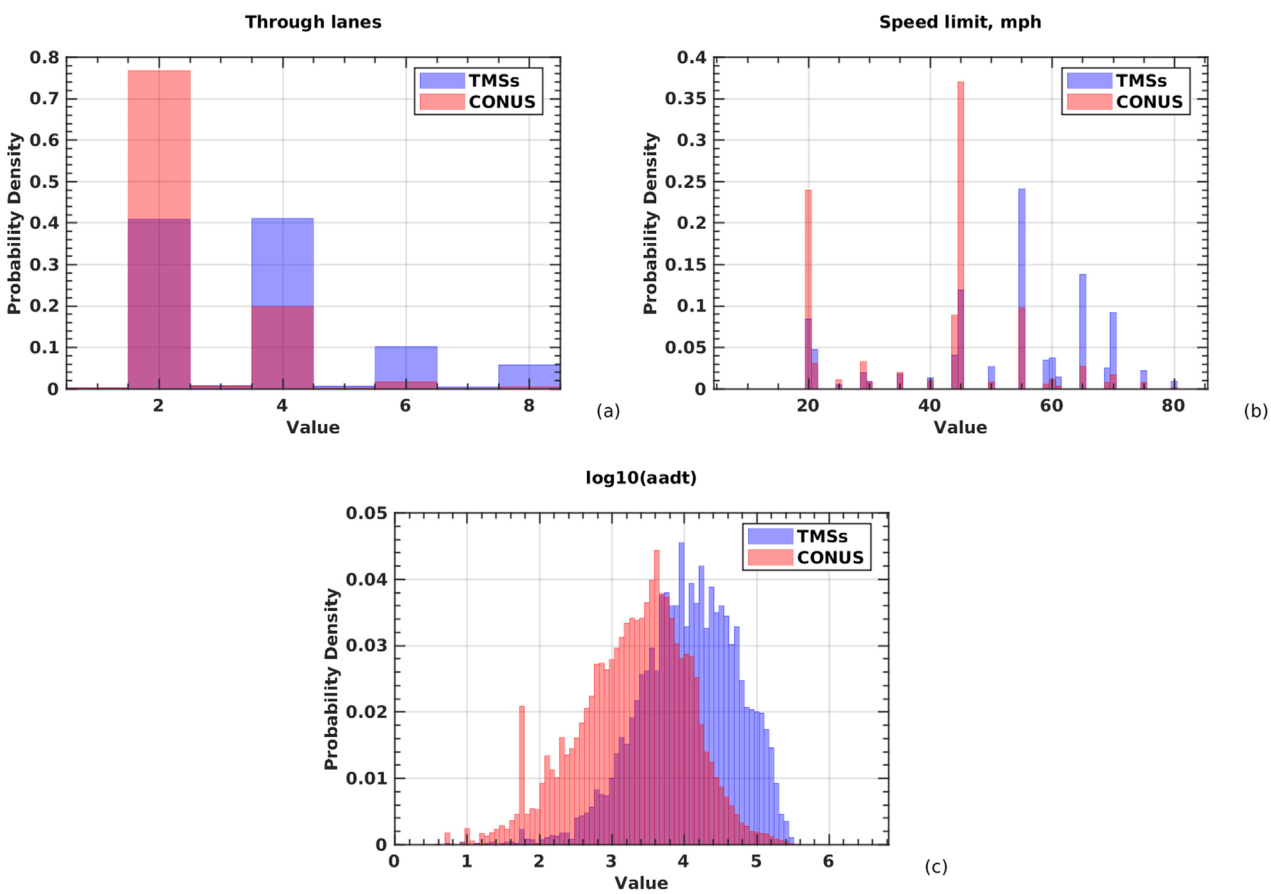

FIG. 11. (Color online) Comparisons of the distributions of through lanes (a), speed limit (b), and logarithmic AADT (c) for TMS locations and all roads across CONUS. TMS locations are more heavily weighted toward a greater number of through lanes, higher speed limits, and higher AADT values than the CONUS distributions.

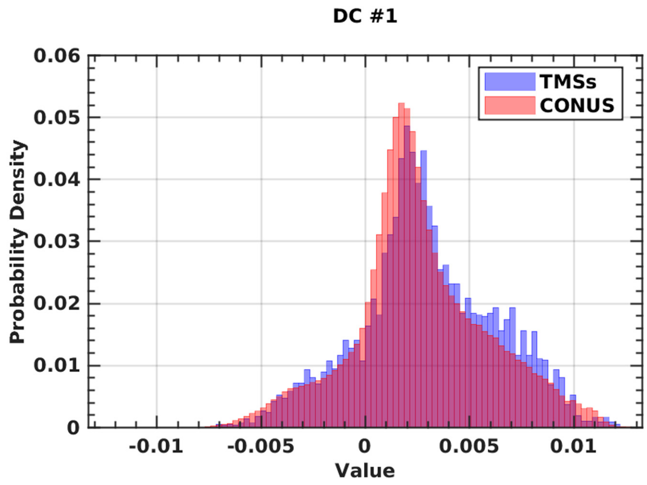

FIG. 12. (Color online) A comparison of the distributions of the first DC at TMS locations compared to those across CONUS. The distributions show high agreement. A spatial map of the first DC is shown in Fig. 2, and maps for all DCs are shown in the supplementary material.

considered. For maps of all DC values, see the supplementary material.

If certain DC values were not represented at TMS locations, then predictions for locations with those DC values would have large uncertainty, as with road data. Fortunately, despite being sparse in some geographic locations like South Carolina, TMS locations span the range of and have similar distributions to the DC distributions across CONUS. Figure 12 shows the distribution of the first DC value at TMS locations together with the distribution of the first DC value at roads across CONUS. Distributions for the other DCs are similar and given in the supplementary material.

In addition to comparing distributions for individual DCs, an uncertainty measure for an individual location in CONUS can be obtained by calculating the standard deviance, or the root mean square (RMS) distance, between that location's DC values and the DC distributions across TMS locations. This is calculated mathematically for a location, l, by using the mean (μ_i) and standard deviation (σ_i) of the DC values at all N TMSs, where DC_i is the value of the ith DC, as

$$\epsilon_l = \sqrt{\frac{1}{12}\sum_{i=1}^{12}\left(\frac{DC_{i,l}-\mu_i}{\sigma_i}\right)^2}, \quad \mu_i = \frac{1}{N}\sum_{s=1}^{N} DC_{i,s},$$

$$\sigma_i = \sqrt{\frac{1}{N-1}\sum_{s=1}^{N}|DC_{i,s}-\mu_i|^2}. \tag{2}$$

The values of ϵ_l can be calculated for each road segment across CONUS and are plotted geographically in Fig. 13. The value is the RMS standard deviation and, thus, a value of three means that the DCs for that location are, on average, three standard deviations away from the distribution of DC values represented at TMS locations. VROOM has lower uncertainty at locations with a lower RMS standard deviation. Although there is some moderate uncertainty at locations such as southern Florida and northern Minnesota, RMS standard deviation values are generally relatively low, which shows that VROOM is likely to have low uncertainty for most geographic locations across CONUS.

C. Additional uncertainty

Additional uncertainty in VROOM can be caused not just by TMS locations relative to input data but by

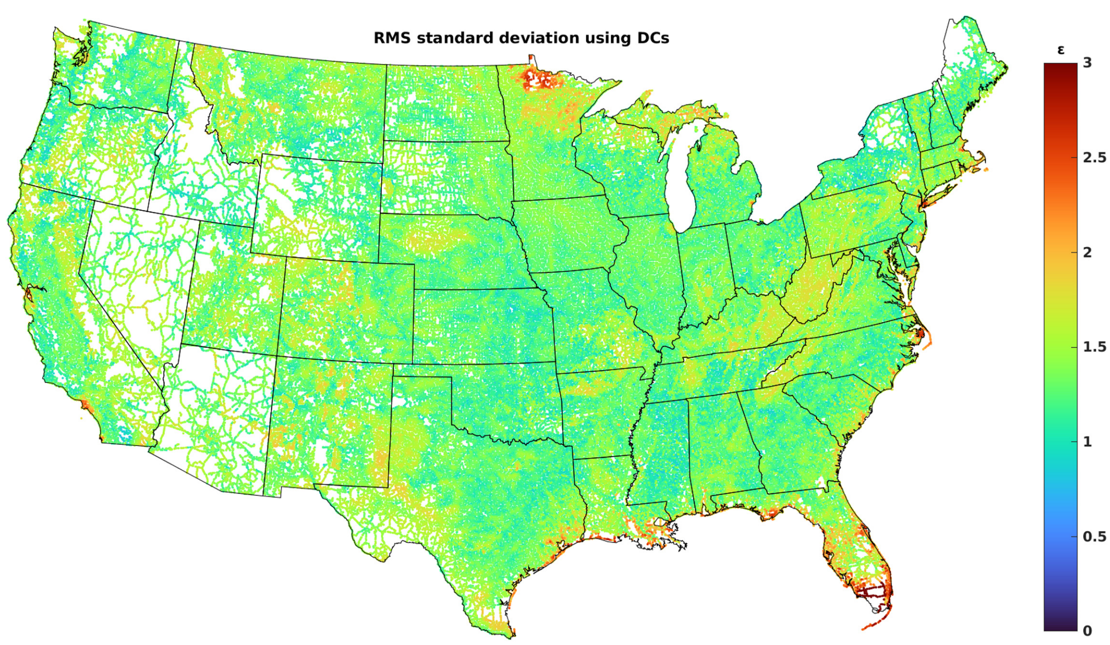

FIG. 13. (Color online) RMS standard deviations of the DCs for each location relative to the distribution across TMS locations are shown geographically. Most locations have small RMS standard deviations, where the most uncertainty is observed in locations such as northern Minnesota and southern Florida.

uncertainty in the reported data that goes into the VROOM models. To mitigate this uncertainty, TMS locations with unreasonable data (e.g., traffic volume that showed strange shifts in reported values such that traffic volume was larger during nighttime hours at irregular intervals) were given a lower weight when creating VROOM coefficients. Sites with twice as much data were weighted twice as heavily, and sites with missing data were weighted less heavily. For more details, see Cook *et al*.[11] Values for and distributions of VROOM coefficients are shown in the supplementary material along with the temporal patterns of VROOM components.

Other forms of uncertainty that are not included but could be considered are the locations at which the Hallenbeck dynamic traffic class mix data were taken,[27] and uncertainty in the source traffic noise emission equations in TNM 3.0.[13] Modern changes in traffic can create additional uncertainty; traffic class variation comes from Hallenbeck's 1997 report, and traffic volume comes from reports from 2015 to 2018. Taking into account the increase in numbers of electric vehicles and, especially, electric trucks in recent years could improve reliability of predicted sound emission levels. Adding new housing developments could change the DCs for a location, which would also change the VROOM predictions.

Uncertainties in model input values, such as vehicle speed, do not result in errors of VROOM traffic mix or volume modeling but are important to consider when looking at predicted vehicle source noise emissions. Modifications could be made to account for changes in vehicle speed with traffic volume rather than just using reported or predicted speed limits. For example, congestion indices could be used as a proxy for speed adjustment, or simple offsets could be used to account for local differences. For spatial improvements, road segments are considered separately, therefore, treating locations as a network rather than individual points would improve reliability of predictions, and time zones could then also be considered. Adding other parameters beyond the road data and geospatial data considered could, likewise, improve reliability.

VI. CONCLUSION

The hourly dynamic nature of traffic noise across CONUS can be predicted using VROOM. The included traffic volume model was first depicted in Cook *et al.*,[11] and using geospatial and road data, VROOM predicts total traffic volume with hourly resolution. Expected errors based on total traffic volume were shown in Cook *et al*.[12] The traffic class mix model exhibited in this paper expands on previous results to include prediction of traffic volume by vehicle class, which is necessary to account for differences in emitted sound spectra and levels produced by different types of vehicles. Using TNM 3.0 equations, the traffic noise source model is used to predict traffic noise source levels with hourly resolution.

Without a major nationwide validation study, either recording the traffic volume by class or recording sound levels 15 m (50 ft) from roads, expected model errors cannot be obtained directly. Instead, this paper shows locations of highest uncertainty as related to geospatial and road data bias in TMSs. Although it is not a fully robust way of calculating expected sound level errors, the results illustrate how VROOM predicts temporal and spectral variability of traffic noise based on reported and published traffic variability and noise emission characteristics. The VROOM-predicted sound levels should not be seen as a fully comprehensive analysis and prediction of traffic noise but rather as a way to account for temporal variability—and by using the TNM noise emission spectra equations, spectral variability—of traffic noise near roads.

VROOM-predicted noise source levels give expected spectrally varying sound levels near roads, and all VROOM predictions exposed in this paper give results in the form of predicted source noise levels, which are valid 15 m (50 ft) from roads. To create true sound maps, the emitted spectral sound levels would need to be used as inputs in a traffic noise propagation model, and other types of noise levels beyond an equivalent noise level, such as percentile exceedance levels, would need to be considered. These are topics of future research.

While not without its limitations, VROOM is a powerful tool for predicting temporal and spectral variability of traffic noise. Predictions are based on observed traffic volume across CONUS and TNM 3.0 traffic noise source emission equations. Expected errors, based on predicted and observed traffic volume where available, are smaller than errors obtained using time-averaged traffic volume, and model uncertainty is low for most locations. By accounting for the temporal variability of traffic volume, VROOM is able to predict traffic noise, not just for an averaged time period, but with hourly resolution.

SUPPLEMENTARY MATERIAL

See the supplementary material for additional figures, which includes spatial maps and distributions that give a greater understanding of the underlying values used in VROOM. These figures include reported road data alongside VROOM road data, DC values, urbanization status, and VROOM components and coefficient values.

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AUTHOR DECLARATIONS

Conflict of Interest

The authors have no conflicts to disclose.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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